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An Improved Infrared Target Tracking Algorithm based on Adaptive Kernel Window-width

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Abstract. *This paper proposes an adaptive algorithm for the infrared target tracking based on Kernel window-width. Traditional kernel function cannot adapt to the size change of the target. In order to solve this problem, an improved approach is presented. The experiment results show that, compared to the traditional algorithm, the improved Mean-Shift algorithm can track the target with an adaptive kernel window, which makes it possible to achieve smaller tracking errors.*
Keywords: Infrared target, Mean-Shift, Kernel Function

1. **Introduction.** Since World War II, as the main detection equipment used to perform operational missions, radar plays an important role in such missions. Meanwhile, with the advancement of technology, new weapons and tactics which combat radar are also emerging, such as those low altitude penetration weapons which take advantage of radar shadow, and those anti-radiation missiles which conduct electronic interference suppression or deception on a radar. Therefore, it is important to develop a new equipment to assist the radar in normal circumstance, or replace the radar when it is exposed to threaten from the low altitude penetration weapons, electronic jamming and those anti-radiation missiles. Modern warfare requires long-range infrared systems to discover, track threat targets, so as to gain time for the chain of command decisions and weapons systems. Infrared tracking system operates passively, has a strong anti-interference ability, good concealment, but a disadvantage is the short distance when it is operating. Due to that the space resolution of optical system, it is quite close to the theoretical limit level, a more realistic way is to improve the performance of target detection algorithm, especially algorithms for small target, in order to compensate the shortness of infrared detection systems. In the process of target identification and tracking, infrared imaging is different from visible imaging, especially in the case of thermal imaging. With a strong "through" capability, infrared imaging is able to penetrate through smoke and darkness, therefore can observe objects that visible light cannot see [1].

For a long time, although infrared imaging technology has significant advantages, infrared target tracking technology is very classical in the field of computer vision. Mean shift has been applied to solve several computer vision problems, e.g., image smoothing and segmentation [2, 3], visual tracking [4] and information fusion [5]. Its basic tasks can be described as effectively locate in a video sequence the object of interest, and estimating motion features such as the determination of the speed. Mean Shift algorithm is a probability density function estimating method based on gradient. Using a histogram modeling kernel on the target rotation and edge cover, this algorithm is not sensitive to the background moving or the target deformation. Moreover, it also has a fast tracking speed and good real-time performance. Scale estimation [6, 7, 8]. And full occlusions are not solved in mean shift tracking method. To solve these drawbacks, many mean shift-based tracking schemes have been proposed. Bradski developed continuously adaptive mean shift (CAMSHIFT) for face tracking [9]. An improved mean shift-based algorithm was developed in [10] that combines a mean shift tracking algorithm and motion information with a Kalman filter. Youness Aliyari Ghassabeh developed a novel approach [11] that is employed to present the MS kernel function, directly and used the investigation in its present form; the capability of the MS kernel is increased. Moreover, by using both color feature and motion information [12], simultaneously, in comparison with single color feature, noises and also uninterested regions can actually be eliminated.

In this paper, a novel target tracking method that infrared target tracking based on adaptive kernel window-width is proposed. When it fails to track the target because of appearance changes scale changes, or fast motion, the detector whose model is updated online. To implement the algorithm in real time, we present a theoretically justified scale estimation mechanism which, unlike the method listed above, relies solely on the mean-shift procedure for the scale-adaptive changes. For long-term tracking, the target model for the mean shift tracker is steadily updated in a weighted manner in the proposed method. The experimental results demonstrate that the proposed method can successfully track target in complex environments that cause difficulties for existing mean shift tracking-based algorithms.

The remainder of the paper is organized as follows. We review other relevant studies in Section 2. In Section 3, the mean shift tracking algorithm is introduced and some drawbacks are reviewed. Section 4 describes the proposed algorithm in detail. Experimental results are described in Section 5; Section 6 includes a paper summary.

2. **Related Work.** Recently, numerous visual trackers have been introduced. There are many difficulties in infrared target tracking. Specifically, occlusions, illumination changes, appearance changes, scale changes, and background clutter, make that it is difficult to track infrared target. To overcome these difficulties, methods with scale adaptation Kernel window-width is proposed. Infrared target tracking is a key technology of infrared imaging guidance and infrared target detection system. Infrared target tracking complexity lies in the targets contour complexity, maneuverability, the irregular movement, and the shadow brought by clouds, solar radiation. Traditional infrared target tracking methods[2,3,4] uses template matching approach, which is relatively simple. But the searching space of the matching process will increase as the image size and the size of the template increase, thereby the efficiency of target tracking decreases greatly. At this time target tracking algorithm based on statistics is more effective[13,14,15] .

The mean shift technique is a simple nonparametric approach that was proposed by Fukunaga and Hostetler [16] to estimate the models of a probability density. MS algorithm is an optimal gradient descent-based approach. It searches for the target by applying iterative approaches, and therefore to realize tracking a moving target. But this method shows bad ability in adapting to changes of the target. Jongmin Jeong[17,18] proposed a method that integrates mean shift tracker with an online learning - based detector and to newly define the Kalman filter -based validation region for reducing computational burden of the detector, which can reinitialize the target when it converges to a local minima. In Youness Aliyari Ghassabeh[11], a tracking method generalizing the connection between the MS algorithm and the asymptotic bias of multivariate kernel regression to provide a theorem to be used to estimate the bias of the estimated clean signal by just observing the noisy. Further, there are some tracking methods based on scale adaptive. They gives an estimate for the asymptotic bias of the multivariate. Nadaraya-Watson use it for deriving a connection between the MS algorithm and the asymptotic bias of the Nadaraya-Watson kernel regression. He investigate the simple one-dimensional and general D -dimensional cases separately and derive formulas for the asymptotic bias as a function of the MS algorithm. For the one-dimensional and the multivariate cases algorithm shows through the simulations that how the provided theoretical results can be used to find the bias for the estimated clean data, when a sequence of noisy observation is available. QIN Jian[19] uses an adaptive scale updating approach based on boundary force which compares the region likelihood in successive frames and analyses of weighted histogram of the target feature.

Recently, a convex kernel [11] function has been proposed through motion information of desired video sequences, where the metric derived from the Bhattacharyya coefficient. The present kernel function helps it to improve the proposed tracking algorithm, because of partial occlusion problem. This kernel has an optimum performance to weight the model and also the inside pixels of the candidate regions.

3. Traditional Mean Shift Tracking Algorithm.

3.1. Mean shift tracking algorithm. In a classical mean shift tracking algorithm, the user selects a target to be tracked in the first frame and a normalized color histogram is used to represent the targets features model.

The area selected manually or automatically is the area where the kernel function searches for the target. It is assumed that the selected image sequence consists of gray-scale images. Every single pixel has its own gray-scale values, for each value we calculate its probability of presence, and then we obtain the object model. For the subsequent image frames in the video, we also calculate the probability of the gray value of the pixel located in the area where the kernel function searches, in order to achieve matching purposes. Generally the selected kernel function is Epanechnikov functions. Using the similarity principle, by continuous iterations, we can obtain the maximum mean shift vector, then the target is found [21].

he normalized pixel locations in the target region are denoted by $x^*_{i\,(}i = 1, , n)$ which has n pixels. The target model is calculated as

$$\hat{q} = \{\hat{q}_u\}_{u=1,...,m} \;\; \hat{q}_u = c\sum_{i=1}^{n} k(||x_i^*||^2)\delta[b(x_i^*) - u] \;\; \sum_{u=1}^{m}\hat{q}_u = 1 \tag{1}$$

Where $\hat{q}$ is the target model that consists of the probability of the uth feature,$c$is the normalization factor and is the number of pixels in the target model, $k(x)$is the normalization factor and is the number of pixels in the target model, $k(x)$is a kernel function that gives a large weight to the center pixel$\delta$is the Kronecker delta function, it is noted that this expression is a kernel estimation expression which is based on the kernel density contour function.

$$k(x) \propto \begin{cases} c(1 - ||x^2||) & ||x|| \leq 1 \\ 0 & otherwith \end{cases} \tag{2}$$

and $b\left(x_i^*\right)$ associate the pixel to the histogram bin. Due to the influence of occlusion or background, those pixels near the center of the target model are more reliable than other pixels.

The target candidate model, in the second frame and subsequent frames, the area where the target may be contained is called a candidate region. The target candidate model centered at position is the center of the area and calculated which is farther used by (3),$\{X_u^*\}_{i=1,\dots,m}$denote the pixels in this area. Our description of the candidate area is called the target candidate model, $u = 1, \dots, m$.

$$\hat{p}\left(y\right) = \left\{\hat{p}_u\left(y\right)\right\}_{u=1,\dots,m} \quad \hat{p}_u\left(y\right) = c_h \sum_{i=1}^{n_h} k\left(\left\|\frac{y - x_i}{h}\right\|^2\right)\delta\left[b\left(x_i^*\right) - u\right] \quad \sum_{u=1}^{m} \hat{p}_u = 1 \tag{3}$$

Where $\hat{p}(y)$ is the target candidate model that consists of the probability of the uth eature,c_h is the normalization factor and n_h is the number of pixels in the target model, $k(x)$ is a kernel function that gives a large weight to the center pixelδ is the Kronecker delta function. And $b\left(X_i^*\right)$ associate the pixel to the histogram bin. Similarity function describes the degree of similarity between the target model and the candidate. In the ideal case the probability distribution of the two models are exactly the same. The classical mean shift tracking algorithm searches for the best similar target candidate iteratively that using the gradient ascent direction approaches. The Bhattacharyya coefficient is defined for measuring the similarity between the target model and target candidate model. It is defined in (4):

$$\rho(y) = \sum_{u}^{m} = 1\sqrt{\hat{p}_u(y)\hat{q}_u} \tag{4}$$

The difference between probability distributions $hatq = \{\hat{q}_u\}_{u=1,\dots,m}$ and $\hat{p}(y)$ is measured by the Hellinger distance of probability measures, which is known to be a metric:

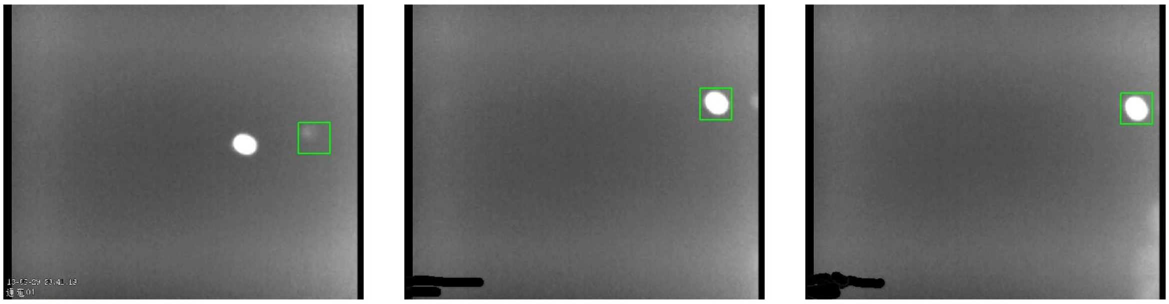
$$H\left(\hat{p}(y), \hat{q}\right) = \sqrt{1 - \rho(y)} \tag{5}$$

3.2. **Drawbacks of mean shift tracking.** The traditional mean shift tracking algorithm is suitable for tracking a generic target. However, this algorithm has limitations as the performance is degraded under some environments. It may fail to track the target when the target scale varies greatly, if the window size is always the same in the tracking process. Similarly, in the traditional tracking algorithm if the target overlaps with other objects, which is defined as an occlusion, the algorithm can not achieve local convergence. Fig. 1 (a) illustrates tracking results when the target moves fast. For solving this disadvantage, an adaptive window changes is necessary. Moreover, one of the limitations of traditional mean shift tracking is template update in time. Because the target varies greatly in the scene, the position of the target cannot be estimated accurately. Fig. 1 (b) illustrates the results of the mean shift tracking algorithm for a sequence in which the target changes. Traditional mean shift tracking cannot deal with full changes.

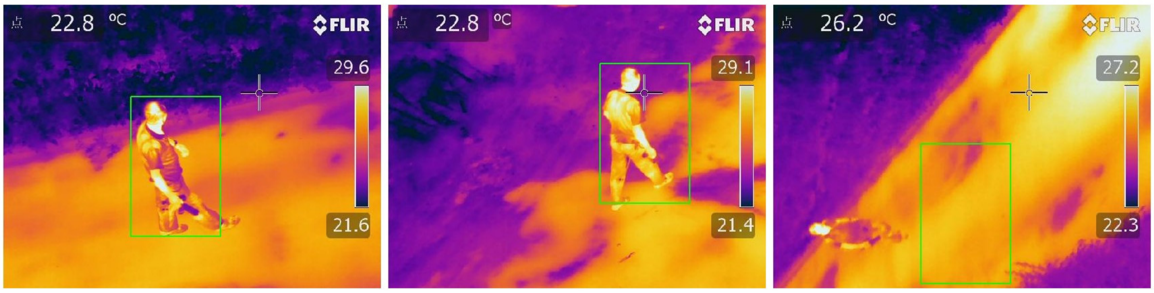
4. An adaptive Mean-Shift Tracking Algorithm.

4.1. **Adjustment Method.** During the movement of the target, the target attitude and lighting conditions keep changing. The original mean-shift algorithm lacks template update algorithm. During the process of tracking, when the target scale exceeds the kernel window, it may lead to loss of targets. Therefore, we can adjust the bandwidth size of the kernel function in case of the target scale changes. It is important to ensure as much as possible that the target is always located within the scope of the kernel window. In this paper, we use a larger tracking window and fusion algorithm to get the target centroid of the current frame. Then by fixing the target centroid, we change the size of the window scale to achieve the adaptive adjustment of the window width.

Select the tracking window W' in the initial frame, the initial probility density function $\hat{q}_u$ of the target in the $I_0(c, d)$ with y_0 as centroid are calculated, and the width of the



(a)



(b)

FIGURE 1. the results of the traditional MS tracking algorithm on (a) a moving fast target and (b) a changing target.

window.

$$w_o = \sqrt{50\sqrt{\frac{\hat{q}_u}{256}}} \tag{6}$$

height

$$h_0 = t_0 w_0 \tag{7}$$

where, t_0 is the ratio of the height and width of the initial tracking window.

Similarity between gray probability distribution $\hat{q}_u$ and $\hat{q}'_u(y)$ of target model in arbitrary frame window W' with y as centroid.

$$H(\hat{q}'_u(y), \hat{q}_u) = \sqrt{1 - \sum_{u=1}^{m} \sqrt{\hat{q}'_u(y)\hat{q}_u}} \tag{8}$$

Non similarity of gray probability distribution $\hat{q}'_b(y)$ and$\hat{q}_u$ in the background area around the target in the window W'.

$$\bar{H}(\hat{q}'_b(y), \hat{q}_u) = \sqrt{1 - \sum_{u=1}^{m} \sqrt{\hat{q}'_u(y)\hat{q}_u}} \tag{9}$$

In this paper, it is considered that the best tracking window W^* scale should satisfy the window containing the complete target, and the background pixels contained in the window should be as few as possible

$$W^* = \underset{W'}{max}[\lambda H(\hat{q}'_u(y), \hat{q}_u) - (1-\lambda)\bar{H}(\hat{q}'_b(y), \hat{q}_u)] \tag{10}$$

where, λ is a weighted function, in this paper, we use the golden section method to obtain the λ value, so as to increase the background ratio, so that $\hat{q}'_u(y)$ occupies a large proportion in the window W^*.

4.2. **Adaptive Adjustment Algorithm Processes.** Adaptive adjustment algorithm is summarized as follows: Step 1: Use fusion algorithm to get the target centroid of the current frame and the current tracking window height and width w_0, h_0;

Step 2: Set a target tracking window with the target's centroid as the center, and the height and width are $\alpha \times h$ and $\alpha \times w$respectively, α is the adjustment coefficient .The $\hat{q}'_u$and $\hat{q}'_b$ of the tracking window corresponding to different values are calculated, and the substitution formula (16) is used to solve the W^*.

Step 3: In order to make the target completely contained in the tracking window in the next frame, and to ensure that the tracking window is always pointing to the center of the target centroid, we set the size of the next frame tracking window as

$W^*(1+\lambda)$, where λ is fluctuation coefficient, $\lambda = 0.1$ is in the simulation test. Since the background image changes during the tracking process, the initial probability distribution model of the target should be used, other than the distribution based on the weighted background. Because those pixels which distinguish well the target and the background in the initial frame may be of poor distinguishing abolish in the current frame. Hence the introduction of background weighted deviation will cause the difference of the background similarity, which may result in the failure of the algorithm. In addition, the process of finding the best tracking window is actually a process of optimization, and optimization algorithms can be used to speed up the computation. In this paper, we use the golden section method to find the best tracking window.

Algorithm 1 Algorithm to explore the adaptive window.

Input:

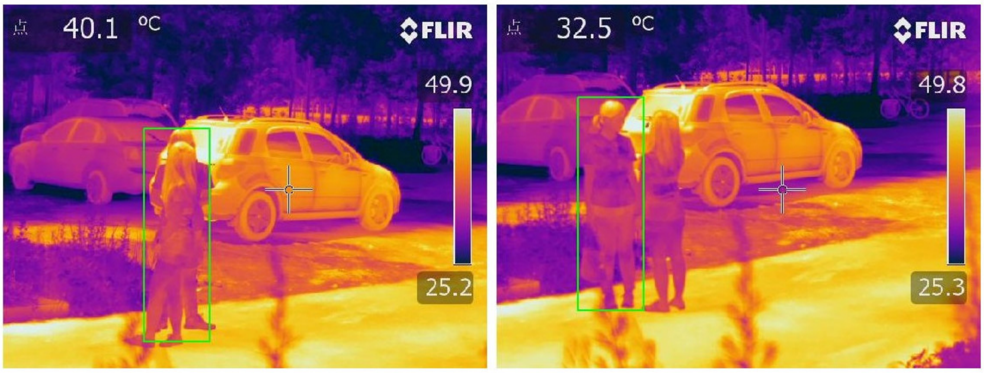
h :Window height
W :Window width
W^* :Adaptive window
α :Adaptive coefficient
λ :Fluctuation coefficient
q_a, q_b :Histogram corresponding to different α

Output:

y :The center of the area

compute initial frame target model location
compute initial window w_0, h_0
compute subsequent frames window w_0,h_0,
if result1¡result
  save previous result
  for n=1:10
    $q_a \leftarrow \alpha_1 \times h, \alpha_1 \times w$
    $q_b \leftarrow \alpha_2 \times h, \alpha_2 \times w$
    compute $\rho(y)$ between q_a,q_b and histogram in the previous frame
  end for
  compute best scale window W^*
  compute window $W^*(1+\lambda)$
end if

FIGURE 2. Implementation of the proposed algorithm.



(a)

(b)

FIGURE 3. The results of the proposed MS algorithm on sequence whose desired target is overlapped.

(a)

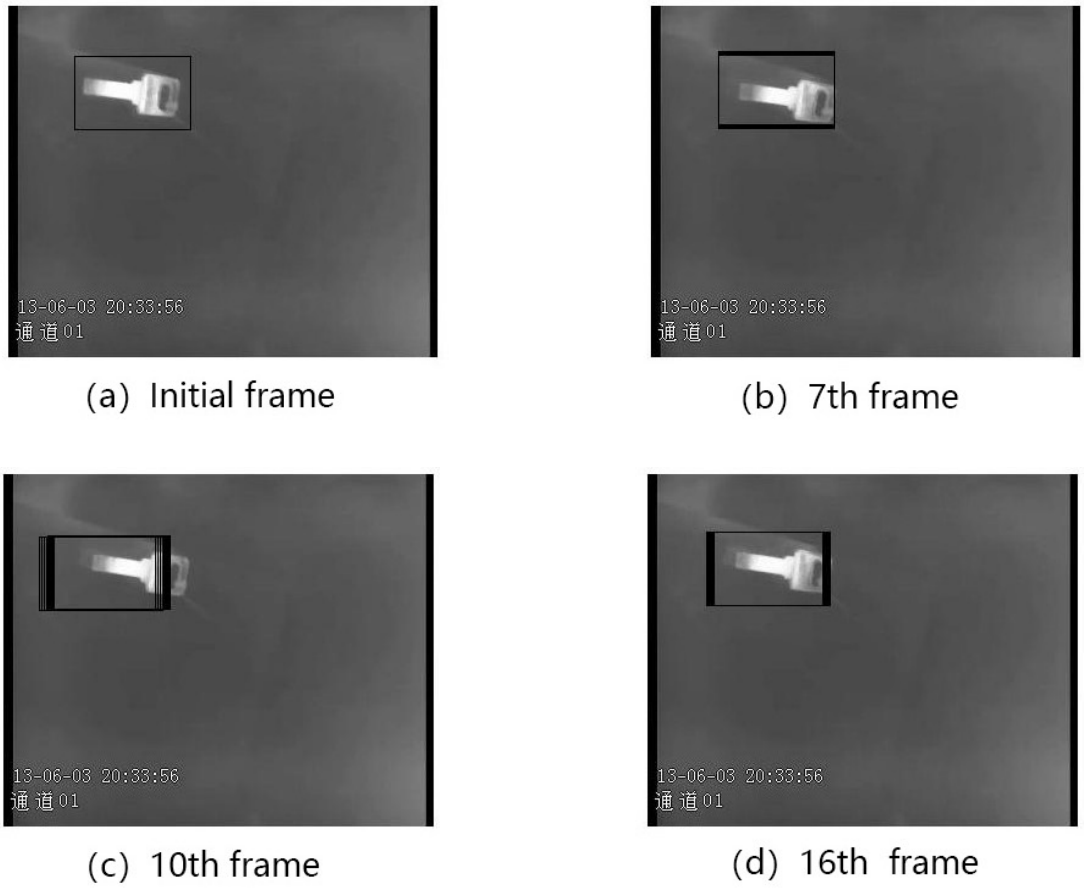
(b)

FIGURE 4. the results of the proposed MS algorithm on sequence whose desired target is moving fast.

5. Simulation Tests.

5.1. Traditional Mean Shift. We select the portion of the image frames of car model and track the target using the traditional Mean-Shift algorithm. We intercept image sequence into 32 frames; the size of each frame image is 320×240. In the first frame of the image sequence, we adopt human-computer interaction to select infrared target to be tracked to determine the initial position as shown Fig.5.

It is noted that the tracking result starts to deviate from the target from the 10th frame, so that the traditional mean shift algorithm in each calculation process, because under normal circumstances, the adjacent two frames with great relevance, Thus began the beginning of the calculation is the center of the frame to determine the center of the target, but when the target velocity between two frames is large, the target between the two frames have a big gap, then again on target if a frame center calculation will result in large errors.



(a) Initial frame (b) 7th frame

(c) 10th frame (d) 16th frame

FIGURE 5. Tracking using traditional Mean-Shift algorithm

5.2. Adaptive Mean Shift Tracking Algorithm. For a traditional goal-means algorithm can effectively track the infrared problem, based on the fusion of gray and texture information, this paper proposes a mean-shift tracking algorithm nuclear adaptive window width adjustment. The algorithm method background feature fusion based on weighted and get a more robust description of infrared target models to achieve accurate positioning of the infrared target, and then use the difference between the target and the target template background similarity is established in order to achieve the objective function to track adaptive window adjustment.

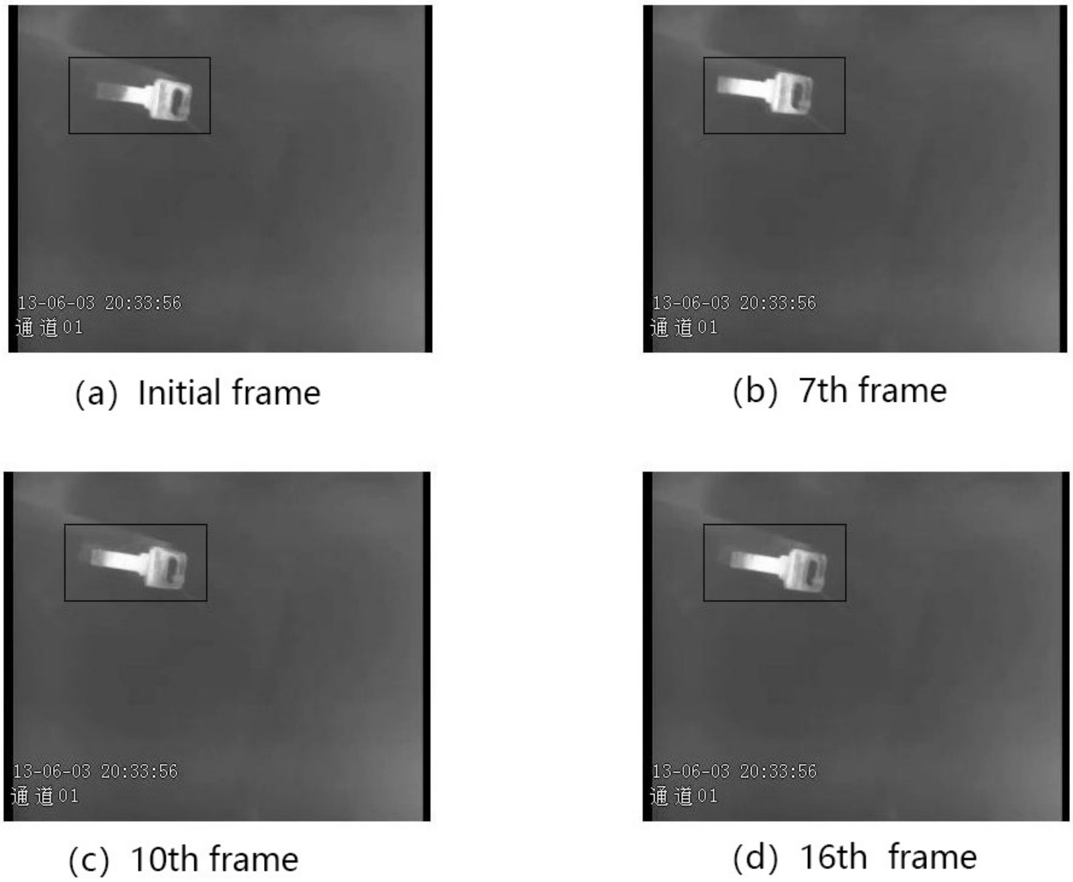
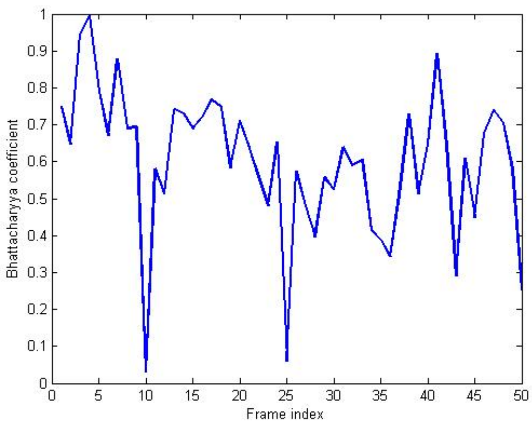


FIGURE 6. Tracking using adaptive Mean-Shift algorithm



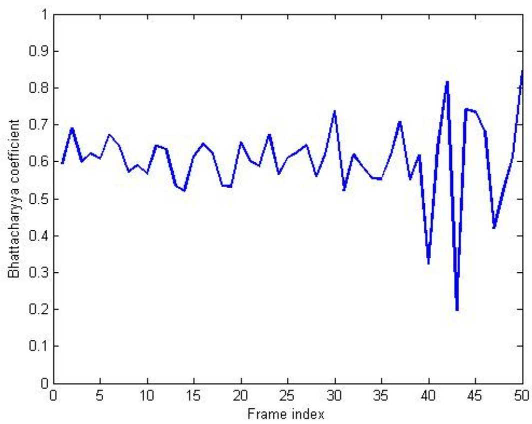
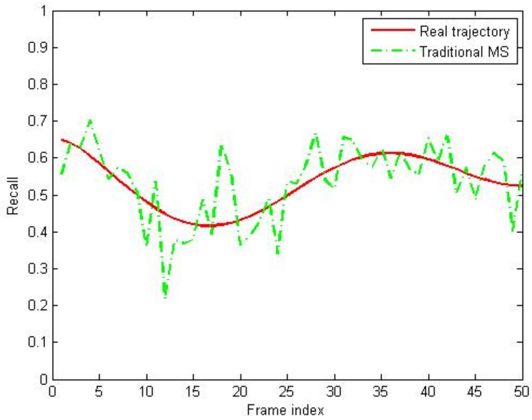


FIGURE 7. The curve of the Bhattacharyya coefficient in case of Fig. 5

FIGURE 8. The curve of the Bhattacharyya coefficient in case of Fig. 6

We test the algorithm on the same image sequence as shown Fig.6. From the results of two kinds of tracking algorithms, the adaptive infrared target tracking algorithm is effective in enhancing the target and background discrimination, and thus be able to more accurately locate targets. Fig.6 shows that as the number of frames to increase the number of iterations gradually become less, with good real-time, can play a very good tracking result. In order to compare the tracking results more intuitive, using deviate from the true position to compare the two kinds of error tracking performance of the algorithm. Figs. 7 and 8 show the curves of the Bhattacharyya coefficient for the above sequences. As resulted from these figures, due to the good performance of the algorithm, its amount is more gently. Figs. 9and 10 show the curves of the tracking trajectory for the above sequences.

The tracking accuracy of the proposed method is superior to the classical Mean-Shift tracking algorithm. Experimental results show that the improved algorithm is more suitable than the original infrared target tracking algorithm, and effectively solve the existing algorithms can not effectively track scale changes in the target problem.



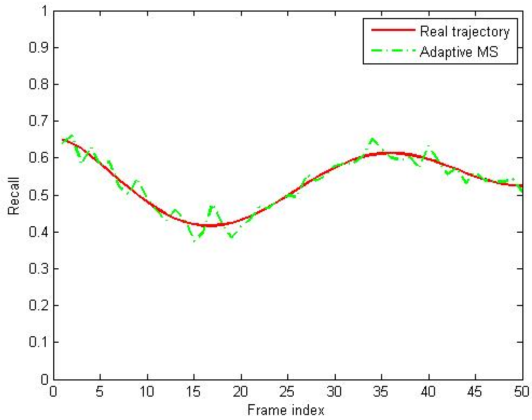


FIGURE 9. The curve of the tracking trajectory in case of Fig. 5

FIGURE 10. The curve of the tracking trajectory in case of Fig. 6

6. **Conclusions.** Traditional mean shift algorithm for infrared target tracking will result in relatively large tracking errors. For the mean shift algorithm, the center of the target in the last frame is used to calculate the center of the target in the next frame. But when the target velocity between two frames is large, the target between the two frames have a big gap, this will result in a big tracking error. This paper presents a mean shift tracking algorithm with adaptive adjustment to kernel window width. The algorithm method background feature fusion based on weighted and get a more robust description of infrared target models to achieve accurate positioning of the infrared target; then use the difference between the target and the target template background similarity is established in order to achieve the objective function to track adaptive window adjustment. Target tracking algorithm development so far, more and more used in practice, but this article only for mean shift algorithm which is part of the shortcomings have been improved, such as when the additional disadvantage of the background and objectives of the exact value is not very different when the gray was reduced and other issues also need to be improved in order to improve the mean shift tracking algorithm performance and real-time problems.

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