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Research Article

An Adaptive Combination Resolution Algorithm for Moving Object Vector Graphics Based on Automatic Programming Optimization Algorithm

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A new moving target adaptive image segmentation algorithm is proposed. On the basis of setting the adaptive tracking wave gate to track the moving target, the adjustment coefficient is adaptively calculated according to the criterion of maximum interclass variance function, and then, the adaptive segmentation of the image is completed by setting the threshold segmentation method. Compared with algorithm, iteration method, and maximum entropy method, the proposed algorithm can not only adapt to a variety of complex backgrounds but also has high precision and high speed. Therefore, it is a practical and effective image segmentation method. As a kind of nonparametric density estimation algorithm, automatic programming optimization algorithm of moving target vector graphic combination and resolution has been widely used in video moving target tracking. The algorithm has fast calculation efficiency and is not sensitive to target deformation and rotation; in the case of a partial shade, it has certain robustness. However, the algorithm moves too fast under clear conditions without considering the direction and speed of the target information, so it is easy to lose tracking when tracking fast moving targets. To solve this problem, a new method based on motion vector analysis and automatic programming optimization of moving target vector graphics combination resolution tracking algorithm is proposed. Firstly, the probability and statistics analysis of motion vectors generated in the process of video coding is carried out to obtain the estimated value of target motion direction and speed. Then, the center position of the candidate region can be split by correcting the combination of moving object vector graphics optimized by automatic programming so that the candidate center position is closer to the actual target center position at the beginning of each search. Compared with the traditional automatic programming optimization algorithm, the new algorithm not only improves the tracking accuracy of the fast-moving target but also reduces the number of search iterations, thus improving the operation efficiency. The algorithm can be applied to the case that video coding and target tracking are calculated simultaneously in the intelligent video surveillance equipment, and the experimental results show that the algorithm is effective and feasible.

1. Introduction

Image segmentation [1] is a basic problem of image processing, and its purpose is to divide the image into meaningful regions, extract the target object from the complex background, and provide a basis for subsequent target detection and recognition. Therefore, the quality of image segmentation will inevitably affect the performance of the whole system and even affect the system scheme of image engineering in the complex background. Therefore, the study of moving target image segmentation in the complex background has a certain practical value. At present, there are many image segmentation algorithms. Due to the real-time requirements of passive positioning of moving objects, the sequential image segmentation algorithm used has a small amount of computation, so the segmentation algorithm should not be too complex. At the same time, as the target changes with the environment in the process of movement, the background of the sequence image is constantly changing, so the segmentation algorithm of the sequence image should have the ability to adapt to the change of environment so as to meet the requirements of the universality of the target to the change of environmental conditions. A new image segmentation algorithm is proposed in this paper, aiming at the problem that the ideal adjustment coefficient must be solved in the segmentation algorithm with set threshold, and the algorithm adaptively calculates the adjustment coefficient by using the maximum interclass variance function criterion and then completes the image segmentation with set threshold method. Experimental results show that it can achieve adaptive segmentation quickly.

Automatic programming optimization of moving target vector graphics combination resolution algorithm is a nonparametric density estimation algorithm [2], as an efficient pattern matching algorithm. It has been successfully applied in the target tracking system with high real-time requirements [3]. Firstly, the automatic programming optimized moving target vector graphics combination and resolution algorithm is applied to image filtering, segmentation, and target tracking [4]. An automatic programming and optimization algorithm of moving target vector graphics combination splitting and target tracking based on the color histogram is proposed [5]. The algorithm first uses the color histogram to get the color projection of each frame image, then adaptively adjusts the position and size of the search window, and takes the optimal center position as the target center through continuous convergence. In addition, particle filter combined with automatic programming optimization of moving target vector graphics combination and resolution method is used for target tracking, but the complex calculation of particle filter itself reduces the real-time performance of tracking [6]. There are three methods of moving object segmentation: moving object segmentation based on Bayesian estimation theory, moving object segmentation method based on clustering theory, and moving object segmentation method based on mathematical morphology theory. Among them, the latter two methods are more practical, especially the moving object segmentation method based on mathematical morphology theory has been widely used. From the perspective of the segmentation domain, moving object segmentation can be divided into space segmentation and time segmentation. Space segmentation is generally a static segmentation, while time segmentation is generally a motion segmentation. Moving object segmentation can also be divided into automatic segmentation and semiautomatic segmentation [7]. Moving object segmentation technology is developed on the basis of static image segmentation technology. The segmentation method of the static image generally uses the gray scale, edge, gradient, texture, and other information of the image for region-based division, which is generally divided into single-level method and multilevel method [8]. Single-level methods are mostly simple to apply such as the traditional method based on edge graph [9]. Multilevel methods have received more and more attention [10], among which morphological filtering method and watershed algorithm are widely used. However, these space-based segmentation methods do not take advantage of the information on the time axis in moving object segmentation, so the workload is heavy, but the results are not ideal. Since the moving target is the projection of the 3D scene on the 2d plane, it can also be segmented by using the information of the sequence image on the time and space axes [11]. At present, there are several automatic segmentation methods: segmentation based on the optical flow field, spatiotemporal method based on change area detection, motion tracking method, etc. The semiautomatic segmentation methods include object tracking based on template matching. In recent years, the advantages of intelligent video surveillance system are becoming more and more obvious. With a high degree of openness, integration, and flexibility, it provides a broader space for the development of the entire security industry. It changes the passive receiving and feeling mode of traditional video surveillance and can automatically detect, track, and analyze the video on the monitoring site [12, 13]. For video images captured by fixed cameras, the main methods of moving target detection include frame difference method, background difference method, and optical flow field method. The frame difference method is simple in operation and easy to implement, but it is prone to fracture and fragmentation of moving targets, which largely depends on the timing of the differential frame selection and the target's movement speed [14]. Optical flow field method is not suitable for real-time processing because of its complexity and poor antinoise ability. Background difference method [15] is the most commonly used method for target detection, with fast calculation speed, accurate detection, and the simplest implementation. However, due to the dynamic scene changes caused by illumination and external conditions, the moving background is unstable, thus increasing the complexity of background extraction, so the adaptive background model is particularly important [16]. Aiming at this problem, an algorithm is designed, which can automatically separate the moving area and the stationary area of each image and then make statistics of all the stationary area to get a reliable background image. At the same time, the separated moving area is finely segmented to get the moving target and achieve a win-win effect. At present, most background reconstruction algorithms are only based on pixel brightness or color features, ignoring the spatial relationship between adjacent pixels, and are greatly affected by noise.

Aiming at the shortcomings of the automatic programming optimization algorithm of moving target vector graphics combination and resolution in fast-moving target tracking, an improved algorithm is proposed. At present, the general solution is to combine Kalman filter or particle filter to predict the space movement position of the moving target. Then, the combination and resolution algorithm of moving target vector graphics optimized by automatic programming based on the color histogram is combined. The two methods are used for tracking at the same time, and the two tracking results are linearly weighted by different scale factors to obtain the final position of the target [17]. The idea of this algorithm is that the automatic convergence range of moving object segmentation caused by moving object is larger than that optimized by vector graphics programming under the condition of fast moving object speed. Firstly, the position of the moving target in the next frame is predicted and preliminarily located, and then it is used as the reference vector graphics resolution for automatically programming and optimizing the search center position of the combined moving target. Then, in order to locate the moving target accurately, a more precise split search is carried out by automatic programming optimization in the central position of the moving target vector graphics combination. However, the tracking efficiency is reduced due to the complex filtering and prediction calculation of the image. Given the current video analysis technology in the application of digital signal processing (DSP) needs more at the same time in the same chip to realize video coding such as target tracking algorithm, therefore, one can use video coding for motion estimation in the macroblock probability and statistics calculation, estimate the motion vector information goal direction and speed of prediction motion target in the next frame image in the spatial location, and improve the automatic programming algorithm to optimize the search to the central location.

2. Automatic Programming Optimization of Moving Object Vector Graphics Combination

2.1. Multimoving Object Vector Image Segmentation. In this paper, a new adaptive algorithm based on the combination of multi vector graphics for accurately segmenting moving objects under complex backgrounds, which is optimized by automatic programming, is proposed. The algorithm combines motion information with frame segmentation, and takes the principle of simple calculation, fast speed, and accurate segmentation of moving objects as the principle. Its basic idea is to use Gaussian filter to enhance the sequence of frame difference images, so as to realize the automatic separation of moving regions and backgrounds. According to the three-frame image sequence, the gray edge overlapped between the front and back frames is the edge of the moving object in the middle frame to effectively solve the occlusion of the front and back frames of the moving object and mark the multimoving area. The initial contour of the moving target is automatically located by the outer contour tracking algorithm for each labeled moving region. Based on the moving edge information, the original dynamic contour algorithm is improved, and the improved dynamic contour shrinkage algorithm is used to accurately identify the target's outer contour, and the characteristics of moving area detection and dynamic contour model are combined to segment multimoving targets. Figure 1 shows the frame diagram of the adaptive combination algorithm.

After the global motion estimation compensation, combining simple image sequence frame difference to detect motion area is the most simple and effective method, but due to the random noise, background brightness changes, etc., simple means of difference image threshold for movement area will produce a lot of noise but also makes the algorithm does not have a single threshold. In this paper, four high-order statistics of interframe difference are used to pre-segment the moving region and the background region. This method is robust to the slow change of noise and background brightness, but the calculation is complicated. In order to achieve a certain real-time performance and compress the noise, Gaussian smoothing filtering is carried out on the difference of two frames of the image sequence.

$$Df(x, y) = D(x, y) * |f(x, y+1) - f(x, y)|. \tag{1}$$

Although such adaptive threshold selection can vary with the overall brightness and slow background, for complex images, such as traffic maps, the background of the image within the frame is also very complex. Therefore, despite the above steps, the simplification of the closed value within the frame still leads to the existence of some noises and background. Therefore, this algorithm analyzes the motion area obtained by Gaussian smoothing filtering, subtracts the above situation, and adopts a three-step search block matching algorithm.

2.1.1. Adaptive Combination and Resolution of Moving Object Vector Graphics. Adaptive combined resolution is an essential operation in the process of editing vector graphics. However, some vector graphics editing software can easily disturb the display sequence of elements (layers) after multiple combination and split operations. The group command does not place all the adjacent graphic elements in the adjacent layers, and the layer order changes, and disordering the order will seriously affect the original display effect of the entire image. In the process of designing and developing vector graphics editing tools, this paper avoids this situation (unless the layer order is changed, the original display order of graphic elements will not change), that is, the combination of graphic and image layers cannot be adjacent.

Create a composite primitive and add the selected primitives to the composite primitives. Remove the pixel corresponding to the layer number in the selected pixel queue (the layer number can be regarded as the unique identifier of the pixel) from the document. Finally, the composite primitives are added to the document.

Combine pixel objects, and then add the split obtained pixel object to the document pixel queue. At the same time, because the pixel obtained by splitting is still in the selected state, we need to update the selected pixel queue. The process is shown in Figure 2.

Table 1 shows the comparison results of the time required for contour contraction of the Greedy and EGreedy algorithms for the above test video sequence. It can be seen that the EGreedy algorithm uses the motion edge information as a prior condition to prevent the overcontraction process of the original Greedy algorithm, and the speed is greatly improved.

2.1.2. Statistical characteristics of moving object vector graphics. Since there is no scene mutation in the video surveillance image sequence, the motion vector has the characteristics of coherence. Motion vector statistical analysis method can be used to calculate the direction of motion, speed, and other important parameters of the

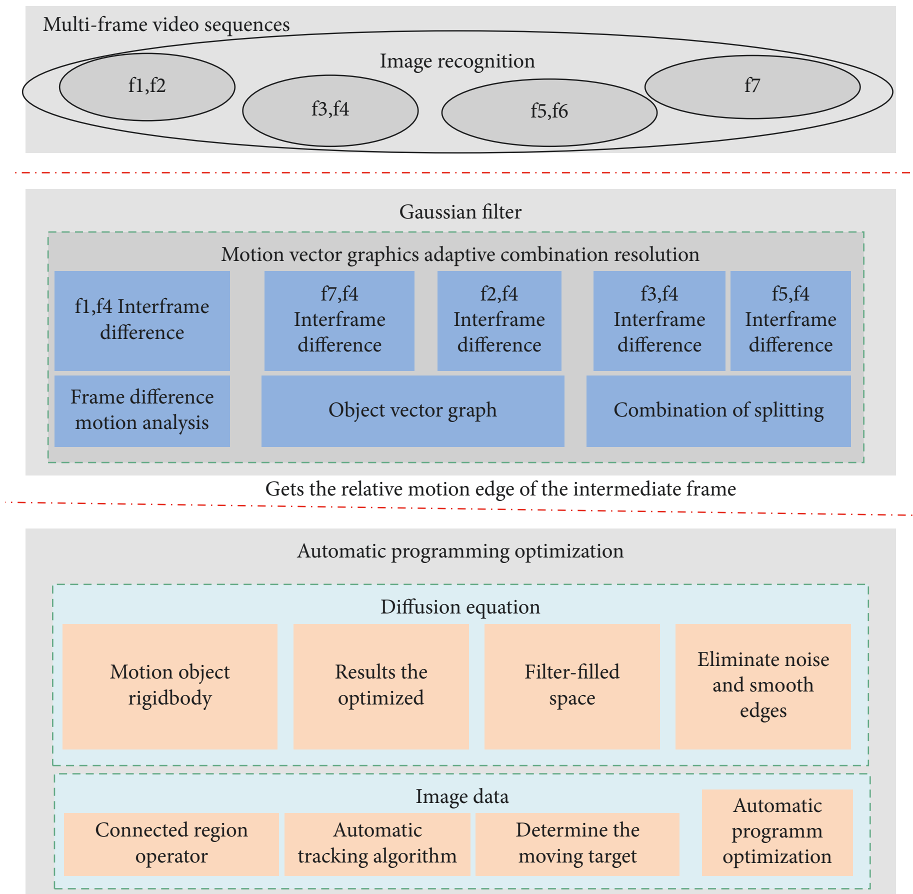

FIGURE 1: Frame diagram of adaptive combination of multimoving target vector graphics under complex background.

moving target. In the case of three different camera movements, the field object moves; the camera and the field object move at the same time; through the statistical analysis of the image motion vector, it can be seen that when the camera is still, almost all the motion vectors in the background area are Q, and the motion vector will generate the moving target area. When the camera moves, all motion vectors are almost the same because the whole image belongs to the background. For the case of the camera and object moving together, the motion vectors in the background area are mostly consistent, but the motion vectors in the moving target area are not consistent with the direction of the background area, and the moving target area has its own local statistical characteristics.

In general, video coding mainly considers the compression efficiency of codestream rather than the accuracy of estimation. Since the motion vectors obtained cannot completely represent the real motion, all motion vectors in the moving target area macroblock do not necessarily face the same direction. Secondly, changes in the external environment, camera movement, and other noises will generate corresponding motion vectors in the process of video coding. These motion vectors are not conducive to the detection of moving targets, so it is necessary to preprocess the motion vectors. For the motion vector D less than a certain threshold, it is highly likely to be noisy, which can be filtered by the following methods.

$$D_{x,y} = D_x^{\text{motion}} + D_y^{\text{motion}}. \tag{2}$$

The included angle between the vertical component and the horizontal component of the motion vector is the direction angle of the motion vector. The direction code of the direction angle can be generated if it belongs to any interval in the graph. In the image, the direction of the motion vector of the macroblock in row I and column J is encoded as

$$I_{i,j} = \text{arctg}\frac{D_y^{\text{motion}}}{D_x^{\text{motion}}} + \frac{\pi}{8}. \tag{3}$$

For the still camera, the motion vector of the macroblock in the background area is basically Q, and only the motion vector exists in the moving target area. The steps for estimating the motion direction and speed of the moving target are as follows:

(1) Calculate the direction coding probability density distribution of all motion vectors in the moving target region, which is the probability of direction coding of motion vectors in s directions, so it can be used to establish the direction coding histogram of motion vectors.

(2) According to the direction of motion vector probability density distribution, direction of motion vector coding can have maximum probability density; it indicates that

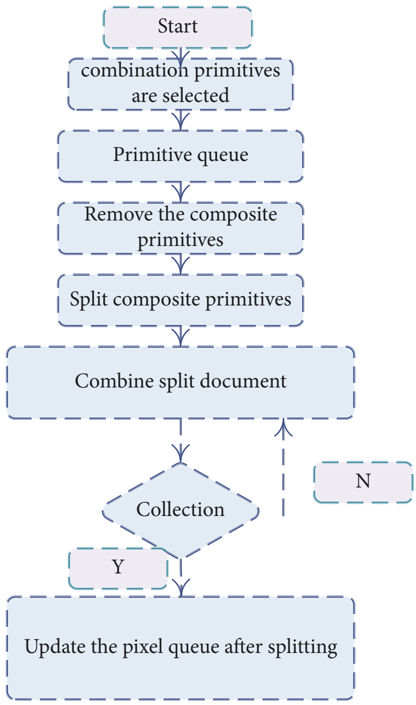

Figure 2: Process of resolution algorithm.

Table 1: Speed comparison results of Greedy and EGreedy algorithms in different test sequences.

	Test sequence parameter				
	Ball (sec)	Car (sec)	Alex (sec)	Traffic (sec)	Stennis (sec)
Greedy	1.095	1 .1284	2.4895	2.0536	1.048
EGreedy	0.143	0.3688	0.6239	0.0178	0.205

the direction in the area of the motion point, in the same direction of motion vector number, exceeds a certain proportion, and has the character of whole displacement which are moving targets, at this time, to estimate the direction and speed of movement. Otherwise, the movement direction and velocity of the target area are considered to be 0.

3. Define the Average Motion Vector

The estimated speed of motion is zero.

$$v = \sqrt{\left(D_x^{\text{motion}}\right)^2 + \left(D_y^{\text{motion}}\right)^2}. \tag{4}$$

The estimated value of the motion direction is

$$\theta = \operatorname{arctg}\frac{D_y^{\text{motion}}}{D_x^{\text{motion}}}. \tag{5}$$

In the case of camera movement, most motion vectors of the whole image will face the same direction. When the probability density of motion vectors in the same direction of the whole image is greater than a certain threshold, the camera movement is considered. At this point, only the statistical characteristics of the motion vector direction coding probability density of the current moving target region are considered, and the motion direction and speed of the moving target can be obtained according to the motion vector direction coding histogram.

Using the method of the compressed domain can be detected in advance by tracking them in the original starting point after the next frame position, and this feature is used to predict the trajectory of the target in the first few frames mobile, recycling automatic programming optimization combination of movement target vector graphics resolution algorithm iterative convergence, to achieve the purpose of locking tracking target. In short, if a target is tracked in 5 frames, for the first time in 8 frames a second, because of the moving target for the vector, motion vector was used to extract target features to estimate the position, then 6, 7 frames do not overlap with the target part of the image, and the compressed domain method is used to detect target in 8 frame position. Then, the position of frame 8 is used to predict and correct its moving track in frame 6 and 7 so as to realize the tracking of the target. This algorithm not only improves the accuracy of fast-moving target monitoring but also corrects the expansion center of the automatic programming optimization algorithm and reduces the number of iterations of the algorithm, reduces the computational burden, and improves the real-time performance of the search. Its algorithm flow chart is shown in Figure 3:

Fusion of compressed domain method can improve the automatic programming optimization combination of movement target vector graphics resolution algorithm in tracking fast-moving targets with good tracking effect, so we need to know whether it is a blend of compressed domain of the improved automatic programming optimization combination of movement target vector graphics resolution algorithm for real-time relative to the original algorithm of target tracking or whether to have change. The following data results were obtained by calculating the average computing time of the two algorithms in each frame as shown in Table 2:

Among them, MMS is the improved algorithm and MS is the original algorithm. According to the calculated data, it can be seen that the average time consuming of the improved algorithm is 0.068 seconds per frame, while the average time consuming of the original automatic programming optimization algorithm of moving target vector graphics combination splitting algorithm is 0.059 seconds per frame, and the average time consuming of each frame is almost the same. But real-time tracking effect of the improved algorithms is improved compared with the original algorithm, so we can conclude that the improved automatic programming optimization combination of movement target vector graphics resolution algorithm compared with the original automatic programming optimization combination of movement target vector graphics resolution algorithm for fast target tracking effect has obvious real time, and the average computation time per frame of the two algorithms is basically the same.

Subblocks that are judged to be static for several consecutive frames are considered as background parts, and background images are added until all subblocks meet the

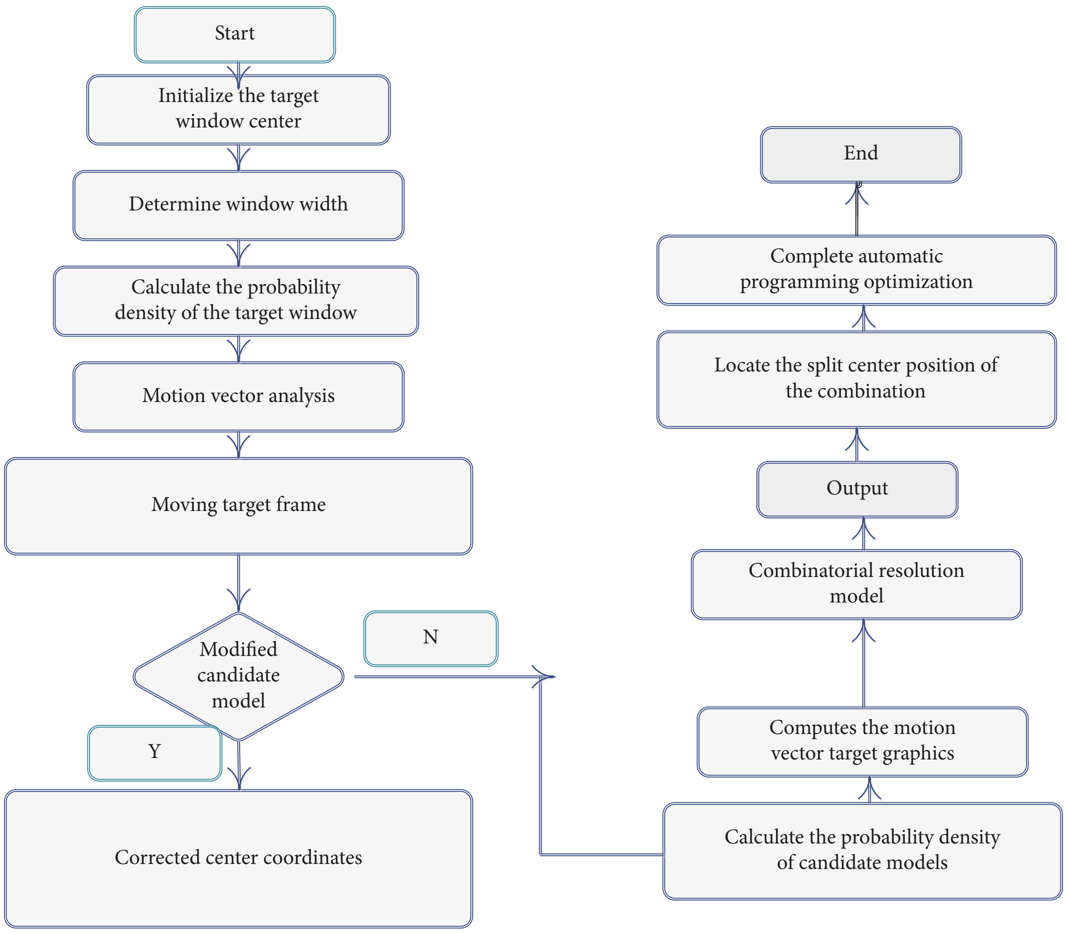

FIGURE 3: Moving target vector graphics combination resolution algorithm flow optimized by automatic programming for monitoring fast-moving target fusion color features.

TABLE 2: Time comparison of the two algorithms.

Algorithm name	Average time per frame (s)	Total number of frames in the sequence
MMS	0.068	64
MS	0.059	65

requirements, that is, background reconstruction is completed. Details are as follows:

(1) Each subblock of the binary image Bk (x, Y) after phase matching is marked. If the subblock contains foreground pixels, it is marked as a moving region; otherwise, it is marked as a stationary region.

(2) Count the number of times that each subblock is marked as stationary region or moving region. A counter is designed for each subblock, and the counter is incremented by 1 if a subblock is marked as a stationary subblock.

(3) If the statistical value is greater than before, it is considered as the background region and the subblock is included in the background image.

(4) Set $k = \text{k}-1$ and go to Step 1 until the background reconstruction is completed. All the images determined as background subblocks are combined and output to obtain the whole background image.

Once the background reconstruction is completed, fine segmentation of background difference can be carried out. For the current frame image, only the difference between the image in the changing area and the background image is made to detect moving objects. Therefore, due to the existence of noise, the difference image contains moving objects as well as a lot of noise, so a threshold value needs to be set to judge. In this detection process, the selection of threshold value is very critical, which is related to whether the moving target can be accurately and completely extracted. At present, there is no good threshold selection method, and common methods to determine the threshold include histogram bimodal method, maximum interclass variance method, and maximum entropy method; they all have specific application conditions, and the operation has a certain degree of complexity. An estimation method for generating minimum mean segmentation error is applied here, that is, the current threshold minimizes the mean error rate in determining whether a given pixel belongs to the target or background. Since there may be a small gray difference between the background and some positions of the moving target, there may be a cavity in the binarization template of the moving

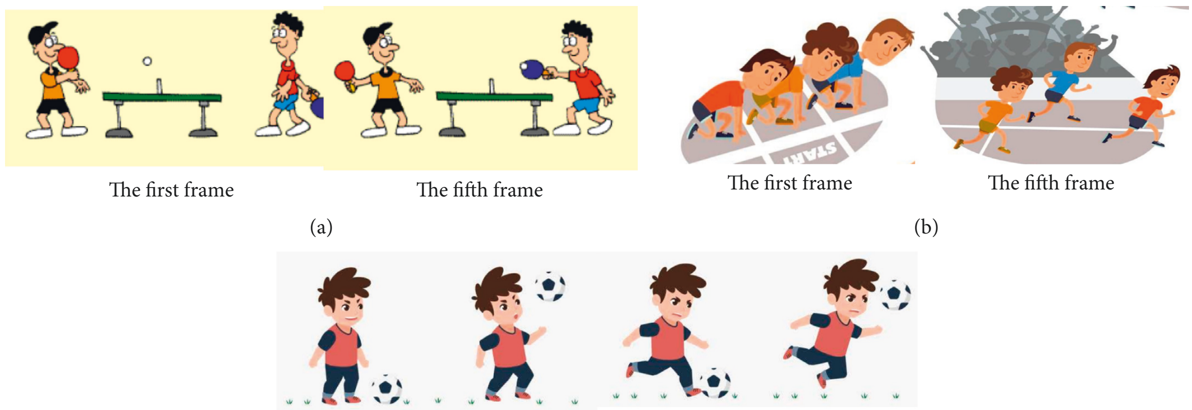

FIGURE 4: An example of adaptive combination resolution of moving target vector graphics by automatic programming optimization algorithm. (a) Experiment I; (b) Experiment II; (c) Experiment III.

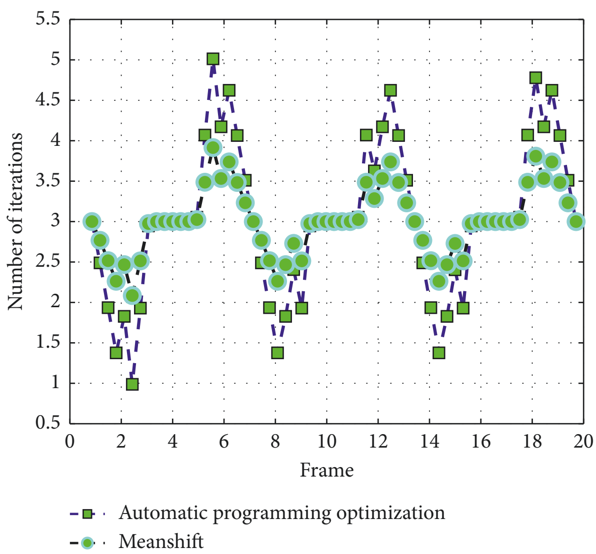

FIGURE 5: The number of split iterations of moving target vector graphics combination optimized by automatic programming of two methods in Experiment I.

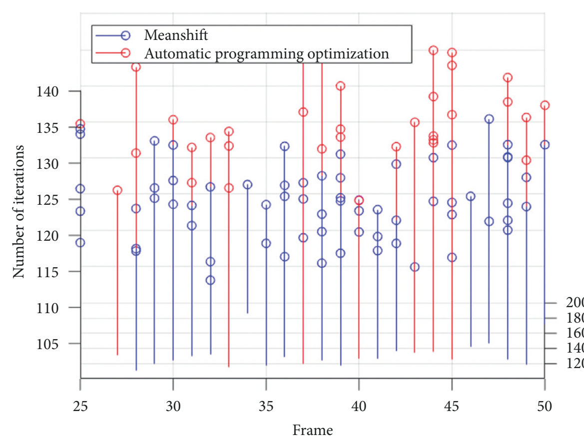

FIGURE 6: Target motion trajectories of the two methods in Experiment II.

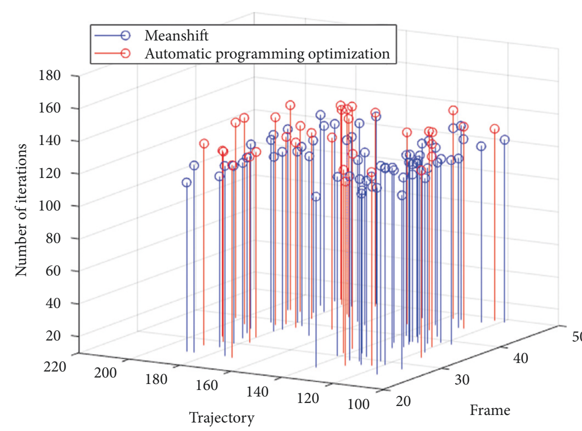

FIGURE 7: Target motion trajectories of the two methods in Experiment III.

target, which requires subsequent operations such as morphology to obtain a truly accurate moving target template.

4. Experimental Design

The theoretical part of the moving target vector graphics adaptive combination split tracking algorithm of the automatic programming optimization algorithm is introduced above. The performance of the algorithm is tested and analyzed through three representative video sequences. The selected videos are all selected in different environments of colleges and universities. “Small space with single background, complex medium space (gymnasium), and external campus space with complex environment and fast target movement” are successively taken as examples, and they are named as example 1, example 2, and example 3, respectively.

The experiment verifies the algorithm from multiple angles and the good performance of the multifeature fusion adaptive combination resolution algorithm of moving target vector graphics as shown in Figure 4.

Table 3: Comparison of several segmentation methods.

Target	Otsu	Iterative method	The largest office method	The manual threshold	Automatic optimization programming
Experiment I [13]	179	179	249	153	158
Experiment II [18]	115	113	223	134	136

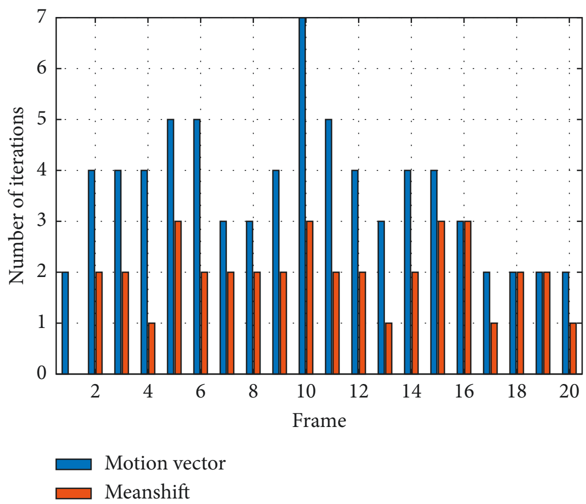

Figure 8: Iteration times of the algorithm.

5. Results and Analysis

We use the original automatic programming optimization combined moving object vector graphics algorithm to segment the indoor small and fast moving scene, indoor large space and multiobstacle occlusion space, as well as the outdoor lighting and tracking object under the condition of high-speed movement. Then, we use the improved multifeature fusion automatic programming optimization algorithm of moving target vector graphics combination resolution algorithm to track the same sample of the target, and the final experimental results are obvious. On the basis of the original target tracking algorithm of automatic moving target planning and optimization of combined vector graphics resolution, this paper optimizes three kinds of complex campus situations. They are small-scale high-speed moving targets under indoor conditions, various obstacles tracked, target status and outdoor lighting changes, and rapid displacement of target track. The original automatic programming optimization algorithm of moving target vector graphics combination and resolution cannot achieve effective tracking of the target, but the improved algorithm through multifeature fusion can effectively track the target in the above several cases. Experimental results show that the original automatic programming optimization method is less robust than the improved tracking algorithm. In the three groups of experimental results, the original algorithm tracking the target box is inferior to the improved algorithm, and there is a certain deviation from the center point. By combining texture and color histogram, the target can be locked and the robustness of target tracking can be guaranteed.

In general, the proposed method takes into account the texture properties of the target feature but still has computational complexity similar to that of the color histogram. At the same time, in the automatic programming optimization algorithm for the resolution of moving target vector graphics combination, the main amount of computation is the iterative calculation of the tracking process, and the number of points processed by the proposed algorithm is significantly reduced, which also reduces the time required for each iteration process. According to the comparison of the number of iterations in Figures 5, 6, and 7, we can see that the improved algorithm of automatic programming and optimization of moving target vector graphics combination and resolution has certain advantages, which indicates that it can effectively save time and ensure real-time performance in the process of target tracking.

The above algorithm is used to carry out detailed image segmentation experiments on moving target images under complex background. For comparison, this algorithm is compared with classical maximum interclass variance method, iterative method, maximum entropy method, and manual segmentation algorithm, which are generally considered better. Some results are shown in Table 3.

In addition, the algorithm of tracking efficiency is shown in Figure 8 and compared with the traditional automatic programming optimization combination of vector graphics resolution algorithm of moving objects, based on the analysis of motion vector, the algorithm of automatic planning and optimization of combined motion object vector graphics greatly reduces the number of iterations after segmentation. Generally, the maximum number of iterations is 3. Then, you will find the center of the moving target is located; thus, the efficiency of the automatic programming optimization algorithm is improved.

In actual motion, there are sometimes multiple moving targets in the scene. Using the contour contraction motion region method proposed in this paper cannot distinguish individuals. Making full use of the image information of independent motion, it also has a good combination and separation effect to divide the sports information overlapping targets into individuals.

6. Conclusion

This paper proposes a moving target vector graphics combination resolution algorithm based on motion vector analysis and automatic programming optimization, which is used for tracking the moving target. The automatic programming optimization algorithm does not consider the macroinformation of the target movement when tracking the moving target. Some Kalman filter or particle filter methods used for moving target prediction have the problem of large amount of computation. The practical intelligent video surveillance DSP front-end equipment usually needs to combine video coding and video analysis on the same processor. Based on this, this paper proposes a motion vector used in the video coding process for moving targets on the combination of automatic programming optimization combination vector graphics resolution tracking algorithm, which not only can solve the problem of fast-moving target tracking is missing, but also can reduce the automatic programming optimization combination of movement target vector graphics resolution algorithm convergence times and improve the computing efficiency of CPU. In the next step, in the actual application of intelligent video surveillance DSP front-end equipment, video coding and video analysis often need to be combined on the same processor, and the motion vector obtained in the process of video coding and Mcan tracking algorithm will not solve the problem of tracking loss of fast-moving target.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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