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Improved motion information-based infrared dim target tracking algorithms

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HIGHLIGHTS

- Three improved dim IR target tracking method based on motion information are proposed.
- Basic principles and the implementing flow of three improved infrared dim target tracking algorithms are described.
- Pedestrian target tracking experiments are performed for IR image and color image.
- We propose subjective and objective evaluation methods for infrared dim target tracking algorithms.

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ABSTRACT

Accurate and fast tracking of infrared (IR) dim target has very important meaning for infrared precise guidance, early warning, video surveillance, etc. However, under complex backgrounds, such as clutter, varying illumination, and occlusion, the traditional tracking method often converges to a local maximum and loses the real infrared target. To cope with these problems, three improved tracking algorithm based on motion information are proposed in this paper, namely improved mean shift algorithm, improved Optical flow method and improved Particle Filter method. The basic principles and the implementing procedure of these modified algorithms for target tracking are described. Using these algorithms, the experiments on some real-life IR and color images are performed. The whole algorithm implementing processes and results are analyzed, and those algorithms for tracking targets are evaluated from the two aspects of subjective and objective. The results prove that the proposed method has satisfying tracking effectiveness and robustness. Meanwhile, it has high tracking efficiency and can be used for real-time tracking.

1. Introduction

With the continuous development of infrared (IR) imaging technology, infrared imaging systems have been applied to many military or civil fields, such as infrared precise guidance, early warning, video surveillance, search and tracking. As a key technique in the above fields, target tracking based on infrared imaging plays an important role in modern defense. In these relevant application cases, it requires that the tracker should be robust enough to clutter, appearance or illumination changes, as well as occlusions. However, infrared targets have their own characteristics which make the tracking work quite difficult. For example, in order to leave enough reaction time to the infrared system, it is needed to detect the targets in the far distance and find the targets as fast as possible. At present, the longest distance that the foreign infrared system can detect the targets is more than 10 km, if the incursive target is missiles or aircraft, which physical dimension is about from 1 m to 5 m in the watching direction, the size of the target is from 0.1 mrad to 0.5 mrad for the infrared imaging system. Since the spatial resolution of military infrared imaging system is about 0.1 mrad at this stage, the pixel size of the target mentioned above is from 1X1 pixel to 6X6 pixels in the image. In addition, because infrared sensor is influenced by atmospheric thermal radiation, long distance and noise, the target signal detected by infrared sensor is relatively weak, especially in the non-stationary background; the target signal is submerged by a lot of complicated background clutter or noise. When the target has the two characteristics mentioned above, it is called the weak small Infrared target. Since the targets are very small and only occupy a few pixels in the image. In addition, the background of infrared small targets is usually contaminated by unknown noise and the contrast ratio and Signal to Noise Ratio (SNR) of the targets under the complicated background are very low. At last, the small

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targets do not have enough pixels to show distinct features, so little information can be provided for the tracking system. Therefore, the detection and tracking of infrared dim target under complex background is a challenging research topic in the fields such as infrared precision guidance and warning [1,2].

Over the past few decades, many researchers have paid attention to the tracking of infrared targets, and numerous algorithms have been proposed in this field. Some familiar methods for achieving this goal include particle filtering methods, optical flow techniques, and mean shift algorithms. From the view of control, the main difficulties for weak small infrared targets detection and tracking can be summarized into three aspects of requirements, namely the requirements for robustness, accuracy and real-time performance of algorithm. The traditional three algorithms: the mean drift. Optical flow and particle filtering methods are unable to meet these three requirements simultaneously, so it is necessary for a robust algorithm to construct the observation model by the target model.

In this paper, three traditional tracking methods were studied, their advantages and disadvantages are analyzed respectively, and the improvement method are proposed in order to make further improvement on detection and tracking accuracy. These three algorithms are all based on motion information. The basic principles and the implementing procedure of these modified algorithms for target tracking are described in detail. Using these algorithms, the experiments on some real-life IR and color images are performed. The whole algorithm implementing processes and results are analyzed, and those algorithms for tracking targets are evaluated from the two aspects of subjective and objective. The results prove that the proposed method has satisfying tracking effectiveness and robustness. Meanwhile, it has high tracking efficiency and can be used for real-time tracking.

2. Improved algorithm based on motion information

2.1. Improved mean shift algorithm

The traditional mean shift algorithm does not depend on the movement information of targets; it has a good real-time performance and robustness and position accurately; however as for the fast moving targets the traditional mean shift algorithm does not perform very well, even worse when there is a large area in the background whose color is the same as the target, then the tracking will be failed [3,4].

So we improve the traditional algorithm, we adopted the method of adjusting the window bandwidth automatically by changing the kernel function of mean shift algorithm from the fixed bandwidth to dynamic changing bandwidth. So that the improvement made the shape, size, direction of kernel functions to be adjusted self-adaptively by the change of the target local structure. The improvement ensures the stability and robustness of effect of tracking. The new algorithm retains the advantage of small calculated amount and real-time tracking from the traditional one, and it can still track the goal when the size of moving target varies as well as scene changes or shakes violently.

The specific algorithm principles are described as follows:

If we use gray or colored distribution to represent corresponding object, and suppose the center of the object is situated in x_0, and then the object histogram distribution can be expressed as

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

In this equation, k is kernel function, m is the number of eigenvalues in saliency space, δ is Kronecker function, $b(x_i)$ is the corresponding eigenvalue of pixel x_i, C is the normalization factor, h is the bandwidth of kernel function, n is the number of sample points contained in kernel window. The role of kernel function k is to give a larger weight value to the pixel near the center of the target, and to give a smaller weight value to the pixel far away from the center due to the pixel near the center is more reliable than the outer under the influence of occlusion or background. In this improved algorithm, we makes mean shift algorithm's fixed bandwidth kernel to be a dynamically changing bandwidth, which not only can retain mean shift algorithm's advantage of real-time tracking because its small amount of computation, but also do not miss target when moving target's size changes. The shape, size, orientation of this kernel function can be adaptive to changes in the local structure of the target so as to ensure that the tracking performance of stability and robustness. $\delta[b(x_i)–u]$ is used to analyze whether the pixel value in the target area is the u-th eigenvalue. If it belongs to the eigenvalue, the value is 1; otherwise, the value is 0.

The candidate target located in y can be expressed by

$$\mathrm{p_u}(y) = \mathrm{C_h}\sum_{i=1}^{n_k} k\left(\left\|\frac{x_i - y}{h}\right\|^2\right)\delta[b(x_i) - u] \tag{2}$$

And then, the problem can be transferred to seek out the optimized y, making $\mathrm{p_u}(y)$ and $\hat{q}_u$ most similar [1,2].

The similarity between $p_u(y)$ and $\hat{q}_u$ can be expressed by coefficient of Bhattacharryya, just as the following Expression (3):

$$\hat{\rho}(y) \equiv \rho[p(y), q] = \sum_{u=1}^{m}\sqrt{p_u(y)\hat{q}_u} \tag{3}$$

Expression (3) in point $p_u(y_0)$ can induce Expression (4) by Taylor's formula:

$$\rho[p(y), q] \approx \frac{1}{2}\sum_{u=1}^{m}\sqrt{p(y_0)q_u} + \frac{1}{2}\sum_{u=1}^{m}p_u(y)\sqrt{\frac{q_u}{p_u(y_0)}} \tag{4}$$

Then Expression (5) can be obtained by taking Expression (2) into Expression (4):

$$\rho[p(y), q] \approx \frac{1}{2}\sum_{u=1}^{m}\sqrt{p(y_0)q_u} + \frac{C_h}{2}\sum_{i=1}^{n}w_i k\left(\left\|\frac{y - x_i}{h}\right\|^2\right) \tag{5}$$

$w_i = \sum_{u=1}^{m}\delta[b(x_i) - u]\sqrt{\frac{q_u}{p_u(y_0)}}$, the second part of the Expression (5), can be optimized with mean shift algorithm. In order to express the iterative character of the algorithm fully, we present the following mean shift Expression (6):

$$M_h(x) = \frac{\sum_{i=1}^{n}G\left(\frac{x_i - x}{h}\right)w(x_i)x_i}{\sum_{i=1}^{n}G\left(\frac{x_i - x}{h}\right)w(x_i)} - x \tag{6}$$

Then, the first right part of the above expression is named as $m_h(x)$,

$$m_h(x) = \frac{\sum_{i=1}^{n}G\left(\frac{x_i - x}{h}\right)w(x_i)x_i}{\sum_{i=1}^{n}G\left(\frac{x_i - x}{h}\right)w(x_i)} \tag{7}$$

The steps of improved mean shift algorithm are as following:

(1) Setting the initial point x, kernel function $G(X)$ and error ε;
(2) Calculating $m_h(x)$;
(3) Assigning $m_h(x)$ to x;
(4) If $\|m_h(x)–x\| < \varepsilon$, then end the whole cyclic process; otherwise, return Step (2)

With the Expression (6), we can know that $m_h(x) = x + M_h(x)$, therefore, it can move in the direction of the probability density function through the above steps, meanwhile, the step length depends on the amplitude of the gradient, besides, it is also related to the probability density of the point. It is easier to find the extreme value of the probability density at the space where has