The application of CAMSHIFT algorithm based on kernel function in laser tracking moving target

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Abstract. According to the characteristics of laser technology, a fast moving target tracking algorithm is designed. Using the spatial information of laser diffuse reflection light points, by adding the kernel function of CAMSHIFT algorithm, the weight of light points in the center of the target is increased by using the weighted histogram, so as to improve the convergence speed of the algorithm and the tracking accuracy of the target. The simulation results show that the improved algorithm can adapt to more complex tracking environment quickly and has better anti-interference, agility and prediction ability.

1. Introduction
With the development of laser technology, it has been widely used in military, medical and social security. It has the advantages of high speed, high precision, strong anti-interference ability and large communication capacity, and is widely used in the military field. Especially for laser guided weapons, the search and tracking is based on the irradiation laser from the diffuse reflection of the target. However, when the diffuse reflection light is interfered by smoke, aerosol, cloud and so on, especially after the interference of black paint, only about 5% of the reflectivity, so the weak diffuse reflection light is difficult to be received by the laser guided weapons, thus losing the guidance effect [1]. In order to track the moving target successfully, the first step is to establish the initial motion and target model according to the collected laser diffuse light information, and then predict the next state of the moving target, such as position, shape, speed, acceleration, etc., in order to achieve the fast tracking scheme [2]. Mean shift algorithm has a fast tracking speed, but it will be lost when the shape and speed of the target change, while CAMSHIFT algorithm can adjust the tracking core window adaptively, which has a good anti-interference for the target deformation, occlusion and illumination change, but the HSV color space used is easy to be interfered by the same color background, which affects the tracking accuracy [3]. How to track the target accurately and quickly when the target appears deformation, occlusion and transience has become a hot topic in the research of high-speed target tracking. In this paper, the spatial information of laser diffuse reflection points is fully utilized. By adding the kernel function of CAMSHIFT algorithm, the weighted histogram is used to increase the weight of light points closer to the center of the target, so as to improve the convergence speed and tracking accuracy of the algorithm. The simulation results show that the improved algorithm can adapt to more complex tracking environment and has better agility and prediction ability.
2. CAMSHIFT algorithm based on probability density function

Laser target detection usually filters the single frame laser echo signal. When the pulse amplitude of the target is higher than the detection threshold, the existence of the target can be determined. The minimum detectable signal-to-noise ratio required for detection is 2-3dB. Because the laser is transmitted in the atmosphere, the modulation of atmospheric turbulence will lead to the flicker effect, making the target pulse intensity and signal-to-noise ratio of each frame echo fluctuate greatly with the decrease of the signal-to-noise ratio. The detection confidence will always fail to reach the decision threshold, resulting in the failure of detection [4].

CAMSHIFT algorithm is based on meanshift algorithm, which uses HSV color space to build a moving target model and realize fast target tracking with variable core window. It is a continuous and adaptive target tracking algorithm. It uses color model, back projection retrieval, adaptive kernel window and other technologies to achieve fast moving between frames, and then combines meanshift algorithm to achieve gradient optimization within the frame and target center point tracking. It has a good anti-interference ability to the target deformation, occlusion and illumination change. CAMSHIFT algorithm transforms the image from RGB color space to HSV color space, establishes the color probability model with H (hue) component in HSV color space, and obtains the back projection figure. Then, according to the back projection and the initial search window position, meanshift algorithm uses the iterative method to move the center of the search window to the center of mass. If the moving distance is greater than the preset fixed threshold value, it continues to iterate until the moving distance between the center of the search window and the center of mass is less than the preset fixed threshold value, or the number of cyclic operations reaches a certain maximum value. It is considered that the convergence condition is met, and it stops iteration.

2.1. Target representation

Set the pixel coordinates of the target area as \( \{ p_0, p_1, \ldots, p_{n-1} \} \), \( n \) as the number of pixel points, and the target histogram is represented by probability density function as follows:

\[
\Phi_k = \varphi \sum_{i=0}^{n-1} \mu_i [E(p_i) - k], \quad k = 0,1,2,\ldots,m-1
\]  

(1)

2.2. Targeting

As the core part of CAMSHIFT algorithm, meanshift algorithm uses the nonparametric density function gradient estimation to quickly find the extreme value of probability distribution through iterative optimization to lock the target in the frame. Let \( IH(x, y) \) be the pixel value at \( (x, y) \) in the back projection graph, and the variation range of \( X \) and \( Y \) is the range of the search window. The algorithm process is as follows:

1. Select the search window \( w \) with width \( h \) in the color probability distribution graph;
2. Calculation of zero order distance:

\[
\mathcal{R}_{00} = \sum_x \sum_y I_h(x, y)
\]  

(2)

Calculation of first-order distance:

\[
\mathcal{R}_{10} = \sum_x \sum_y xI_h(x, y), \quad \mathcal{R}_{01} = \sum_x \sum_y yI_h(x, y)
\]  

(3)

Calculate the centroid of the search window:
(4) Repeat (2) and (3) until the convergence or change of the center of mass is less than a certain threshold, the target locking is achieved.

3. Tracking target
The process of tracking one frame above is continued by CAMSHIFT algorithm. By means of the meanshift operation on each frame of the video image, the size and centroid of the search window obtained from the current frame are taken as the initial value of the search window of the next frame, so that the continuous tracking of the target can be realized by iteration. The algorithm process is as follows:

(1) Initialize the position and size of the search window;
(2) Calculate the color probability distribution of the search window;
(3) Call the meanshift process to calculate the location and size of the new search window.
(4) Read the next video image, move the center of the window to the center of mass, and jump to (2) continue to iterate until the end of the video.

4. Iterative algorithm
The above matrix form is transformed into the iterative form of pixel points. The iterative equation for moving the target from the center position $y_t$ of the current frame tracking window to the center position $y_{t+1}$ of the next frame window is as follows:

$$Y_{t+1} = \left( \sum_{i=1}^{n} x_i w_i \right) / \sum_{i=1}^{n} w_i$$

From formula (4), it can be seen that the convergence of CAMSHIFT algorithm depends entirely on the weight of points in the target region. It is also determined by the probability density of the color of the point in the target model. In the process of tracking, the points belonging to the target have larger weights, which makes the algorithm converges to the target's moving direction.

But in fact, the credibility of each point in the target is different due to the influence of environmental noise. Generally, the credibility of the point near the center of the target is greater than the point away from the center. This is also the direct reason that CAMSHIFT target histogram can't suppress noise and is easy to be interfered by the same color background, resulting in the loss of target. Therefore, it is necessary to increase the kernel function, make full use of the spatial information of the pixel points, and give different weight values to the pixels in different positions of the target with the weighted histogram, so that the closer the point is to the center of the target, the greater the weight. The following gives the kbca algorithm with kernel function and its convergence proof.

5. Improved CAMSHIFT algorithm
In the tracking algorithm, this paper uses Gaussian kernel function: $g(x) = \exp(-0.5x^2)$, $x \geq 0$. Let $x_0$ be the center point of the $\{x_i | i = 1, 2, \ldots, n\}$ of the pixel set in the target template, $n$ be the number of pixel points, and apply the kernel function to the sample set, then the probability density function of the target in the current frame is obtained as follows:

$$\hat{\Psi}_u = C \sum_{i=1}^{n} g(\|x_i - x_0\| / h) \left[ \delta(\hat{b}(x_i) - u) \right]$$

(6)
The kernel density of the sample set is estimated by the following formula:

$$\hat{H}_{h,k}(x) = \frac{C_{k,d}}{nh^d} \sum_{i=1}^{n} w_i k \left( \frac{||x - x_i||^2}{h} \right)$$

(7)

The improved iteration formula is obtained

$$p_{t+1} = p_t + \sum_{j=1}^{w} \hat{\Psi} \left( \frac{||p_t - x_j||^2}{h} \right) \left( x_j - yp_t \right) / \sum_{j=1}^{w} \hat{\Psi} \left( \frac{||p_t - x_j||^2}{h} \right)$$

(8)

6. Target simulation and performance analysis

6.1. Target modeling and simulation

Formula (5) is used to get the center position of the tracking window, then weight image is used to search the maximum density, and formula (8) is used to iteratively converge, so as to achieve accurate target positioning. The following takes Gaussian kernel function weighting as an example to illustrate the difference between before and after weighting for the same object modeling. The gray value range is 256 levels, and 16 histogram segments are used, that is, the image gray level is divided into 16 quantization levels, each segment contains 16 gray values. The kernel density value of the target model is calculated by formula (1) and weighted by Gaussian kernel function. After weighted by kernel function, the original histogram approximates to the gray level of the image center. The final estimation results are close to the high gray value, which is consistent with the main silver gray in the center of the target template. As shown in Figure 1.

![Figure 1](image_url)  
**Figure 1** Comparison of histogram and position tracking errors of different algorithms

6.2. Comparison of tracking accuracy

In order to further compare the advantages and disadvantages of various algorithms, the algorithms described in other literature are compared with those in this paper, and the tracking accuracy error simulation curves obtained by tracking the same color video target are respectively shown in Figure 2.
Figure 2. Simulation comparison of tracking accuracy of different algorithms

The algorithm deviation in literature [1] is the largest and that in this paper is the smallest. This is because the algorithm in document [1] is less sensitive to color targets and does not have the function of updating the core window width; while the algorithm in document [2] has the ability of self-adaptive updating the search window width and overcoming the target deformation, and the tracking effect is better than that in document [1], but compared with the algorithm in this paper, its tracking accuracy is significantly reduced. This is due to the fact that the reference [2] did not use kernel function weighting when the target model was established, which could not reduce the environmental noise.

6.3. Comparison of noise resistance

In order to compare the anti-jamming ability of various algorithms to noise, this paper simulated several different algorithms in the aspects of anti Gaussian noise, salt and pepper noise, and the number of iterations. As shown in Table 1, different algorithms compare the ability of the same image under two kinds of noise interference. The ratio (deviation degree) of the distance between the maximum value point and the real center point is used to measure the deviation degree between the extreme value point and the real center point. Under the same noise, the average number of iterations is used to measure the anti noise ability. It can be seen from table 1 that the deviation degree of literature [1] algorithm is the largest, because it has no adaptive core window width capability, and the average number of iterations of literature [2] and literature [3] algorithm is the largest, which is due to the target model distortion caused by noise interference, while the algorithm in this paper shows relatively robust noise reduction capability.

Table 1. Comparison of anti noise capabilities of different algorithms

| Algorithm name | Gaussian noise (%) | Salt and pepper noise (%) | Number of iterations | Deviation (%) |
|----------------|--------------------|--------------------------|----------------------|--------------|
| Literature 1   | 1.3%               | 45%                      | 3.214                | 28.9%        |
| Literature 2   | 0.65%              | 35%                      | 4.5623               | 25.6%        |
| Literature 3   | 0.86%              | 41%                      | 3.812                | 22.4%        |
| OUR            | 2.41%              | 71%                      | 1.105                | 14.7%        |

7. Conclusion

Based on the characteristics of laser diffuse reflection points, this paper improves the calculation speed by improving the Camshift algorithm of kernel function. The simulation results show that the improved algorithm can quickly adapt to more complex tracking environment, has better agility and
prediction ability, and achieves stable tracking effect in target model building, convergence performance and tracking accuracy.

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