Weighted Sub-block Mean-Shift Tracking with Improved Level Set Target Extraction

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ABSTRACT: *Mean-shift tracking algorithm is a widely used tool for efficiently tracking target. However, the background change and shade usually lead to tracking errors and low tracking accuracy. In this paper, we introduce a novel Mean-shift tracking algorithm based on weighted sub-block which incorporates the improved level set target extraction. The weight of each sub-block is determined by the similarity of target sub-block and candidate sub-block, also by the ratio of the target sub-block area and the overall area. At the same time, the target sub-block area is found by means of the narrow band level set combined with penalty to improve the extraction accuracy and operating efficiency. Both of the target region's RGB color information and the pixel's position information are taken into consideration while describing the feature model of target and candidate region inside each sub-block. Many experimental results demonstrate the successful tracking of targets with background change and shade during the dynamic scene, where the basic Mean-shift tracking algorithm fails. And the proposed method has better tracking performance with higher tracking accuracy and adaptability.*

Keywords: Target Tracking, Mean-shift Algorithm, Target Extraction, Level Set, Dynamic Scene, Weighted Sub-block

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1. Introduction

In the dynamic scene, moving target tracking is one of important subjects in the field of computer vision, whose tracking effect directly influences the performance of the whole tracking system. The tracking method based on Mean-Shift algorithm is optimal gradient ascent method [1], which searches maximum of the probability density. So Mean-Shift algorithm in the dynamic scene has been researched deeply by many scholars, and many important results [2] are obtained. Moving target tracking is implemented by matching clustering blocks, which is obtained by establishing clustering of the target model and target candidate model [3]. A target is blocked and each sub-block's weight is determined by matching degree of similarity between the target region and target candidate region, which leads to success tracking [4]. A kind of real-time visual tracking modeled by adaptive pyramid is proposed, and good results are implemented [5]. A target is blocked and each sub-block is described by histogram features of gradient direction, which decreases the errors caused by background's shade and improves robustness of the algorithm[6].The special pyramid technique is used for blocking the target and target tracking is highly precise[7].A new fragmean shift based on foreground is proposed[8]. In this paper, we use weighted sub-block Mean-Shift tracking algorithm. The algorithm divides the target region into sub-blocks whose weight is obtained by the similarity and the area ratio.

During weighted sub-block Mean-Shift tracking in this paper, the area of each sub-block is important to weight determination. Closed planar curve is described by implicating in the level set. And curve evolution is transformed to the problem of solving numerical partial differential equation, and this avoids the parameterization procedures during curve evolution and can be effectively used to solve topology problems (split or merge). So the level set can improve the target extraction accuracy. Many scholars re-searched on target extraction based on the level set and achieved important results. Bayesian risk is used to control the accuracy target extraction after classifying the pixels [9], which extract the complicated shapes of targets in medical images. Ref. [10] proposed the combination of Sobel operator and level set algorithm to solve the target extraction of holographic images. Ref. [11] combines level set algorithm with morphological top-hat and bottom-hat transformation, which leads to good target extraction. Image segmentation method based on region fusion and narrow band energy graph partitioning is proposed [12], which achieved the segmentation of skin lesion images. Ref. [13] proposed that morphological closing operation is utilized to smooth the level set function, which guarantees the effectiveness of the evolution of level set function and obtained target extraction with high accuracy. In this paper, we study improved level set target extraction. The area is determined by using the proposed extraction method, which combines the narrow band level set with penalty.

This paper is organized as follows: Section II expounds the weighted sub-block Mean-Shift tracking algorithm. Section III proposes the improved level set target extraction. In Section IV, we detail weighted sub-block Mean-shift tracking algorithm with improved level set target extraction. Section V presents experimental results and analysis. Section VI is the conclusions and future work about moving target tracking. The last Section is the acknowledgment.

2. Weighted Sub-block Mean-Shift Tracking Algorithm

The target region is divided into J (j =1, 2, ..., J) sub-blocks. The color probability distribution of the sub-block target region centered at location $x^{(j)}_0$ is denoted as $\hat{r}_u = \{\hat{r}_u^{(j)}(x_0), u = 1, 2, ..., m\}$, where $\hat{r}_u^{(j)}(x_0)$ is calculated by [8]:

$$\hat{r}_u^{(j)} = C^{(j)} \bullet \sum_{i=1}^{n^{(j)}} k\left(\left\| \frac{x_0^{(j)} - x_i^{(j)}}{h^{(j)}} \right\|^2\right) \delta[b(x_i^{(j)}) - u] \tag{1}$$

where ensure that $\sum_{u=1}^{m} \hat{r}_u^{(j)} = 1$, $n^{(j)}$ is the total pixel number in the sub-block region, $C^{(j)}$ is a normalization constant which is calculated by:

$$C^{(j)} = \frac{1}{\sum_{i=1}^{n^{(j)}} k\left(\left\| \frac{x_0^{(j)} - x_i^{(j)}}{h^{(j)}} \right\|^2\right)} \tag{2}$$

Color probability distribution of the overall target region is expressed as:

$$\hat{q}_u^{(J)} = \sum_{j=1}^{J} C^{(j)} \sum_{i=1}^{n^{(j)}} k\left(\left\| \frac{x_0^{(j)} - x_i^{(j)}}{h^{(j)}} \right\|^2\right) \delta[b(x_i^{(j)}) - u] \tag{3}$$

Similarly, the color probability distribution of the sub-block candidate target region centered at location $y^{(j)}$ in following image frames is denoted as $\hat{t}_u^{(j)} = \{\hat{t}_u^{(j)}(y), u = 1, 2, ..., m\}$.The function $\hat{t}_u^{(j)}(y)$ calculated by [8]:

$$\hat{t}_u^{(j)} = C^{(j)} \bullet \sum_{i=1}^{n^{(j)}} k \left(\left\| \frac{y^{(j)} - y_i^{(j)}}{h^{(j)}} \right\|^2 \right) \delta[b(y_i^{(j)}) - u] \tag{4}$$

where ensure that $\sum_{u=1}^{m} \hat{t}_u^{(j)} = 1$, $n^{(j)}$ is the total pixel number in the sub-block region $C^{(j)}$ is a normalization constant which is calculated by:

$$C^{(j)} = \frac{1}{\sum_{i=1}^{n^{(j)}} k \left(\left\| \frac{y^{(j)} - y_i^{(j)}}{h^{(j)}} \right\|^2 \right)} \tag{5}$$

Color probability distribution of the overall candidate target region is expressed as:

$$\hat{p}_u^{(J)} = \sum_{J=1}^{J} C^{(j)} \sum_{i=1}^{n^{(j)}} k \left(\left\| \frac{y^{(j)} - y_i^{(j)}}{h^{(j)}} \right\|^2 \right) \delta[b(y_i^{(j)}) - u] \tag{6}$$

The similarity between sub-block target region and sub-block candidate target region is calculated by [4]:

$$\rho^{(j)} [\hat{t}^{(j)}(y^{(j)}), \hat{r}^{(j)}] \approx \frac{1}{2} \bullet \sum_{i=1}^{m} \sqrt{\hat{t}_{\mathrm{u}}(y^{(j)}) \bullet \hat{r}_{\mathrm{u}}} + \frac{C^{(j)}}{2} \bullet \sum_{i=1}^{n^{(j)}} w_i^{(j)} \bullet k \left(\left\| \frac{y^{(j)} - y_i^{(j)}}{h^{(j)}} \right\|^2 \right) \tag{7}$$

where $w_i^{(j)}$ is the weight factor and is calculated by:

$$w_i^{(j)} = \sum_{u=1}^{m} \delta[b(y_i^{(j)}) - u] \bullet \sqrt{\frac{\hat{r}_u^{(j)}}{\hat{t}_u^{(j)}(y^{(j)})}} \tag{8}$$

So the similarity between whole target region and whole candidate target region is calculated by:

$$\rho[\hat{p}(y), \hat{q}] = \sum_{j=1}^{J} \rho^{(j)} \bullet \lambda^{(j)} \approx \frac{1}{2} \sum_{j=1}^{J} \lambda^{(j)} \sum_{u=1}^{m} \sqrt{\hat{t}_u(y^{(j)}) \bullet \hat{r}_u}$$

$$+ \frac{C^{(j)}}{2} \sum_{j=1}^{J} \lambda_i^{(j)} \sum_{i=1}^{n^{(j)}} w_i^{(j)} \bullet k \left(\left\| \frac{y^{(j)} - y_i^{(j)}}{h^{(j)}} \right\|^2 \right) \tag{9}$$

where $\lambda^{(j)}$ is the weight factor of j sub-block,

$$\sum_{j=1}^{J} \lambda^{(j)} = 1.$$

According to Mean-Shift moving target tracking algorithm, the centre y of candidate target region which is the most similar to target region is calculated as below:

$$y = \frac{\sum_{j=1}^{J} \lambda^{(j)} \sum_{i=1}^{n^{(j)}} y_i^{(j)} \omega_i^{(j)} g\left(\left\| \frac{y_0^{(j)} - y_i^{(j)}}{h^{(j)}} \right\|^2 \right)}{\sum_{j=1}^{J} \lambda^{(j)} \sum_{i=1}^{n^{(j)}} \omega_i^{(j)} g\left(\left\| \frac{y_0^{(j)} - y_i^{(j)}}{h^{(j)}} \right\|^2 \right)} \tag{10}$$

where $\lambda^{(j)}$ is the weight factor of each sub-block, which is calculated by:

$$\lambda^{(j)} = \alpha\lambda_1^{(j)} + \beta\lambda_2^{(j)} \tag{11}$$

In the video image, through many experiments to adjust α and β , $\alpha + \beta = 1$.

where $\lambda_1^{(j)}$ is determined by ratio between sub-block similarity and sum of each sub-block similarity:

$$\lambda_1^{(j)} = \frac{\rho^{(j)} [\hat{t}^{(j)} (y^{(j)}) , \hat{r}^{(j)}]}{\sum_{j=1}^{J} \rho^{(j)} [\hat{t}^{(j)} (y^{(j)}) , \hat{r}^{(j)}]} \tag{12}$$

$\lambda_2^{(j)}$ is determined by the ratio between the area of each sub-block and the area of whole target:

$$\lambda_2^{(j)} = \frac{S^{(j)}}{\sum_{j=1}^{J} S^{(j)}} \tag{13}$$

where each sub-block's area $S^{(j)}$ is obtained by the pixel number of target region, which is determined by the proposed narrow band level set combined with penalty in this paper.

3. Improved Level Set Target Entraction

Narrow band level set method updates pixels close to the latest Level Set contour by optimizing the narrow band energy based on a similarity measure [14]. Band will be established again when curve evolution reaches boundary of narrow band.

The energy function is represented as follow:

$$E(\phi) = E_s(\phi) + E_{nb}(\phi) \tag{14}$$

where $$E_s(\phi) = \mu \,\text{Length}(\phi) + v \,\text{Area}(\phi) = \mu \int_\Omega \delta(\phi) |\nabla\phi| \, dxdy + v \int_\Omega H(\phi) \, dxdy$$

is the smoothness energy, length (Γ) denotes the length of closed curve Γ, *Area* $(\Gamma)\cdot$ denotes the area inside the closed curve $\Gamma\cdot$

$$H(\phi) = \begin{cases} 1 & \phi \geq 0 \\ 0 & \phi < 0 \end{cases}, \quad \delta(\bullet)$$

is Dirac function.

$$E_{nb}(\phi) = \int_{\Omega}\int_{0}^{B}(I\ (c+bn) - k_{in})^2 l\ (1-bk)\ dbdu +$$

$$\int_{\Omega}\int_{0}^{B}(I\ (c-bn) - k_{out})^2 l\ (1+bk)\ dbdu$$

is narrow band energy, which de-crease the calculation range from whole image to the part inside the band around the closed curve[15],where k is curvature $n = kc$, c is a position vector, n is a normal vector, $l = \left\| \dfrac{dc}{du} \right\|$ is the length element (or velocity), k_{in} and k_{out} are intensity descriptors inside and outside the closed curve,

$$k_{in} = \frac{1}{|B_{in}|} \int_{\Omega}\int_{0}^{B}(I\ (c+bn)\ \ l\ (1-b\kappa)\ dbdu,$$

$$k_{out} = \frac{1}{|B_{out}|} \int_{\Omega}\int_{0}^{B}(I\ (c-bn)\ \ l\ (1+b\kappa)\ dbdu,$$

$$B_{in} = \int_{\Omega} l\ (B + \frac{B^2}{2}\kappa)\ du,$$

$$B_{outt} = \int_{\Omega} l\ (B + \frac{B^2}{2}\kappa)\ du$$

In narrow band level set algorithm, level set function has to keep re-initializing in the evolution process. At the same time, although the narrow band level set algorithm solve the problem of slow calculation speed to some extent, it needs re-initialization after several iterations.

The calculation time will be quite considerable if the image data is large. According to the characteristics of dynamic scene images, to improve the extraction accuracy and operation efficiency, narrow band level set combined with penalty algorithm is proposed in this paper.

This algorithm is a level set model without re-initialization, and the energy penalty term is defined as [11]:

$$P(\phi) = \int_{\Omega} \frac{1}{2} (|\nabla\phi|)^2\ du \tag{15}$$

So in this paper, the proposed energy function of narrow band level set combined with penalty algorithm is:

$$E[\phi] = P(\phi) + E_s[\phi] + E_{nb}(\phi)$$
$$= \int_{\Omega} \frac{1}{2} (\left|\nabla\phi\right|)^2\ du + \mu \int_{\Omega} g\ \delta(\phi) \left|\nabla\phi\right|\ du + v \int_{\Omega} gH(\phi)\ du$$

$$+\int_{\Omega}\int_{0}^{B} g\,(I\,(c+bn)-k_{in})^2\, l\,(1-bk)\,dbdu$$

$$+\int_{\Omega}\int_{0}^{B} g\,(I\,(c-bn)-k_{out})^2\, l\,(1+bk)\,dbdu \tag{16}$$

where g is the image edges index, and the computation formula is

$$g = \frac{1}{1+\left|\nabla G_{\sigma} * I_0\right|}.$$

Its partial differential equation is:

$$\frac{\partial \phi}{\partial t} = [\nabla\phi - div\,(\frac{\nabla\phi}{|\nabla\phi|})] +$$

$$\delta\phi = [\,u div\,(g\frac{\nabla\phi}{|\nabla\phi|}) - gv]$$

$$+\,gl\,[-(I\,(x,y)-k_{in})^2 + (1-Bk)(I\,(x,y)_{[B]} - k_{in})^2$$

$$-(1+Bk)(I\,(x,y)_{[-B]} - k_{out})^2 + (I\,(x,y)-k_{out})^2]\,n \tag{17}$$

$$\text{where } \delta\phi = \frac{1}{\pi} \bullet \frac{\varepsilon}{\varepsilon^2+\phi^2},$$

Its numerical solution is:

$$\phi_{i,j}^{n+1} = \phi_{i,j}^{n} + \Delta t \bullet \left[max\,(E,0) \bullet \nabla^{+} + min\,(E,0) \bullet \nabla^{-} + \mu \bullet K_{i,j} \bullet \left(\left(D_{i,j}^{0x}\right)^2 \left(D_{i,j}^{0y}\right)^2 \right) \right]^{1/2} \tag{18}$$

$$\text{where } \nabla^{+} = \left[max\,(D_{i,j}^{-x},0)^2 + min(D_{i,j}^{+x},0)^2 + max\,(D_{i,j}^{-y},0)^2 + min\,(D_{i,j}^{+y},0)^2 \right]^{1/2},$$

$$\nabla^{-} = \left[min\,(D_{i,j}^{-x},0)^2 + max\,(D_{i,j}^{+x},0)^2 + min\,(D_{i,j}^{-y},0)^2 + max\,(D_{i,j}^{+y},0)^2 \right]^{1/2},$$

$$E = -gv + gl\left[-(I\,(x,y)-k_{in})^2 + (1-B\kappa)(I\,(x,y)_{[B]} - k_{in})^2 - (1+BK) \bullet (I\,(x,y)_{[-B]} - k_{out})^2 + (I\,(x,y) - k_{out})^2 \right],$$

$k_{i,j}$ is the curvature of level set at point $(i,\ j)$

$$K_{i,j} = \nabla \bullet \frac{\nabla \phi}{|\nabla \phi|.} = \frac{\phi_{xx} \bullet \phi_y^{\,2} - 2 \bullet \phi_x \bullet \phi_y \bullet \phi_{xy} \bullet \phi_{yy} \bullet \phi_x^{\,2}}{(\phi_x^{\,2} + \phi_y^{\,2})^{3/2}}$$

In the original Mean-Shift tracking algorithm, only color information was taken into consideration when describing the feature model of target and candidate region, while the pixel position information is ignored, which influences the tracking accuracy. In this paper, number the sub-blocks from 1 to 4, and then calculate the color histograms respectively. Finally one color histogram will be composed by the four histograms in order of number [16].

4. Detail of the Proposed Tracking Algorithm

The flow chart of the proposed target tracking algorithm is represented in Figure1.

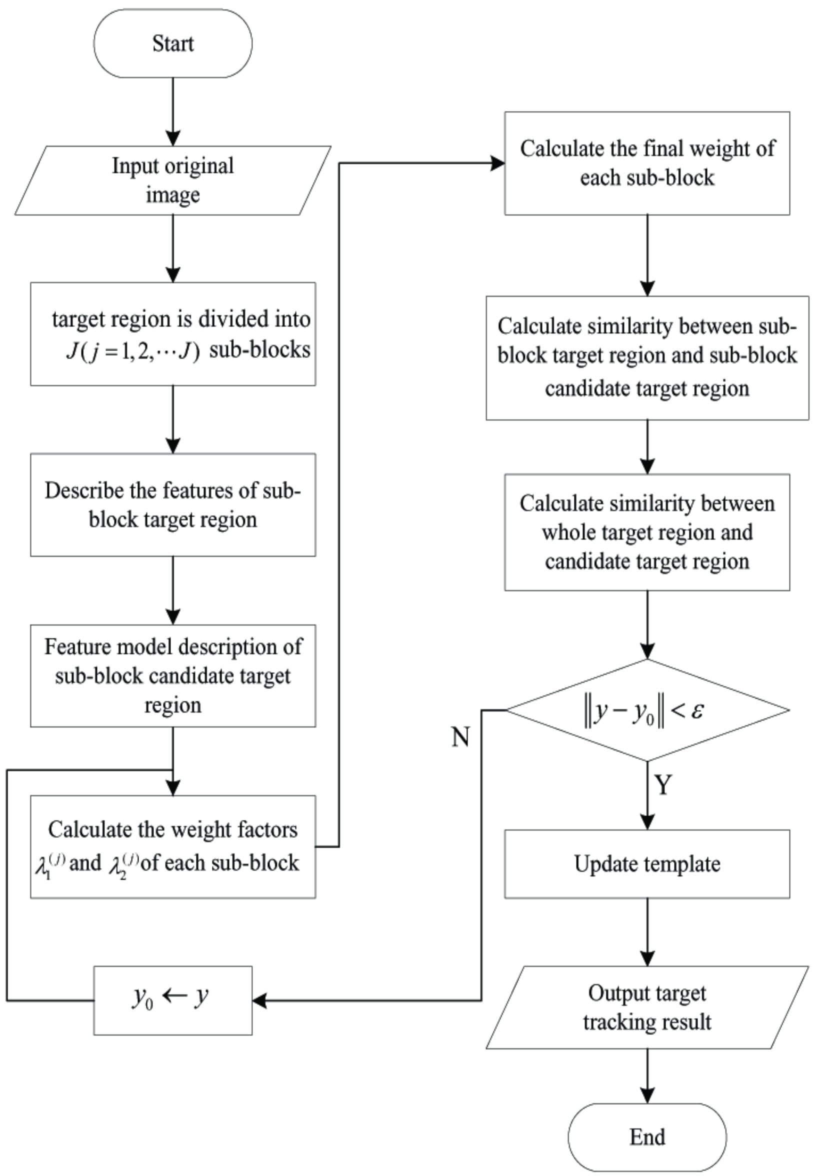


Figure 1. Flow chart of target tracking algorithm

The process is illustrated as follow:

1) The target region is divided and described the features of sub-block target region and sub-block candidate target region.

a) The tracking target is divided into J (j = 1, 2, .. J) sub-blocks.

b) The color probability distribution of sub-block target region centered at location $x_0^{(j)}$ is denoted as $\hat{r}_u = \{ \hat{r}_u^{(j)}(x_0), u = 1,2,.., m \}$.

c) The color probability distribution of the sub-block candidate target region centered at location $y^{(j)}$ in following image frame is denoted as $\hat{t}_u = \{ \hat{t}_u^{(j)}(y), u = 1, 2, .., m \}$.

2) Determine the weight of each sub-block.

a) $\lambda_1^{(j)}$ is determined by the similarity between sub-block target region and sub-block candidate target region.

b) $\lambda_2^{(j)}$ is determined by the ratio between the area of sub-block target region and the area of whole target region.

c) Calculate the final weight of each sub-block $\lambda^{(j)} = \alpha\lambda_1^{(j)} + \beta\lambda_2^{(j)}$, where α and β are coefficients.

3) Calculate the similarity between target region and candidate target region.

a) Calculate the similarity between sub-block target region and sub-block candidate target region $\rho^{(j)}[\hat{t}^{(j)}(y^{(j)}), \hat{r}^{(j)}]$.

b) Calculate the similarity between whole target region and whole candidate target region $\rho[\hat{p}(y), \hat{q}]$.

4) Update template, obtain the tracking result.

Update template if $\| \boldsymbol{y} - y_0 \| < \varepsilon$ and output the moving target tracking result; else $y_0 \leftarrow y$ and go to step 2).

5. Results and Analysis of Experiment

The experiments of the Coastguard standard and the practical image sequence with dynamic scene were conducted to measure the effectiveness of the proposed weighted sub-block Mean-Shift tracking algorithm with improved level set target extraction. And experimental results are given.

The first group of experiments is to track the Coastguard standard image sequence. Part of the results is shown in Figure 2 (image size is 352×288). Figure 2 (a) shows the initial target position of the 120^{th} image frame and the target extraction area. The matrix of initial target region is [60, 113, 221, 71], the coordinate of rectangle's upper-left corner in the whole image is (60,113), and width is 221 pixels, height is 71 pixels. Initial target template of moving target is obtained on the basis of above. At the same time, target is blocked into two sub-blocks, the values of α and β for each sub-block are 0.38, 0.62 and 0.43, 0.57. The tracking result of 125^{th} frame and the target extraction area are shown in Figure 2 (b) by updating target template during tracking next image frames. The tracking result of 130^{th} frame and the target extraction area are shown in Figure 2 (c). The tracking result of 135th frame and the target extraction area are shown in Figure2 (d). The tracking result of 140^{th} frame and the target extraction area are shown in Figure.2 (e). The tracking result of 145^{th} frame and the target extraction area are shown in Figure.2 (f).

For comparison, experimental results of original Mean-Shift tracking algorithm are shown in Figure3 and weighted sub-block Mean-Shift tracking algorithm with Sobel operator target extraction in Figure.4.

Initial target template of moving target in Figure.3 (a) is obtained on the basis of Figure.2 (a), Figure.3 (a) shows the initial target position of 120^{th} and the target extraction area. Target is blocked into two sub-blocks, the values of α and β for each sub-block are 0.515, 0.495 and 0.51, 0.49. The tracking result and the target extraction area by Sobel operator in Figure.3 (b)-Figure.3 (f) are obtained by updating target template of Figure.3 (a) during tracking the next image frames.

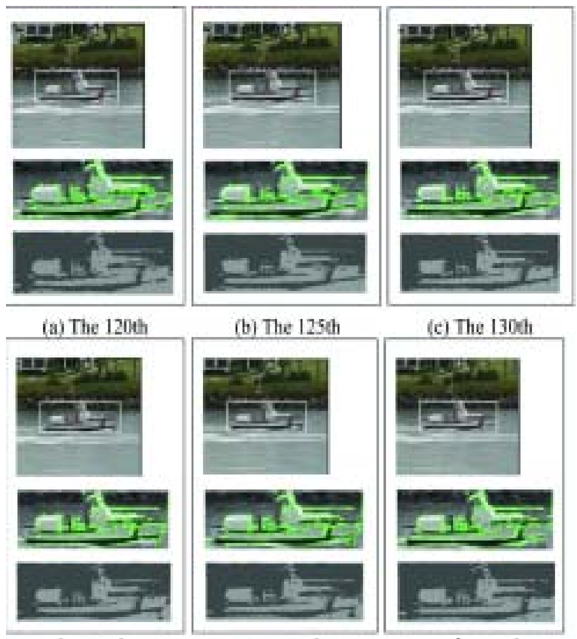
Initial target template of moving target in Figure.4 (a) is obtained on the basis of Figure.2 (a). Figure.4 (b)-Figure.4 (f) are obtained by updating target template of Figure.4 (a) during tracking the next image frames.

In order to objectively evaluate the tracking results of the proposed algorithm, Overlap ratio is used to analyze quantitatively the 121th image frame to the 140 image frame in Coastguard standard image sequence. Overlap ratio is defined as [6]:

$$\Omega = 2 \bullet \frac{|R_{object} \cap R_{Tacked}|}{|R_{object}| + |R_{Tacked}|}. \tag{19}$$

where R_{object} is the real position of target, which is usually delineated manually, $R_{tracked}$ is the target region obtained by tracking algorithm, $|\bullet|$ is the area of given region. Apparently, $\Omega \in [0,1]$. Ω is bigger, the more accurate of the tracking result. Average overlap ratio Ω demonstrate the average performance of an algorithm on the sequence.

The detailed evaluation result of three tracking algorithms is shown in Figure 5.



(d) 135th **(e) 140th** **(f) 145th**

Figure 2. The results of proposed tracking algorithm

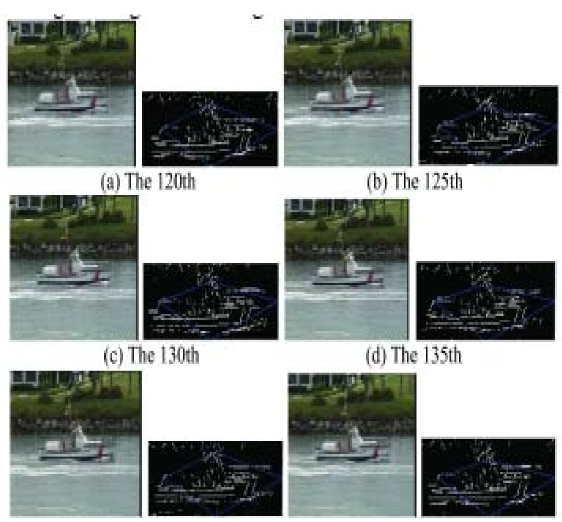


Figure 3. The results of weighted sub-block mean-shift tracking algorithm with Sobel operator target extraction

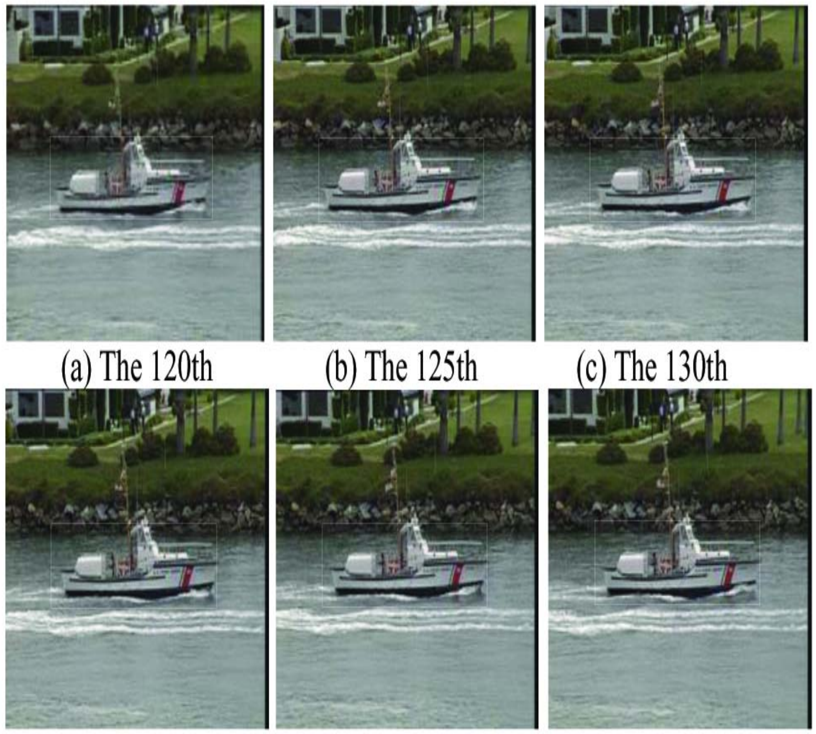


Figure 4. The results of original Mean-Shift tracking algorithm

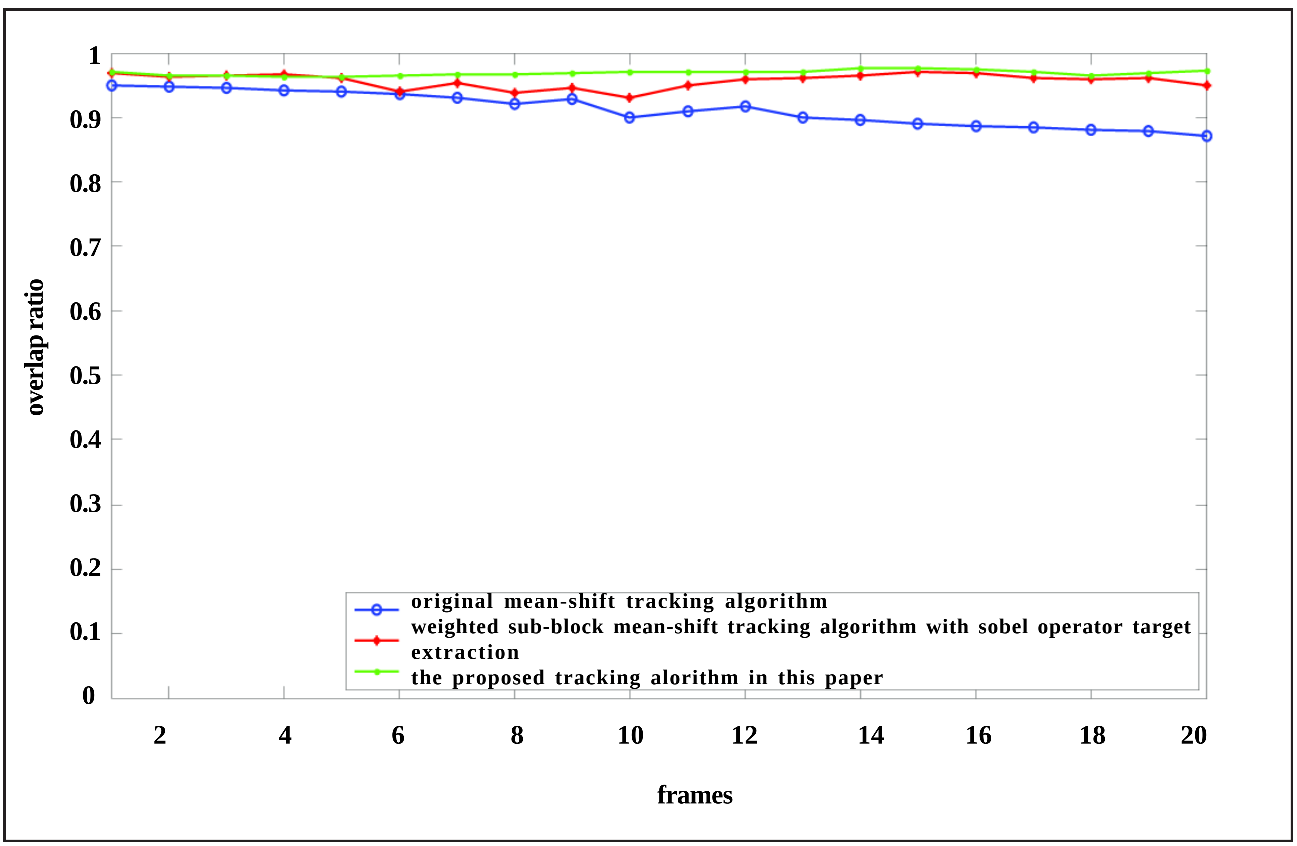


Figure 5. Evaluation result of three tracking algorithms

Figure.5 shows that the proposed tracking algorithm is highly accurate during tracking moving target, and target position is detected more exactly.

From above subjective effect and objective evaluation, in this paper, the proposed algorithm is effective with highly accurate tracking performance.

Likewise, the second group of experiments and the third group are also conducted to verify the adaptability of the proposed algorithm in the case of tracking target under occlusion.

The second group of experiments is to track the practical image sequence with dynamic scene of mouse. The experimental results are shown in Figure.6 (image size is 256×256).Figure.6 (a) shows the initial target position of the 10^{th} image frame and the target ex-traction area. The matrix of initial target region is [75, 88, 133, 90], the coordinate of rectangle's upper-left corner in the whole image is (75, 88), and width is 133 pixels, height is 90 pixels. Initial target template of moving target is obtained on the basis of above. The tracking result and the target extraction area in Fig.6 (b)-Figure.6 (f) are obtained by updating target template of Figure.6 (a) during tracking the next image frames.

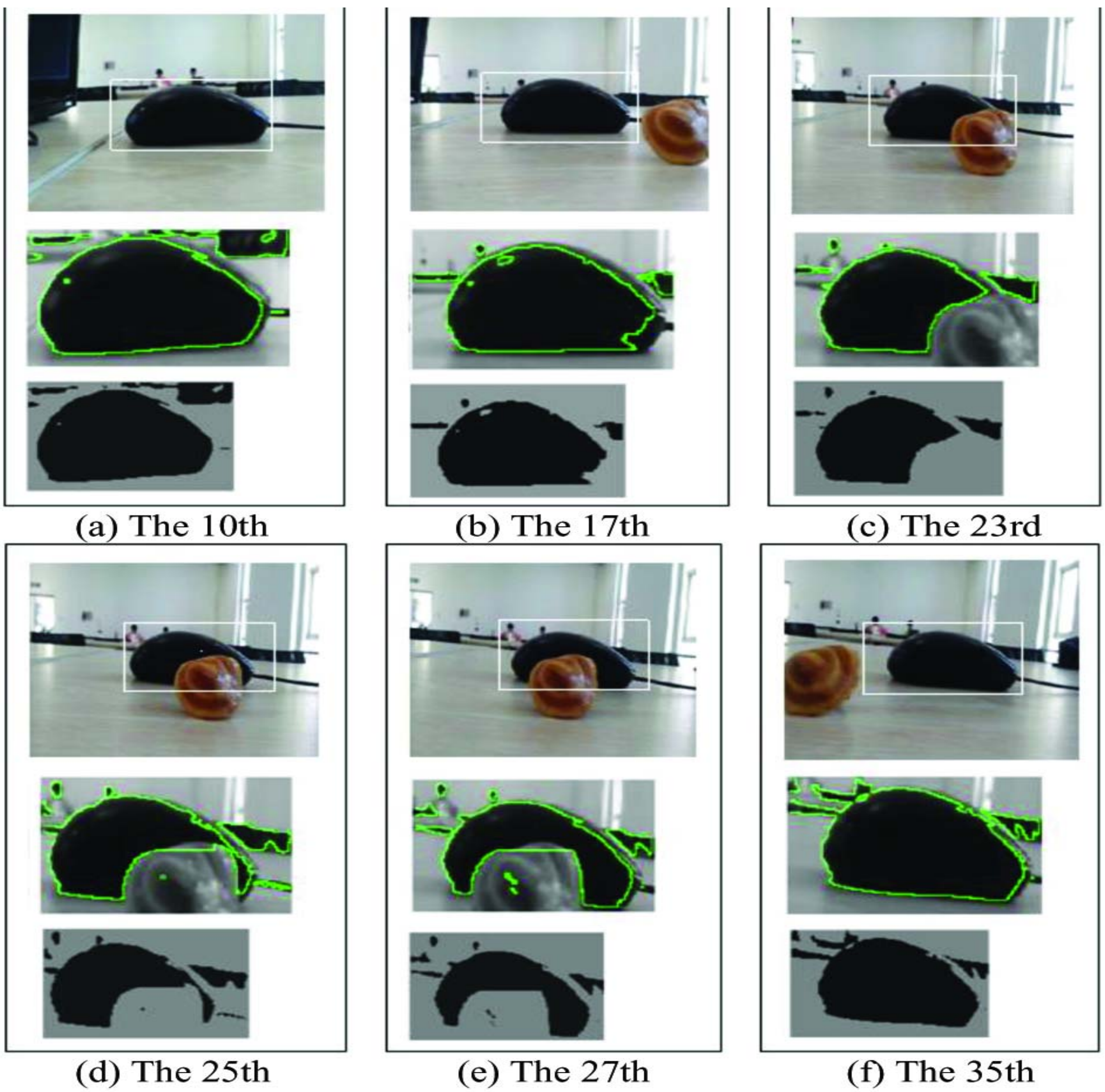


Figure 6. The results of the proposed tracking algorithm (mouse)

The third group of experiments is to track the practical image sequence with dynamic scene of human. The experimental results are shown in Figure.7 (image size is 256×256).Figure.7 (a) shows the initial target position of the 47th image frame and the target ex-traction area. The matrix of the initial target region is [60, 68, 54, 129], the coordinate of rectangle's upper-left corner in the whole image is (60, 68), and width is 54 pixels, height is 129 pixels. Initial target template of moving target is obtained on the basis of above. The tracking result and the target extraction area in Figure.7 (b) -Figure.7 (f) are obtained by updating target template of Figure.7 (a) during tracking the next image frames.

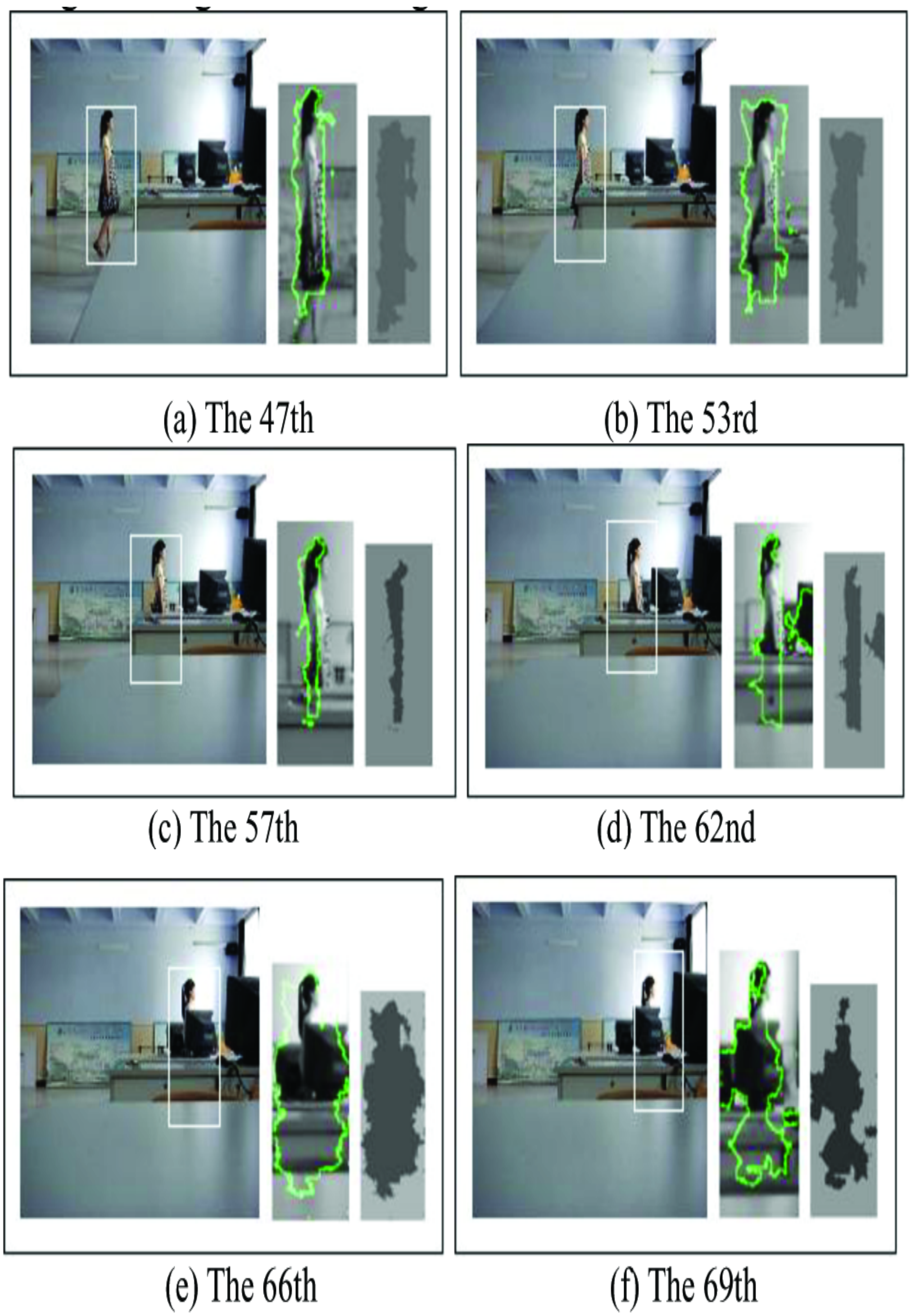


Figure 7. The results of the proposed tracking algorithm (human)

The number of sub-blocks and the value of and for each sub-block of experiments in second group and third group are listed in Table 1.

Dynamic image sequence	Number of sub-blocks	The value of α and β for each sub-block
The second group	4	$\alpha = 0.9, \beta = 0.1$ $\alpha = 0.8, \beta = 0.2$ $\alpha = 0.8, \beta = 0.2$ $\alpha = 0.99, \beta = 0.01$
The third group	3	$\alpha = 0.5, \beta = 0.5$ $\alpha = 0.3, \beta = 0.7$ $\alpha = 0.3, \beta = 0.7$

Table 1. The Number of Sub-Blocks and the Value of and for Each Sub-Block

From the experimental results of the practical image sequence with dynamic scene, in this paper, the proposed algorithm is highly accurate and adaptive in the case of shade issue.

The experimental results of the Coastguard standard and the practical image sequence with dynamic scene demonstrate that the proposed algorithm has better tracking performance, and has high accuracy and adaptability.

6. Conclusions

This paper presented a method of the Mean-Shift tracking algorithm against the change of background and shade problem by using weighted sub-block Mean-Shift tracking algorithm with improved level set target extraction. The target is blocked into J (j=1,2,...J) sub-blocks. The weight of each sub-block is determined by the combination of the similarity between target sub-block and candidate sub-block and the ratio of the target sub-block area and the overall area. Coefficients α and β f are used to adjust the importance degree of two indexes, $\alpha + \beta = 1$. The area in each sub-block is obtained by target extraction using narrow band level set combined with penalty. Both RGB color information and pixel position information are taken into consideration when describing the feature model of target and candidate region.

The extended Mean-Shift tracking algorithm was experimentally verified in many dynamic scenes where the background changes and shade. For these dynamic scenes, the original Mean-Shift tracking algorithm is obviously inappropriate. The proposed algorithm has advantages of robustness when target is under change of background and shade problem, and target extraction is relatively accuracy.

For our future work, we will apply this tracking algorithm in other kinds of image sequence to pick-up moving target region and realize target recognition the next step.

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