Small target detection and window adaptive tracking based on continuous frame images in visible light background

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Abstract. Due to the difficulty in distinguishing the target and the noise in the visible light background and the loss of the target for a short period of time, a scheme of track association and target tracking for the small target in the sky is carried out. Multi-feature similarity is taken into account, such as the maximum intensity, the maximum brightness, the size and the moving speed. Firstly, the trajectory prediction is carried out by the least square prediction method. By updating the real-time data to deduce the trajectory parameters, the target position in the next frame image is predicted. Based on the trajectory confidence test, all current recorded trajectories are traversed. The over-confidence trajectory is detected and the trajectories of continuous lost points are deleted, as well as the trajectories below the threshold of confidence. For the trajectory of the over-confidence, the target trajectory without the significant motion feature is deleted by judging the magnitude of the moving speed, so that the effective trajectory can be displayed while the false target is eliminated. Then, the target tracking is carried out, which is based on the LOG filter and the constant false alarm rate segmentation. Considering the temporal and spatial continuity of the target trajectory and the randomness of the amplitude and position of the noise, the false alarm rate can be reduced by eliminating the high amplitude noise by using the difference between the two in terms of temporal and spatial correlation. Owing to that the setting of the division threshold is not less than 5 times the background variance of the window image, the generation of the noise by the constant false alarm rate segmentation can be avoid when there is no target. In addition, the target coordinates may be abrupt due to sudden changes in target speed and the jitter of the image acquisition equipment. Therefore, we propose a dynamic adjustment scheme for the tracking window size to enable window adaptive tracking, which can set the length and width of the rectangular window to k times of the original size according to actual needs. At the same time, the number of points of the relatively stationary target in each frame of the image can be counted in real time. Finally, the reliability of the method is verified by simulation experiments, and the running speed is relatively fast and the recognition accuracy is relatively high.

1. Introduction
As an important technology, weak target detection technology has been widely used in search and tracking, early warning systems, precision guidance and large field of view target detection [1, 2]. In the visible light background, the image sometimes has a low contrast, the target is weak and small, and there is inevitably a large amount of noise interference. Therefore, weak target detection in the visible light background has always been a difficult and hot topic in the field of computer vision.
A multi-feature similarity is integrated, such as maximum intensity, maximum brightness, size and motion speed. And a scheme for trajectory correlation [3] and target tracking [4] for small targets in the sky is proposed. In terms of trajectory correlation, the algorithm mainly includes least squares prediction method [5, 6, 7] and trajectory confidence test [8]. In terms of target tracking [9], it mainly relies on LOG filtering [10, 11] and constant false alarm rate segmentation [12] to realize window adaptive tracking [13] while real-time counting the number of points of relatively stationary targets in each frame of image. Finally, the method is proved to be reliable, the running speed is fast, and the recognition accuracy is relatively high.

2. **Trajectory association**

Trajectory correlation is an effective means to perform target detection and noise filtering by using the continuity of state changes in the space-time domain. It can establish correlation between multiple short tracking segments of the tracking target to obtain a continuous and smooth tracking trajectory of the tracking target. The process is as shown in Figure 1.

In the calculation of the predicted points, we use the least squares prediction method, which can predict the position of the target in the next frame by recursive trajectory parameters. The trajectory of the confidence is detected, which is based on the trajectory confidence test. And the trajectory of consecutive lost points and the trajectory lower than the lower confidence threshold are deleted. For the trajectory of the confidence level, the target trajectory without significant motion features is deleted by judging the magnitude of its motion speed.

Considering the continuity of the target motion, we use the least squares method to fit the polynomial to approximate the trajectory, and the trajectory equation can track the target. In the process of tracking the target, the moving speed and the direction of the target will change with time according to a certain law. In order to extract the useful signal, the target motion law should be assumed first. The least squares method is a widely used optimal estimation method. The basic idea is to choose a polynomial \( P(x) \) to approximate \( f(x) \) with a minimum mean square error.

The trajectory confidence detection traverses the trajectories of all the current records and finds the trajectory of the confidence. First, a confidence test is performed only for tracks whose length can be greater than the set length. The trajectory with confidence higher than the high threshold is counted and recorded. For the trajectory with confidence lower than the low threshold, it is set as the trajectory to be deleted, and will be deleted in subsequent processing. Similarly, if there is a phenomenon of consecutive lost points in the trajectory, it is also set as the trajectory to be deleted. Next, the merging of the overlapping trajectories is performed. The criterion for judging the overlap of two trajectories is to calculate the trajectory between the current position of the two trajectories and the position of the trajectory points before the three frames. If the distance is smaller than the threshold value we set, it is determined that the two trajectories overlap. For the way of overlapping trajectories, we choose to keep the trajectory with high confidence and delete the other trajectory. Finally, we judge the motion speed of the confidence track based on the total offset of the X and Y directions and delete the target track with obvious motionless features. Whether the target moves by the total number of relatively stationary targets, if there are more than five frames of relatively stationary targets in the same frame picture, it is determined that the target trajectory is a clutter.
3. Target tracking

The main task of target tracking is to estimate the position of the target object in the first frame of the video image, and to estimate the state information of the target in the next multi-frame image through the appearance model and the motion model. The target tracking process is as shown in Figure 2.

LOG filtering is a combination of Gaussian filtering and Laplacian filtering. The LOG operator obtained by finding the second-order derivative of the two-dimensional Gaussian function is denoted as \( \nabla^2 G(x, y, \sigma) \), where \( \sigma \) is the mean square error of the Gaussian function.

\[
A = \left( x^2 + y^2 \right) / \sigma^2, \quad \text{and} \quad K \text{ is a scale factor.}
\]

The Gaussian part \( G \) can smooth the image and effectively eliminate all image intensity changes that are much smaller than the Gaussian distribution factor( \( \sigma \) ). To select a suitable and orientation-independent operator, we choose the lowest order isotropic differential operator, Laplacian \( \nabla^2 \), which can reduce the computational complexity to a large extent.

\[
G(x, y, \sigma) = \left( \frac{1}{(2\pi\sigma^2)} \right)^2 \exp \left( -\frac{1}{2} A \right)
\]

(1)

\[
\nabla^2 G(x, y, \sigma) = K(2 - A) \exp \left( -\frac{1}{2} A \right)
\]

(2)

In the signal detection, the Newman-Pearson criterion is often used in the detection because the probability that the target appears under certain conditions is not known in advance and the loss caused by the missed detection is not known. This criterion can effectively deal with hypothesis testing problems when both prior probabilities and costs are difficult to determine. Set the false alarm rate \( P(D_1 | H_0) = P_{fa} \) to a constant value to maximize the detection probability. For a detection system, the input signal and the discrimination result can be represented.

\[
\text{When } x(t) = n(t), \text{ the situation is judged as } H_0, \text{ indicating that there is only noise and no signal.}
\]

\[
\text{When } x(t) = n(t) + s(t), \text{ it means that there are both signals and noise.}
\]

Let the probability density function be \( p(x | H_0) \) only under the condition of noise, and the probability that the noise level exceeds the discriminating threshold \( V_T \) to cause false alarm is

\[
P(D_1 | H_0) = \int_{V_T}^{\infty} p(x | H_0) dx
\]

(3)

\( V_T \) is decided by \( P(D_1 | H_0) = P_{fa} \). Similarly, under the condition that the signal and noise are simultaneously input, the probability density function of the signal plus noise is \( p(x | H_1) \), and the probability that the discrimination result is \( H_1 \) is

\[
P(D_1 | H_1) = \int_{V_T}^{\infty} p(x | H_1) dx
\]

(4)

The following criteria are given.
When \( \frac{p(x \mid H_1)}{p(x \mid H_0)} > a_0, \quad (a_0 \propto V_1) \), the discrimination result is \( H_1 \).

When \( \frac{p(x \mid H_1)}{p(x \mid H_0)} < a_0, \quad (a_0 \propto V_1) \), the discrimination result is \( H_0 \).

4. Results and analysis

Firstly, the least squares prediction method is used to predict the trajectory. The corresponding optimal approximation mode is determined according to different trajectory lengths. The trajectory parameters are recursively updated by updating the real-time data to predict the target position in the next frame image. Based on the trajectory confidence test, all current recorded trajectories are traversed, from which the trajectory of the confidence is detected and the trajectory of consecutive lost points and the trajectory lower than the lower confidence threshold are deleted. For the case where two tracks appear, if the distance between the current frame and the track point before the 3 frames is lower than the threshold, it is determined that the two tracks coincide, and only one with a high degree of confidence is reserved. For the trajectory of the confidence level, the target trajectory without the significant motion feature is deleted by judging the magnitude of the motion velocity, thereby displaying the effective trajectory while rejecting the false target.

The trajectory association matching is to match the trajectories of the candidate targets in each stage, and try to eliminate the false target trajectory and obtain the real target trajectory. A potential target trajectory within a phase can be obtained through a dynamic programming approach. Due to the low signal-to-noise ratio of the target, the target trajectory may be lost and the false alarm trajectory may exist. Therefore, we match the potential target trajectory according to the trajectory association condition to obtain important information such as the direction, velocity, position and gradation accumulation of the target.

During the target tracking process, there may be a sudden change in the spatial position of the target due to a sudden change in speed or a sudden change in the target coordinates in the adjacent acquisition frame due to burst jitter of an image acquisition device such as a camera. If the tracking window is too small, it may cause the tracking target to be lost within the shooting range. If the tracking window is too large, it will slow down the target lock. To this end, we propose a dynamic adjustment scheme for the tracking window size. The scheme can take the target centroid position in the image of the previous frame lost as the target as the center of the rectangular tracking window, and set the length and the width of the rectangular window to the original \( k \) times according to actual needs until the target is re-locked into the tracking window. If two frames of data are continuously lost, the target tracking process is terminated, the target detection recognition process is waited for the tracking to be turned on again. At the same time, it is also necessary to judge whether the target identified by the detection and the target position of the current tracking are consistent. If they are inconsistent, the tracking process has an error and accumulates the number of errors. When it exceeds the upper limit of the set number of errors, the tracking is turned off. The details are shown in Figure 3 and Figure 4.

The image we captured with the camera has a resolution of 768*517 (width 768, height 517). A total of four frames of images from 6361 to 6364 were collected, and the two-dimensional coordinates of the target centroid pixels were obtained by calling the image coordinate information function. Qualitative analysis and modeling of coordinates help us to perform target motion state analysis and image acquisition device jitter research. The obtained target pairs are shown in Table 1.

We randomly selected four frames of images, and obtained the number of points of relatively stationary targets in each frame by algorithm. Comparing it with the actual relative static point, the accuracy of the algorithm is obtained, as shown in Table 2 and Figure 5. The results show that our algorithm obtains 100% accuracy of relative static points. Therefore, the algorithm can count the number of targets and suspected targets in each frame in real
time and effectively, which has certain practical value.

Figure 6(a) is a picture taken by the camera in which the target is mixed with noise and the difference between the two is not large. The three-dimensional effect of the brightness intensity is shown in Figure 6(b).

Fig. 3 Tracking effect when the dynamic adjustment multiple of tracking window is 2 times.

Fig. 4 Tracking effect when the dynamic adjustment multiple of tracking window is 1.2 times, 1.5 times, 2 times and 3 times respectively.

| Frame number | 6361   | 6362   | 6363   | 6364   |
|--------------|--------|--------|--------|--------|
| Pixel info:(X,Y) | (199,346) | (182,460) | (182,467) | (182,470) |
Table. 2. The calculation of the accuracy of relative stationary point number.

| Frame number | 6188 | 6222 | 6288 | 6388 |
|--------------|------|------|------|------|
| Relative static points (obtained by algorithm) | 3    | 6    | 5    | 5    |
| Relative static points (actual) | 3    | 6    | 5    | 5    |
| The algorithm obtains the accuracy of relative static points (percentage) | 100% | 100% | 100% | 100% |

Fig. 5 Statistics of relative static points.

It can be seen that the intensity of the noise is up and down and fluctuating in the two-dimensional coordinate distribution. Thus, to a certain extent, we can distinguish between the target and the noise to be identified by having a transition phase. However, the results obtained in this way are not intuitive enough. In order to better improve the recognition speed and recognition accuracy, we use LOG filtering and image multiplication. Through the combination of the two, we can concentrate the value of the target and its surrounding high-intensity pixel points on the same pixel while filtering out the noise, and then distinguish the target from many noises. As shown in Figure 6(c), the obtained three-dimensional intensity effect is shown in Figure 6(d). Although Figure 6(d) can visually represent the two-dimensional coordinate position of the target, it is difficult to find the target position only by visually observing the Figure 6(c). To this end, we use the image coordinate information acquisition function to find the coordinate value of the pixel point 3 of the target centroid through the Figure 6(c) and then enlarge the target in the Figure 6(c) several times to obtain the Figure 6(e), and then draw the three-dimensional strength effect is shown in Figure 6(f). It has been found that the coordinates of the target centroid pixels in the Figure 6(d) and the Figure 6(f) obtained by our algorithm are the same. At the same time, it also verifies the feasibility of the method.
5. **Summary**

A method of trajectory correlation and target tracking of small targets in the sky under visible light background is proposed. Firstly, the least square prediction method is used to predict the trajectory, and all the tracks are traversed based on the trajectory confidence test, from which the trajectory of overconfidence is detected and the trajectory of continuous lost points and the trajectory below the threshold of confidence are deleted. Then, the target tracking is carried out based on LOG filtering and constant false alarm rate segmentation. The feasibility of the filtering effect is verified by comparing the filtered images and their corresponding 3D images. In addition, due to the sudden change of target speed and image acquisition equipment jitter, we also proposed a tracking window size dynamic adjustment scheme to reduce the impact of target coordinate mutation. The two-dimensional coordinate values in each frame of the image and the number of points of the relatively stationary target are also counted in real time.

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