Moving target tracking and recognition fusion algorithm based on multi-source

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Abstract: - For tracking accuracy of moving target in wide-area video surveillance system is not high, a tracking and recognition algorithm based on multi-source moving target is proposed. The fusion algorithm preliminarily determines candidate moving target by frame difference algorithm, and then matches candidate target with primary template by SIFT algorithm and treats the matching result as initial position, and at last tracks the target by CBWH algorithm. Experimental results show that the proposed algorithm can track the moving target well in the multi-source cases and has good robustness.

Key-Words: - Frame Difference;CBWH; SIFT; Fusion Algorithm; Target Tracking;Target Recognition

1 Introduction

Object tracking has been always a hot research in intelligent monitoring system. Moving target tracking in the case of single-source [1-2] has drew a lot of attention in computer vision literature. It is impossible to track the moving target in a long time and a large range in actual monitoring scene because of limit of single-source. Moving target tracking based on multi-source [3-4] in the wide monitoring scene has got lots of attention. A main task of the multi-source monitoring system is to uniquely identify the multi-source target in the scene. For example, in reference [5], it requires the system with a calibrated camera and scene model; in reference [6], there is no need for calibrating the camera, but overlapping vision domain is required; in reference [7], calibrated camera and completed scene model is not required in non-overlapping multi-camera system, but the labeled trajectory need to be entered manually; Therefore, a moving tracking and recognition algorithm based on multi-source is proposed, which is without camera lens calibration and scene modeling.

Multi-source target tracking includes two levels, first is to manually selecting moving target in the case of single-source, which belongs to target matching of longitudinal time domain. But in the case of multi-source, it is not only matching the target in longitudinal time domain but also in horizontal space. The matching is a process of multi-information fusion. This paper studied the tracking and recognition technology of moving target based on features registration, which mainly includes inter-frame difference algorithm, corrected background weighted histogram (CBWH) algorithm and scale invariant feature transform (SIFT) algorithm.

2 Related Algorithms Carding

2.1 Frame Difference

Inter-frame difference is also called frame difference [11]. By comparing the gray value of corresponding pixels in current frame and adjacent frames to find difference and detect the moving target. Frame difference method principle block diagram is shown in figure 1.

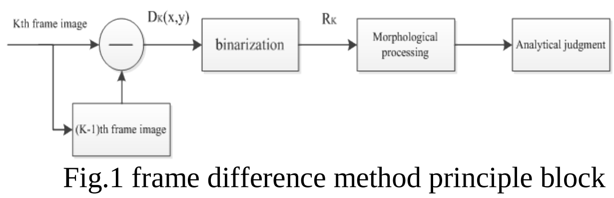


Fig.1 frame difference method principle block diagram

At first, calculating the difference between the kth frame image $f_k(x,y)$ and the k-1th frame image $f_{k-1}(x,y)$, and differential image can be expressed as $D_k(x,y)$. The difference method has positive difference, negative difference and total difference. The total difference corresponding formula is as follows:

$$D_k(x,y)=\left|f_k(x,y)-f_{k-1}(x,y)\right| \tag{1}$$

Then doing the binarization processing to the differential image $D_k(x,y)$, when the difference is above a given threshold T_t, setting the corresponding pixel value at 255, on the other hand setting at 0. Judging the area by the connectivity at last. When the area of some connectivity is above the threshold T_t, the area is regarded as the target area.

$$f_k(x,y,t)=\begin{cases}0 & background, \quad D_x(x,y)\le T_t \\ 1 & foreground, \quad D_x(x,y)>T_t\end{cases} \tag{2}$$

2.2 SIFT Algorithm

SIFT algorithm was proposed by David Lowe in 1999 and improved in 2004. This algorithm not only keeps invariance to image rotation, scaling and brightness change, but also to the visual change, noise influence and affine transformation. SIFT algorithm has been widely used in image matching, image classification, image retrieval and target recognition and other fields. Extracting SIFT feature points includes the following five steps:

1.Building the DOG scale space. DOG scale space is a simple approximation to the Laplacian of Gaussian, which can be achieved by calculating the difference of different scale factor of Gaussian kernel function and image. DOG scale space can be obtained by the following formula:

$$D(x,y,\sigma)=L(x,y,k\sigma)-L(x,y,\sigma)=\left(D(x,y,k\sigma)-D(x,y,\sigma)\right)*I(x,y) \tag{3}$$

Where, k is the scale multiple of two adjacent scale space. DOG forming process is shown in figure 2.

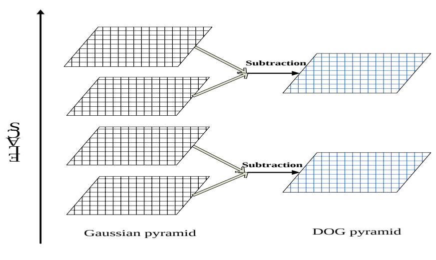


Fig.2 forming process of DOG scale space

2.Detecting the extreme points in scale space. Calculating the extreme points in scale space not only needs to compare each pixel point on the space with its 3×3 neighborhood points but also the relative 3×3 neighborhood points in the upper and lower layers in the pyramid image (a total of 26 points).Only when the point is the maximum or minimum in the 26 points, which can be regarded as the extreme value. Comparing process is shown in figure 3.

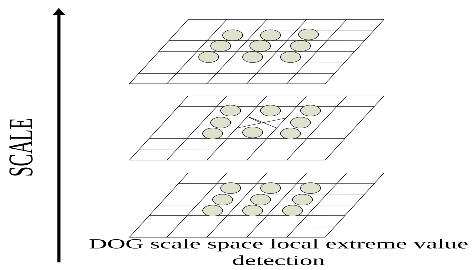


Fig.3 comparing process of extreme value

3.Precise extreme value point. Due to the points detected in the scale space are just candidate points, which contains a lot of low contrast and unstable edge response points. Therefore, the real extreme points can be obtained by filtering out these points.

4.Calculating the amplitude and direction of the key point. Calculating the amplitude $m(x,y)$ of key point according to the distribution of the amplitude of the pixels around the extreme point, and gradient direction is $\theta(x,y)$:

$$m(x,y)=\sqrt{\left(L(x+1,\ y)-L(x-1,y)\right)^2+\left(L(x,y+1)-L(x,y-1)\right)^2} \tag{4}$$

$$\theta(x,y)=\arctan\left(L(x,y+1)-L(x,y-1)/L(x+1,y)-L(x-1,y)\right) \tag{5}$$

5.Forming the SIFT feature vector descriptors.

2.3 CBWH Algorithm

2.3.1 Mean Shift

Mean Shift tracking algorithm using kernel function to model, similarity measure standard adopted Bhattachayya coefficient. It can obtain new location by Mean Shift iteration, so as to achieve the purpose of tracking target.

1.Target model. Setting $\{x_i^*\}$, $i=1,\cdots,n$ as the n pixel points set of the target area normalization, x_0 is the center of target area. With the kernel function histogram distribution to describe the target model, it can be represented as:

$$\hat{q}=\left\{\hat{q}_u\right\}_{u=1,2,\ldots,m}, \sum_{u=1}^{m}\hat{q}_u=1 \tag{6}$$

$$q_u=C\sum_{i=1}^{n}k\left(\left\|\frac{x_0-x_i^*}{h}\right\|^2\right)\delta\left[b\left(x_i^*\right)-u\right] \tag{7}$$

Where, $\hat{q}$ is the target model, $k(x)$ is the profile function of kernel function. The use of kernel function is due to the interference of the edge pixels and the background noise,so it is a function of weakening the edge pixels to highlight the central pixels. The function of $\delta(x)$ is to judge the characteristic interval of $b(x_i^*)$. C is a normalized constant.

$$\sum_{u=1}^{m}\hat{q}_u = 1, \quad C = 1\Big/\sum_{i=1}^{n} k\left(\left\|x_i^*\right\|^2\right) \tag{8}$$

2.Candidate model. In the subsequent frames may contain the target area known as the candidate targets, its center coordinates is y. The pixels in the area can be represented as $\{x_i\}$, $i = 1,\cdots,n_h$. Using the kernel function histogram to describe the candidate model, which can be represented as:

$$\begin{cases} p(y) = \{p_u(y)\}_{u=1,2,\ldots,N} \\ p_u(y) = C_h \sum_{i=1}^{n_k} k\left(\left\|\frac{y-x_i}{h_h}\right\|^2\right)\delta[b(x_i)-u] \end{cases} \tag{9}$$

Where, C_h is a normalized constant.

$$\sum_{u=1}^{m}\hat{p}_u = 1, \quad C_h = 1\Big/\sum_{i=1}^{n_k} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right) \tag{10}$$

Using Bhattachayya coefficient to measure the similarity of candidate model distribution $\hat{p}_u(y)$ and target distribution $\hat{q}_u$:

$$\rho[p(y),q] \approx \frac{1}{2}\sum_{u=1}^{N}\sqrt{p_u(y_0)q_u} + \frac{C_h}{2}\sum_{i=1}^{n_k} w_i k\left(\left\|\frac{y-x_i}{h_h}\right\|\right) \tag{11}$$

Where,

$$w_i = \sum_{u=1}^{N}\sqrt{\frac{q_u}{p_u(y_0)}}\,\delta[b(x_i)-u] \tag{12}$$

It can be seen from (11). In order to make $\rho(y)$ maximum, it just needs to take the maximum in the second item of the left equation, and the item is the kernel function density estimation of y points in current frame and weighted it by $\{w_i\}_{i=1,2,\ldots,n_k}$. Therefore, the maximization problem of type (11) is converted into the kernel density estimation problem of equation right. In this processing, recursive direction of kernel function is moving to the new target center y_1:

$$y_1 = \frac{\sum_{i=1}^{n_k} x_i w_i g\left(\left\|\frac{y-x_i}{h_h}\right\|^2\right)}{\sum_{i=1}^{n_k} w_i g\left(\left\|\frac{y-x_i}{h_h}\right\|^2\right)} \tag{13}$$

2.3.2 CBWH Algorithm

In target tracking, if the correlation of target and background is high, the tracking algorithm is easy to fall into local optimum, which leads to tracking failure. In many cases, the target is difficult to be accurately portrayed, and the target model usually contains the ingredients of background information and noise. In the case of the non-distinction, the incorrect usage of background will affect the target positioning. Therefore, it is an effective method to improve the tracking accuracy by using local background information to improve the ability of target description. Comaniciu tried to introduce the local background information into the target color histogram. Ning proved that the method of Comaniciu did not introduce the background information, and they realized the real purpose by only introducing the background weighted on the target histogram, namely CBWH algorithm.

1.Background model and weight coefficient. The background model is represented as:

$$\{\hat{o}_u\}_{u=1,2,\cdots,m}, \quad \sum_{i=1}^{m}\hat{o}_u = 1 \tag{14}$$

Type (14) is calculated by surrounding area of the target.

Calculating weight coefficient by using background feature distribution:

$$\left\{v_u = \min\left(\hat{o}^* / \hat{o}_u, 1\right)\right\}_{u=1,2,\cdots,m} \tag{15}$$

In this type, $\hat{o}^*$ is the minimal non-zero value in $\{\hat{o}_u\}_{u=1,2,\cdots,m}$. Therefore, it can be seen from that the value of background feature u is inversely proportional to the value of the weight coefficient v_u. Therefore, the new target model can be obtained by using the weight coefficient.:

$$\hat{q}_u' = C' v_u \sum_{i=1}^{n} k\left(\left\|x_i^*\right\|^2\right)\delta\left[b\left(x_i^*\right)-u\right] \tag{16}$$

With normalized coefficient:

$$C' = 1\Big/\sum_{i=1}^{n} k\left(\left\|x_i^*\right\|^2\right)\sum_{u=1}^{m} v_u \delta\left[b\left(x_i^*\right)-u\right] \tag{17}$$

The weight coefficient v_u defines a conversion to the target model. The feature component values of the smaller v_u corresponding to the target model will reduced, and these feature components are also the salient features in the background. To enhance the salient features of the target is realized by transformation of the target model, and weakened the influence of the background information on the target location. The new weight is expressed as:

$$w_i' = \sqrt{\hat{q}_u' \Big/ \hat{p}_u'(y)} = \sqrt{C'/C} \times \sqrt{v_u} \times \omega_i \tag{18}$$

$\sqrt{C'/C}$ is a constant scale factor, which does not affect the tracking procedure of Mean Shift.

2. Background model updating. The CBWH algorithm establishes a background histogram model when the target is initialized. In the course of tracking, however, the background is often changed due to the light, the angle of view, the block or the content of the scene and so on. If the original background model has not been updating all the time, the tracking result of CBWH algorithm will become unpredictable, therefore it is necessary to update the background dynamically in order to ensure the stability of CBWH algorithm. The background area model of target and its weight coefficient in current frame can be represented as:

$$\left\{\hat{o}_u^{'}\right\}_{u=1,2,\cdots,m}, \left\{\hat{v}_u^{'}\right\}_{u=1,2,\cdots,m} \tag{19}$$

Bhattachayya measures the similarity between the original background model and the current background model:

$$\rho=\sum_{u=1}^{m}\sqrt{\hat{o}_u \hat{o}_u^{'}} \tag{20}$$

Setting the threshold at $threshold$, if $\rho < threshold$, it means the local background of the target has been changed, at this time, it should update the background model and weight coefficient, and re-filter the features of original target model, so as to ensure the feature of the model is the obvious feature of target in the current frame. Otherwise, it is unable to perform any operation.

2.3.3 CBWH Algorithm Experiment

Using CBWH algorithm to track the standard video, the experimental tool is MATLAB 2011a, the experimental platform is Core i7-2760QM, the video is 25 frame /second.

(a) Standard video 2nd and 16th frame images

(b) Standard video 66th and 100th frame images

Fig.4 CBWH algorithm tracking results

CBWH algorithm can well track the moving target, even when the target has light and other external factors changes, but just only using CBWH algorithm can not track moving target in the multiple sources cases.

3 Multi-source target tracking and recognition fusion algorithm

Through the above carding, the frame difference method has the advantages of simple realization and fast operation, which can quickly locate the candidate moving target. SIFT algorithm has affine invariance and scale invariance, and it is not sensitive to the light change and other external factors. Therefore, the paper uses SIFT algorithm to match the target template and candidate target template. Although the CBWH algorithm can track the moving target in single-source case, the algorithm cannot be applied to multi-source cases. Therefore, this paper puts forward a frame difference method, sift and CBWH combination fusion algorithm, and the fusion algorithm is applied to multi-source moving target tracking. Experimental results find that the algorithm has good robustness.

3.1 Fusion Algorithm Thinking

The main idea of the fusion algorithm is as follows: in the first step, selecting the moving target in video A manually, and intercept box selection as target template; in the second step, using the frame difference to the video B, and find the moving target area in the video; in the third step, using SIFT algorithm to match the target template in the video A with candidate area in the video B, and find out the moving target; in the forth step, finding out the moving target, and automatically selected. The flow chart of the algorithm is shown in Figure 5.

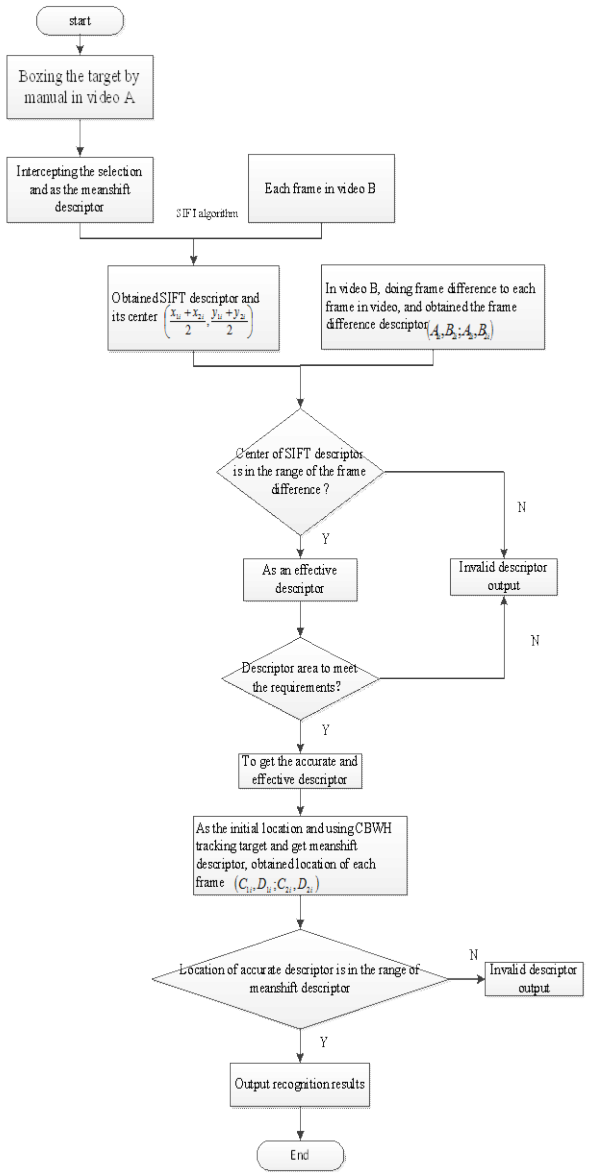


Fig 5 flow chart of multi-source moving target tracking and recognition

3.2 Fusion Algorithm Step

This paper assumes that select moving target in video A manually and need to identify the moving target in video B. The main steps are:

Step 1: selecting the moving target manually in video A, and uses CBWH algorithm to track moving target. If obtaining m frames of moving target in video A, each of m frames can get a moving target area manually. And intercept the moving target of m frames, forming m meanshift descriptors;

Step 2: for each frame of video B, the paper needs to find out the moving target at first, therefore using frame difference to find out moving target of each frame. If in each frame of video B, respectively using the frame difference method to get n difference descriptors (namely moving target), its coordinates are $(x_{1i},y_{1i},x_{2i},y_{2i})$, where (x_{1i},y_{1i}) means the descriptor on the upper left corner of the video, (x_{2i},y_{2i}) means the descriptor on the lower right corner of the video.

Step 3: in each frame of video B just has one target to be recognized, therefore, n frame difference descriptors obtained in step 2 have error descriptors, in order to eliminate the error frame difference descriptors. This paper combines the SIFT algorithm. At first, using m frames matches with each frame of video B by SIFT algorithm, so it can get m SFIT descriptors, its coordinates are $(z_{1i},t_{1i},z_{2i},t_{2i})$, its center is $\left(\frac{z_{1i}+z_{2i}}{2},\frac{t_{1i}+t_{2i}}{2}\right)$;

Step 4: n frame difference descriptors obtained in step 2, m SIFT descriptors obtained in step 3, and the paper obtains the correct descriptor by voting method to judge which descriptor is right, namely calculating how many SIFT descriptors falling into the frame difference descriptor in a frame, having the largest number of frame difference descriptors is the effective descriptor of the frame, which can meet the $(x_{1i},y_{1i},x_{2i},y_{2i})$ of $\max_i \sum_j I\left(x_{1i}<\frac{z_{1j}+z_{2j}}{2}<x_{2i},y_{1i}<\frac{t_{1j}+t_{2j}}{2}<y_{2i}\right)$ and will eventually be selected as effective descriptors. For some frames of B video may can not find frame differential descriptors, or sift descriptors, or the frame difference descriptors and sift descriptors are inconsistent, so such a frame should be considered invalid descriptor;

Step 5: assuming that finding several frames having effective descriptors in step 4, but in some frames do not find effective descriptors, and some descriptors are wrong in some frames. In order to improve the recognition accuracy, the paper combines CBWH algorithm in video B;

Step 6: using the initial location founded in the step 5 to track the moving target by CBWH algorithm, for each frame of video B, using CBWH algorithm can find a meanshift descriptor, its coordinates are $(s_{1i},d_{1i},s_{2i},d_{2i})$. At the same time, for part of frames in video B, in step 4 also obtained some effective descriptors $(x_{1i},y_{1i},x_{2i},y_{2i})$. Therefore, combining these two descriptors, in order to ensure the moving target exact position in each frame of video B, the paper determines the constraint conditions as follows:

Condition 1: if between the consecutive two frames, the displacement of the meanshift descriptor is too big or too small, then not given the recognition results, namely each frame of video B calculating an average speed and an instantaneous velocity formula respectively (19) and (20):

$$V_i=(V_{1i},V_{2i})=\left[\frac{\left(\frac{s_{1i}+s_{2i}}{2}-\frac{x_{1i_0}+x_{2i_0}}{2}\right)}{i-i_0},\frac{\left(\frac{d_{1i}+d_{2i}}{2}-\frac{y_{1i_0}+y_{2i_0}}{2}\right)}{i-i_0}\right] \quad (21)$$

$$v_i=(v_{1i},v_{2i})=\left[\frac{\left(\frac{s_{1i}+s_{2i}}{2}-\frac{s_{1(i-1)}+s_{2(i-1)}}{2}\right)}{i-i_0},\frac{\left(\frac{d_{1i}+d_{2i}}{2}-\frac{d_{1(i-1)}+d_{2(i-1)}}{2}\right)}{i-i_0}\right] \quad (22)$$

At the same time, $v_{1i}/5<V_{1i}<5v_{1i}$, $v_{2i}/5<V_{2i}<5v_{2i}$, and $\cos(v_i,V_i)\geq 0$. These results are obtained by a lot of experiments.

Condition 2: in the presence of a valid descriptor frame, if the result given by effective descriptor and meanshift descriptor is inconsistent, then the frame recognition result outputs. Namely the paper asked: $s_{1i}<\frac{x_{1i}+x_{2i}}{2}<s_{2i}$, $d_{1i}<\frac{y_{1i}+y_{2i}}{2}<d_{2i}$.

Condition 3: if the results not output in a continuous two descriptors, then the paper thinks CBWH algorithm has failed, at the failure frame to recalculating the new moving target position, and the new position can calculate by step 5.

4. Experiment Results and analysis

4.1 Experiment Results

The paper uses three non-overlap videos in this experiment, respectively called video A, video B and video C. There are more than one moving characters in video A, the first thing need to do is to box the moving target by manual, and intercept the target selection and regard as meanshift descriptor. Secondly, obtain the frame difference descriptor and its coordinates by doing frame difference to video B. At the same time, matching meanshift descriptor with frame difference by SIFT algorithm, and obtain the center coordinates of SIFT descriptor. Judging the center coordinates of SIFT descriptor whether fall into the range of frame difference descriptor. Finally, obtain the effective descriptor and combine the CBWH algorithm to get the recognition results.

Boxing the moving target in the video A and intercept the box area manually, result shown in figure 6.

(a) 1st frame

(b) Target image selected manually

(c) Target area interception

Fig 6 tracking results in video A

Through the above target recognition steps, the target characters can be identified in video B, and the identification results are shown in Figure 7.

(a) 7th frame

(b) 10th frame

(c) 46th frame

Fig 7 target recognition in video B

For video C, repeat steps1 to step 6, thereby finding the target characters in the video A, the recognition results shown in Figure 8.

(a) 8th frame

(b) 19th frame

(c) 56th frame

Fig 8 target recognition in video C

From Figure 7, we can see visually that there are other moving targets in video B, and still recognize the target needed to be identified. The scene of video C is more complicated than video B. There are other moving targets in the video and the target wearing similar with the one needed to be identified. This paper also can well identify the moving target.

Table 1 SIFT and this algorithm matching rate

Video number	SIFT algorithm		This algorithm	
	Correct matching points	Incorrect matching points	Correct matching points	Incorrect matching points
Video B	0	124	55	5
Video C	1	101	76	3

The above three videos are intercepted from an eight-way video, and the eight-way video is taken in different places at the same time. It is shown in figure 9.

(a) The 118th frame in the eight-way video

(b) The 121th frame in the eight-way video

Figure 9 eight-way video images

Using CBWH algorithm to track the target, and tracking results are shown in figure 10.

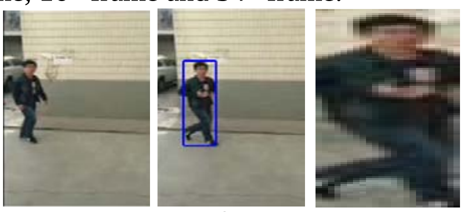
Figure 10 CBWH tracking results in video B (from left to right are:7th frame, 10th frame and 46th frame)

Using CBWH algorithm to track the target and tracking results are shown in figure 11.

Figure 11 CBWH tracking results in video C (from left to right are:8th frame, 19th frame and 56th frame)

In order to validate the effectiveness of the proposed algorithm, the author takes three videos in the Xi'an University of science and technology. The time of three videos is 30 seconds, 23 seconds and 45 seconds, 25 frames/second. The three videos are shown in figure 12.

It can be seen from figure 12, the first line is the captures of first video, from left to the right are: original video image, box the moving target by manual and interception of the moving target template. The second line is the recognition results of the second video, from left to the right are: the recognition of the 7th frame, 20th frame and 45th frame. The third line is the recognition of the third video, from left to the right are: the recognition of 4th frame, 16th frame and 34th frame.



(a) The first video

(b) The second video

(c) The third video

Figure 12 the captures of three videos

4.2 Experiment Analysis

Compare the fusion algorithm with CBWH algorithm on data, so as to prove the robustness of the algorithm in multi-source.

Table 2 tracking center coordinate deviation statistics

Video & Algorithm	Central Difference （unit：Pixel)	X-max	X-min	X-mean	Y-max	Y-min	Y-mean
Video B	CBWH	15	0	10.25	12	0	8.25
	This Algorithm	8	0	7	5	0	3
Video C	CBWH	218	0	98.67	31	0	25.67
	This Algorithm	5	0	3	4	0	2

Table 2 gives the statistics of the absolute value of the fusion algorithm and the CBWH algorithm in tracking target. From the above table can be seen that this algorithm is more accurate than the CBWH algorithm in the tracking process. In the video C of first experiment, when the target selected manually, the CBWH algorithm is quickly tracking failure due to the interference of the target, in subsequent frames without tracking moving target. The fusion algorithm proposed in this paper can solve the problem and can be recognized and tracked in the following frame. In the video taken by the author, the first and third video backgrounds are relatively simple and there are no other moving targets, but in the second video, there are not only other moving targets but also having changes of light and shade. However, this algorithm can still recognize and track the target. This fusion algorithm has better robustness and accuracy by above experiment and data.

5 Conclusions

This paper proposed an algorithm, which combines frame difference, SIFT and CBWH algorithm together. This algorithm can still track the moving target well in the case of multi-source cases without the need of calibration of the camera and environment model. However, it is very easy to block or rotate when the target is in the process of movement, therefore, immediate and accurate tracking moving target is the problem to be solved in the next step.

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