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# RESEARCH ON A HUMAN MOVING OBJECT DETECTION METHOD BASED ON GAUSSIAN MODEL AND DEEP LEARNING

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**Abstract.** In order to understand human motion object detection methods, the author proposes a research on human motion object detection method based on Gaussian model. Firstly, traditional Gaussian models are unable to detect complex scenes or slow moving targets. Therefore, an improved Gaussian model based moving object detection algorithm is proposed. Secondly, multiple Gaussian models are used to represent the features of each pixel in the moving target image, and based on the matching of each pixel in the image with the Gaussian model, it is considered as a background point. Conversely, it is based on the principle of the foreground, and the Gaussian model is updated. Finally, by updating the foreground model and calculating short-term stability indicators, the detection effect of moving targets is improved. By determining the Gaussian distribution and pixel relationship, new parameters are set to construct the background model and eliminate the impact caused by sudden changes in lighting. The experimental analysis results show that this method can effectively detect and track moving targets, with good noise resistance, high clarity, and an accuracy rate of up to 99%. Compared with traditional Gaussian model methods, the improved method can more effectively detect moving targets and has better robustness.

**Key words:** Gaussian model, Human movement, object detection

**1. Introduction.** The ways in which humans perceive the world include touch, taste, hearing, vision, etc. Due to the presence of the human brain, eyes, nose, and other organs, these perception methods can accurately and harmoniously process the information obtained by these ”sensors” from the outside world, enabling humans to have a good understanding of the external world. With the continuous accumulation of human knowledge, as well as the development of scientific and technological foundations and computer information technology, and the increasing maturity and popularity of computer software and hardware at present, the demand for using computer technology to help humans perceive and understand the world is also increasing. A large portion of the various information that humans obtain from the outside world is obtained through visual information channels. Visual information also includes static image information and image sequence information (video information). Due to its temporal stillness, static image information can only contain information within one frame of an image, which cannot demonstrate the temporal correlation of information, on the contrary, video information, relying on its spatial and temporal connections and correlations, can contain a lot of information that is of interest to humans, especially the motion part of the video signal. It also includes the main information in the video signal, making it a key object in video signal processing. With the continuous deepening of research, video image signals play an increasingly important role in information processing and computer cognition, thus forming the emerging discipline of computer vision [1,2].

At present, the commonly used moving target detection methods are as follows: Optical flow method, time difference method, background difference method, etc. These three methods have their own advantages and disadvantages. The Optical flow can detect the moving area when the camera is not fixed, but its calculation is large, stability and accuracy are not ideal; The time difference method calculates the difference between the corresponding pixels of two or more consecutive frames of the image, and then uses a certain threshold to determine whether there is a moving object. It has good adaptability to environmental changes, but the detected motion area is incomplete, which may lead to the phenomenon of voids in the moving entity; The background subtraction method is currently the most commonly used method. By learning from existing video scenes and using mathematical models to model the background of video image scenes, the corresponding motion

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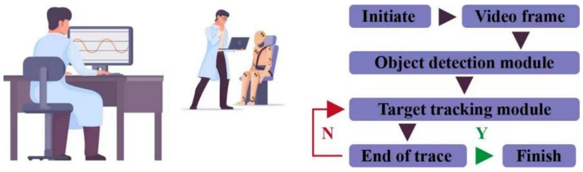


Fig. 1.1: Human motion target detection

region can be obtained by subtracting the simulated background from the current video scene frame image. The processing effect of this method depends on whether the selected mathematical model can effectively simulate the background in real time. Due to the flexibility of the mathematical modeling method and its strong adaptability to different scenarios, this method has become a fundamental method in the field of motion detection research. Many related research work in this field is based on background subtraction methods [3] (as shown in Figure 1.1).

**2. Literature Review.** When detecting and tracking moving targets, such as leaves and water surfaces, the motion frequency of background images is high, and traditional background subtraction methods cannot effectively extract dynamic backgrounds. Therefore, some scholars have proposed using Gaussian models to solve the interference caused by these background images in detecting and tracking moving targets. The Gaussian model can update certain parameters through pixels in the time series, while using the Gaussian model to expand modeling at each pixel position. However, the Gaussian model also has some drawbacks, such as: If the background conditions are complex or the moving target speed is low, the Gaussian model cannot detect and track well, therefore, improving the Gaussian model has always been a direction of effort for relevant researchers. Gaussian M ix ture M odel (GMM) is a semi parametric estimation method that can effectively represent background changes by replacing the old Gaussian distribution with a new learning distribution. At present, this method is one of the most effective methods for studying moving object detection, which has been recognized by many scholars and various improved methods have been proposed. Vaina, L. M. et al. proposed an improved method that combines the spatial depth information and color brightness information of images. This method can effectively detect the motion of multiple targets, but when different targets are at the same pixel depth, although there is different color information, it is difficult to detect moving targets [4]. Liang, S. et al. used EM learning to update the Gaussian model, and through the introduction and analysis of the algorithm, the EM algorithm is an effective algorithm for parameter estimation, but it requires pre allocation of a large amount of storage space and has poor real-time performance. Here, an improved Gaussian model for moving object detection is proposed [5]. In order to make the mean as close as possible to the background signal while ensuring the stability of variance, a weighting idea is proposed based on adaptability, which is to give different weighting values for the mean and variance in model updates to ensure that the mean updates relatively large points and the variance updates relatively small points. Finally, median filtering and pixel connectivity are used to suppress the influence of noise.

Moving object detection refers to extracting moving objects from video image sequences to obtain their differences from the relative background, and clearly marking the regions of the moving objects, thereby providing conditions and convenience for subsequent research work. The research on moving object detection has significant practical research value, making it a research hotspot in this field in recent years. With the continuous deepening of research on moving object detection, its application fields are also expanding, resulting in various practical applications and increasing research difficulty and challenges. People have also put forward higher requirements for the stability, accuracy, and robustness of detection systems. The author improves the traditional Gaussian model to achieve detection and tracking of moving targets, and verifies it through experiments [6,7].

**3. Methods.**

**3.1. Gaussian model.** The features of each pixel in the moving target image are represented by N Gaussian models, which update with each frame of the image. The Gaussian model matches each pixel in the current image, if it cannot be matched, determine that the pixel is the front attraction. If it can be matched, then the pixel is the background point. Set the grayscale value of a certain pixel in the image to g, and the grayscale values of the pixel from time 1 to time t are represented as (a1,..., ai,..., at,). The detailed description of the pixel grayscale value requires the use of N Gaussian distributions, which need to be weighted to obtain the probability density function as shown in Equation 3.1:

$$g(a_t) = \sum_{i=1}^{t} \lambda_{t,i} \gamma(a_t, u_{t,i}, \sum_{t,i}) \tag{3.1}$$

In the equation: y$(a_t, u_{t \cdot i}, \sum it)$ represents the probability density function of the Gaussian distribution; Ut, i is the mean of the Gaussian distribution; $\lambda_{ti}$ is the weight; $\sum it$ is the Covariance matrix of Gaussian distribution. The probability density function of the Gaussian distribution is calculated as follows Equation 3.2:

$$y(a_t, u_{t+i}, \sum_{t,i}) = \frac{1}{(2\pi)^{\frac{d}{2}} \sum_{t,i}} s^{-\frac{1}{2}(a_t - w_{t,i}) \sum_{i=1}^{i} (a_t - w_{i,t})} \tag{3.2}$$

The dimension of at in the equation is d. When the observation point is updated to $a_{t+1}$, compare the pixel value and the mean value $\pi_{t,i}$ of N Gaussian function distribution, and use Equation 3.3 as the judgment rule to match and select the Gaussian function.

$$a_{t+1} - \tau_{t,i} < 0 \cdot \varepsilon_{t,i}^2, i = 1, 2, ..., N \tag{3.3}$$

In the equation, 0 represents a custom parameter, typically with a value of 2.6. When Equation 3.3 is satisfied, the ith Gaussian function matches $a_{t+1}$.

When the Gaussian function is not matched successfully, the variance and mean value remain unchanged. Equation 3.4 represents the parameters generated after the Gaussian function and at are matched, and it is updated by Equation 3.4:

$$\tau_{t,i} = (1 - \varsigma) \cdot \tau_{t-1,i} + \varsigma \cdot a_t \tag{3.4}$$

where $\varsigma$ is the parameter Learning rate.

**3.2. Improved Gaussian Model for Moving Object Detection and Tracking** (Figure 3.1)**.**

**3.2.1. Modeling methods.** In common methods of moving object detection and tracking, the use of foreground models is relatively limited and only used as an auxiliary. However, in improved Gaussian model modeling, the foreground model generated when background matching fails is utilized, combined with short-term stability indicators for comprehensive foreground judgment. On the basis of the Gaussian model, if all N corresponding background models fail to match the current pixel value, the variance and mean of the minimum weight model will be replaced by the larger value and the current pixel value, the model generated at this time is the foreground model $y = T_f \varepsilon_f$. If the threshold value Hf is greater than the difference between the mean of the foreground model and subsequent points, Equation 3.5 needs to be used to update the foreground model and Equation 3.6 needs to be used to calculate short-term stability:

$$R = \frac{p \sum_{i=1}^{p} a_{t+1}^2 - \sum_{i=1}^{p} a_{t+i}}{p(p-1)} \tag{3.5}$$

$$\tau_{f,t+1} = (1 - u_f) \tau_{f,t} + u_{fat+1} \tag{3.6}$$

where: $uf\epsilon[0, 1]$ represents the Learning rate of the foreground model; P represents the frame range of the sliding window. When matching the current pixel point, the foreground model is prioritized to reduce the decision risk caused by errors in matching the background model and the front attraction.

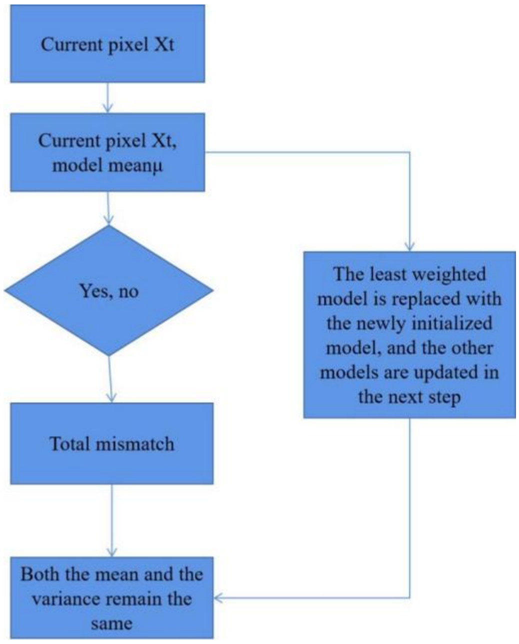


Fig. 3.1: Flow Chart of Parameter Update for Improved Gaussian Model

The appearance of moving targets varies, and the calculation window length for short-term stability of moving targets with uniform colors value setting range is 2-5. If the color of the moving target is relatively rich and the pixel value change time is too short, it will cause the target to be mistaken for the background. At this time, it is necessary to The value is controlled within 5-20, and the P-value is positively correlated with the detection effect, but if If the value is too large, the response speed of the indicator will slow down [8,9]. After obtaining the stability through Equation 3.7, the judgment threshold Rth is obtained as:

$$R_{th} = R_{min} + \frac{R_{max} - R_{min}}{L} \tag{3.7}$$

The maximum value of stability in the current L frame is Rmax, the minimum value of stability is Rmim, and L is a constant. The condition for determining the current pixel as the previous attraction is that within a continuous L-frame range, the current pixel exceeds the short-term stability threshold. The change in stability is positively correlated with the pixel value, so stability can fully describe the appearance and persistence of the foreground. If the pixels in the moving target area change in a short time, it is easy to be incorrectly detected as the background. Using short-term stability index to improve the Gaussian function can effectively avoid this situation. When traditional Gaussian models detect target motion at a slow speed, they may fail to detect. The author adopts a combination of short-term stability indicators and foreground models to solve common problems with Gaussian models and improve the detection effect of target motion [10].

**3.3. Eliminating Light Mutations.** The improved Gaussian model can improve the impact of slow target motion on background extraction, but once disturbed by sudden changes in lighting, pixels will be incorrectly detected as foreground pixels. The movement of targets and changes in lighting can cause pixel grayscale mutations, and the mutation area caused by lighting changes is larger than that caused by target movement. Therefore, to achieve better detection and tracking results, it is necessary to eliminate lighting mutations.

The specific methods are as follows.

In order to determine whether the Gaussian distribution within the current frame matches pixels, it is necessary to set a new parameter w for each pixel in the image, and set the value of w to improve background

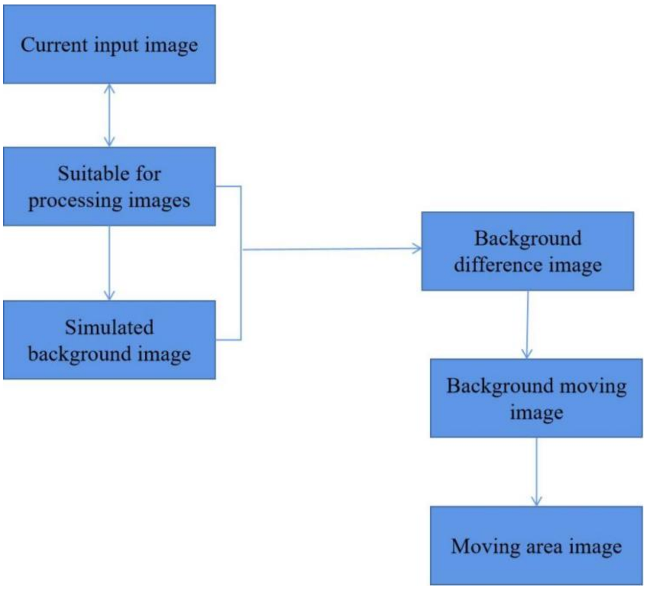


Fig. 3.2: Flow Chart of Background Difference Method for Motion Detection

estimation. If N Gaussian function and pixels can match, the value of w is 0; If it is not matchable, the value of w is 1. If the area of pixel mutation is large, it is caused by lighting mutation. Count the number of w values in the image with a value of 1. If equation 3.8 is met, it indicates that the background lighting has undergone a mutation.

$$\frac{\sum_{i=1}^{k} w_i}{k} > H_1 \tag{3.8}$$

When there is a sudden change in lighting, the proportion of pixels with grayscale changes in the image is the threshold, represented by H1. In actual experiments, H1=0.66. If the image can comply with Equation 3.8, the background pixel is determined as a pixel block with a value of w of 1. In this case, by improving the background model to implement updates, the one with the smallest weight in the first N distributions is replaced by a Gaussian distribution based on the grayscale value of the pixel block as the mean, becoming the background model.

**3.4. Background subtraction method.** The background subtraction method is currently the most commonly used method in moving object detection algorithms. Its main idea is to create a background model image corresponding to the image sequence, then calculate the difference with the corresponding input image, and then determine the moving area through a certain threshold.

In moving object detection based on background subtraction methods, the accuracy of background image modeling and simulation directly affects the detection effect. Regardless of any moving object detection algorithm, it is necessary to meet the processing requirements of any image scene as much as possible. However, due to the complexity and unpredictability of the scene, as well as the presence of various environmental disturbances and noise, the sudden changes in lighting, fluctuations in some objects in the actual background image, camera jitter, and the impact of moving objects entering and exiting the scene on the original scene make background modeling and simulation more difficult [11,12].

Regardless of the mathematical model used to simulate the background image, the general background subtraction method includes several steps such as image preprocessing, background image mathematical modeling, foreground object detection, and motion object post-processing, as shown in Figure 3.2.

As shown in Figure 3.2, the workflow of the commonly used background subtraction method is as follows:

1. Read a frame of image from the original image sequence that needs to be processed, and perform some preprocessing operations on the frame of image, such as filtering the image data in a simple spatiotemporal or frequency domain to eliminate noise caused by camera jitter, focal blurring, environmental disturbances, etc., so that subsequent processing can detect the image data more accurately; Alternatively, the format of the original image frame can be transformed into an image format that is convenient for subsequent processing, such as RGB, HVS color space, etc. Introducing color space can achieve better processing results than simply grayscale or brightness space.
2. After preprocessing, a suitable image is obtained, and then a background model corresponding to the processed image of that frame is established using the processed image of that frame and the previously obtained background model. This enables the background model to be updated with changes in input image data, in order to more realistically simulate an accurate background image corresponding to the current input.
3. After obtaining the background model corresponding to the current input image data through the previous step, the background difference image can be obtained by calculating the difference between the current input image and the simulated background image. This image represents the change of each pixel in the current image and the corresponding pixel point of the simulated background. This change is the displacement change between the current input image and the theoretical background image pixels [13,14].
4. The difference map obtained in the previous step is binarized using the preset threshold to obtain the motion region. Suppose that the current input image after preprocessing is F (x, y, t), the simulated background is B (x, y, t), the processed Binary image is I (x, y, t), and T is the threshold value for binarization, then the expression for determining the motion region can be written in Equation 3.9:

$$I(x,y,t) = \begin{cases} 1 & F(x,y,t) - B(x,y,t) > T \\ 0 & \text{otherwise} \end{cases} \tag{3.9}$$

   In Equation 3.9, when the difference between the current input image and the simulated background is greater than the threshold T, the binarized image is represented as 1 (we use the number 1 to represent the value of the foreground motion area), when the difference between the current input image and the simulated background is equal to or less than the threshold T, the binarized image is represented as 0 to indicate that the pixel is part of the background. For all motion detection algorithms that use background subtraction method for judgment, the selection of threshold during binarization is the key to detection processing, so the selection method of this threshold has become a hot research issue in this type of algorithm.
5. The previous step calculated the motion region after binarization, but due to factors such as the complexity of the image sequence, noise interference, and imperfect threshold selection, there may be some errors or errors in the binarized image. At this point, it is necessary to perform some post-processing on the binarized image, try to eliminate some errors that can be processed, and obtain the most accurate detection results.

There are several commonly used methods for post-processing:

① Morphological filtering: This method can eliminate small and disconnected false motion information caused by periodic moving objects in the background, such as leaves and water waves, and can merge the required disconnected motion regions to obtain a complete and accurate motion region.

② Optical flow: The average optical flow vector is obtained by calculating the differential equation of optical flow, which can be used to distinguish the moving area and "ghost", because the motion region has a relatively large motion vector, and because the "motion" of the "phantom" is instantaneous, the "phantom" part of the Mean motion vector is very small.

③ Color segmentation method: In general, the colors of the same moving target pixel have similar features, so similar colors can be segmented to make the detected motion area more complete.

The principle of using background subtraction method for motion detection is simple, but it is indeed difficult to simulate a highly accurate and stable background image, which is also the core and difficulty of this type of algorithm. The quality of background image modeling directly affects the final detection effect.

For video images captured by fixed cameras, the simplest way to model the background is to directly select a certain frame of image as the background image and calculate the difference between other images and that image. The background of this method cannot be updated with changes in the scene, and the detection effect will have a significant degree of error with changes in the scene; And the detection effect of this method is very good only when the scene image without any moving target is selected as the background, which restricts the use of this method.

The background subtraction method has now become the mainstream algorithm for moving object detection, and many studies in this field are based on the background subtraction method. Although this method can be implemented through various background modeling methods, it still has some common characteristics as follows: These background subtraction algorithms build models based on single pixel features and Areal feature, while ignoring the high correlation between adjacent pixels in the same image; They all learn and model the background by utilizing a known sequence of adjacent finite images; In order to make the background model better simulate the real background, it is necessary to update the background model in real time. The update speed can be controlled by adjusting the length of the time window or changing the size of the model's Learning rate [15,16].

## 4. Experiments.

**4.1. Simulation testing.** The simulation platform selects Matlab, and the parameter selection of this method is to determine the number of Gaussian models as 4, the threshold as 0.8, and the weight as 0.4. Compare the detection and tracking effects of optical flow field detection method and median filtering method on moving targets with this method. The image detected and tracked by the optical flow field detection and tracking method is greatly affected by background interference, the detection range is too wide, there is too much useless information, the detected moving targets have many holes and noise, the moving targets are not clear, and the accuracy is low. The median filter detection and tracking method detects and tracks moving targets with less noise compared to the optical flow field detection and tracking method, but the detected moving target details are missing and still not accurate enough. This method detects and tracks moving targets with clear contours, and the detection effect is relatively accurate. The detection results are not affected by noise interference, which is better than the median filter detection and tracking method and the optical flow field detection and tracking method.

Compare the detection and tracking effects of three methods under sudden changes in lighting conditions. Under the influence of sudden changes in lighting, many color blocks appear in the images detected and tracked by the optical flow field detection and tracking method. The noise impact is even more severe, the detection range is still large, and there is too much interference information, indicating that sudden changes in lighting have a significant impact on detection. The median filter detection and tracking method is affected by changes in lighting, resulting in many burrs in the detection results and serious leakage of details. When tracking moving targets, the noise continues to increase, and the detection effect becomes worse and worse. After being affected by sudden changes in lighting, this method still performs well in detection and tracking, with minimal noise interference, clear detection results, and good tracking performance [17].

The image integrity of the comparison of moving object detection results is shown in Figure 4.1.

From Figure 4.1, it can be seen that the median filter detection and tracking method has a wide detection range, and as the sequence increases, the detection range shows an upward trend, indicating that the increase in validation sequences leads to a greater impact on the detected moving target noise. The detection range of this method has always been stable, with an increase in validation sequences but no significant changes in the detection range. Therefore, the detection results of this method are more accurate and effective.

Extract the clarity of the tracking results of the three methods and compare their ability to handle interference, as shown in Figure 4.2.

In Figure 4.2, the tracking image clarity of this method remains at its highest, while the anti-interference ability of the optical flow field detection and tracking method is the weakest. As the tracking image verification sequence increases, the clarity gradually decreases. Therefore, the optical flow field detection and tracking method has the worst anti-interference effect when tracking moving targets. The clarity fluctuation of the median filter detection and tracking method is relatively smooth. As the validation sequence increases, there is no significant change in clarity, but the clarity is only around 380, so the anti-interference effect is not

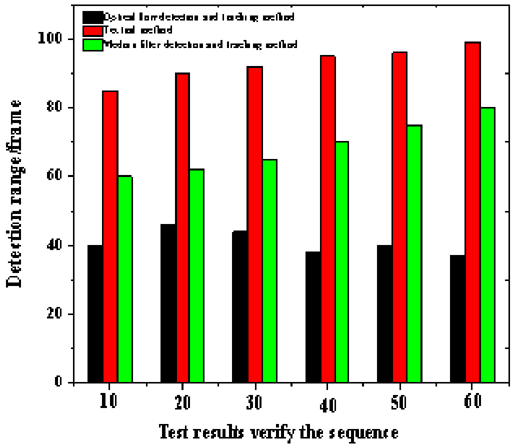


Fig. 4.1: Comparison of Detection Range Effects

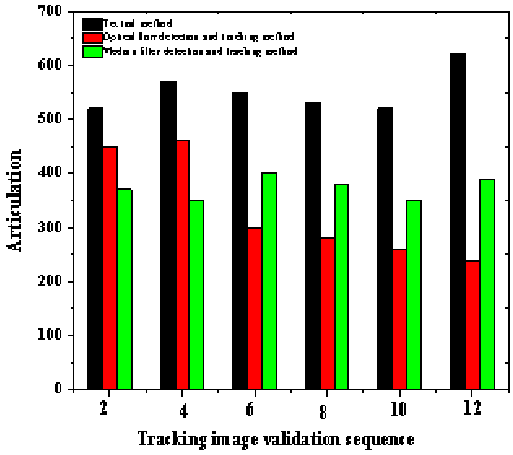


Fig. 4.2: Comparison of anti-interference ability results

good. From Figure 5, it can be seen that this method has the highest tracking clarity, can effectively handle interference, and has a good tracking effect [18].

According to the experimental comparison of the detection accuracy and error rate of the three methods, the results are shown in Table 4.1.

From Table 4.1, it can be seen that the accuracy of this method has been maintained within the 99% range, with an error rate controlled at 3%. The accuracy of the optical flow field detection and tracking method and the median filter detection and tracking method is less than 91%, with an error rate above 11%. This proves that the performance of this method is superior and more suitable for the detection and tracking of moving targets [19,20].

Table 4.1: Performance Comparison (%)

| Experimental content | test method | accuracy | error rate |
|---|---|---|---|
| Scenario 1 | Optical flow detection and tracking method | 79 | 21 |
| | Median filtering detection and tracking method | 88 | 15 |
| | Author's Method | 99 | 3 |
| Scenario 2 | Optical flow detection and tracking method | 78 | 22 |
| | Median filtering detection and tracking method | 87 | 13 |
| | Author's Method | 99 | 3 |

**5. Conclusion.** In traditional research, the foreground model generated by foreground matching failure in Gaussian models has not received academic attention, but it is precisely the foreground object information contained in this long neglected foreground model that is the key to moving object detection and tracking. The author uses the foreground model generated by matching failure and stability indicators to comprehensively detect and track moving targets on the basis of traditional models, and obtains a new improved Gaussian model that overcomes various influencing factors to obtain accurate moving target detection and tracking results. On the basis of the original Learning rate, the mean and variance are given different weights, and the median filter and object space connectivity are used for post-processing. Finally, the moving target detection is completed. The experimental results show that compared with traditional methods, this method can detect moving targets more effectively and has strong robustness. Eliminate shadow interference from moving targets to achieve more accurate detection and tracking results.

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