Multi-sensor and Multi-target Tracking Based on Laser Technology

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Abstract: In this paper, we design and implement a variable scale adaptive SIFT algorithm to identify and track multiple targets by using the fast and high-precision characteristics of laser detection. By creating the target scale space, determining the location and main direction of the target feature points, we form the feature vector of the target feature points, and design a multi-target scale adaptive algorithm to track and predict the state of the target, so as to achieve the goal Now the effect of multi-target continuous matching tracking is achieved. The experimental results show that the algorithm is simple, adaptive, real-time, multi-target remote tracking effect is good, the environmental requirements are low, and the project is easy to achieve.

1. Target recognition algorithm based on Multisensor

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 change of atmospheric turbulence will lead to the flicker effect, which makes the target pulse intensity and signal-to-noise ratio of each frame echo fluctuate greatly. With the signal-to-noise ratio the detection confidence will always fail to reach the decision threshold, resulting in the failure to detect the real target. In this paper, simultaneous interpreting of targets under different sensors can be achieved by SIFT algorithm, which is based on variable scale extraction of target feature points. Because of the feature point sequence detected in different scale space, which has good anti scale scaling, rotation, noise, affine transformation, occlusion, perspective change and other characteristics, it has become a research hotspot. The following steps are to create image scale space, build dog Gauss difference scale space, determine the location and main direction of feature points, and generate feature vectors of feature points.

2. Create target scale space

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By using different scales to extract image characteristics, important image information can be obtained effectively. Set σ as scale space factor, convolute two-dimensional image *I(x,y)* with Gaussian kernel $G(x,y,\sigma)$, and generate scale space L by changing the size of σ:

$$L(x,y,\sigma) = I(x,y) * G(x,y,\sigma) \tag{1}$$

Where: $G(x,y,\sigma) = \dfrac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$ is the variable Gaussian kernel function and (x,y) is the pixel coordinate.

Construct the Gauss difference scale space DOG. Subtract two Gauss kernels of different scales to get Gauss difference kernels, and then do convolution operation with image I (x, y), thus forming the Gauss difference scale space dog (difference of Gaussian):

$$D(x,y,\sigma)=(G(x,y,k\sigma)-G(x,y,\sigma))I(x,y)=L(x,y,k\sigma)-L(x,y,\sigma) \tag{2}$$

3. Determine the position and main direction of target feature points

For the candidate points in the DoG scale space, further determine the target feature points through gray value comparison and quadratic function fitting, and filter out the points with low contrast and unstable edge points at the same time:

$$D(x)=D+\frac{\partial D^r}{\partial x}x+\frac{1}{2}\frac{\partial^2 D}{\partial x^2}x^r \tag{3}$$

Gaussian function is used to weight the pixels in the neighborhood of the feature point, and histogram is used to count the gradient direction in the window. The direction corresponding to the maximum value in the histogram is the main direction of the feature point, and the gradient amplitude m and direction θ of the feature point are:

$$m(x,y)=\sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2} \qquad \theta(x,y)=\tan^{-1}\frac{(L(x,y+1)-L(x,y-1))}{(L(x+1,y)-L(x-1,y))} \tag{4}$$

4. Generate feature vectors of target feature points

Take the feature point as the center, intercept the 16×16 rectangular window, and then evenly cut it into 4×4 sub windows. At the same time, rotate the coordinate axis clockwise θ^o to the direction of the feature point, as shown in Fig1.

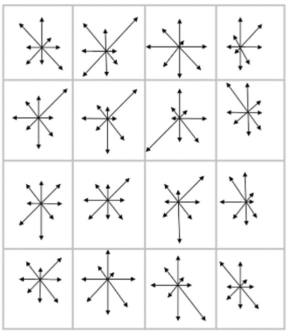

Figure 1. Eigenvector diagram of target feature points.

For each sub window, eight directional gradient histograms are counted, and the length of the eigenvector is normalized to generate a 128 dimensional sift eigenvector, which ensures the invariance of sift eigenvector to scale, rotation and illumination. The direction of the arrow in each small grid represents the gradient direction of the pixel, and the length of the arrow represents the size of the gradient mode. In Fig1, the 64 small squares around the key points represent the positions of the current key points on the left side of the square with the same scale as the key points, and the length of the 64 pixel arrows in the neighborhood of the key points represents the size of the gradient mode. The arrow direction in each small grid represents the gradient direction of the pixel, and the range contained in the circle represents the range statistics weighted by Gauss The accumulated value of each direction is to a seed point. A feature point is described by 4*4 totally 16 seed points, and each seed point has 8 direction vector information. Therefore, each feature point generates 4*4*8 totally 128 data, that is, the final 128 dimensional SIFT feature vector or feature descriptor is formed. In this paper, the key point feature vector is described by 128 dimensions.

5. Multi-objective scale adaptive algorithm

When creating sift scale space, the selection of scale space factor σ can not only affect the number of target feature points, but also affect the extraction speed. The experimental results show that when σ is close to 1.5, the detail features of the target image are obvious, and when it is increased, it will be a little fuzzy. Therefore, in order to make the scale factor σ automatically adjust with the size of the target, this paper proposes an adaptive SIFT algorithm based on the scale of the target, which can automatically adjust the scale factor size according to the proportion of the target in the whole image, so as to adaptively extract the features of the image.

$$\sigma_k = \begin{cases} 1.5(1 - S_{\max} / S_0), & \text{When } S_{\max} < S_0 / 15 \\ 1.5 & \text{Other} \end{cases} \tag{5}$$

Where: S_0 is the area of the k frame image, S_i is the rectangular area of the i target in the image, $S_{\max} = \underset{i=1,\dots,n}{MAX}(S_i)$, σ_k is the scale factor value of the k frame image.

6. Tracking target status prediction

Compared with the whole image, the dynamic target is much smaller. If we can predict the approximate position of the target in the next moment, we can only extract and match the feature vectors of the possible areas of the dynamic target, which can not only shorten the matching time to meet the real-time requirements, but also effectively eliminate the noise interference outside the area of the target and improve the matching accuracy. As a fast and effective state estimation algorithm, Kalman filter can well meet this goal.

7. To determine the Kalman filter's two-dimensional space

The motion equation and observation equation of the two-dimensional space target of the Kalman filter are determined as follows:

$$x_k = F_{k-1}x_{k-1} + U_k \qquad y_k = H_k x_k + V_k \tag{6}$$

Among them, $x_k = (\mathrm{X}_x, v_{xk}, \mathrm{X}_y, v_{yk})$ represents the X,y coordinates and speed of the target at k time, and its covariance matrix is represented by P_k; U_k is $U_k \in (0, R_k)$ is the system zero mean white noise; V_k is $V_k \in (0, Q_k)$ is the observation zero mean white noise; F_{k-1} is the system state transition matrix at k-1 time; H_k is the observation matrix at k time, and K_k is the gain matrix.

Update target time:

$$\hat{x}_k = F_{k-1}\dot{x}_{k-1} \qquad \hat{P}_k = F_{k-1}\dot{P}_{k-1}F_{k-1}^T + Q_k \tag{7}$$

Determine the state estimation vector of the target in frame K. Among them, ^ and · represent time update and observation update results respectively.

$$K_k = \hat{P}_k H_k^T (H_k \hat{P}_k H_k^T + R_k)^{-1} \qquad \dot{x}_k = \hat{x}_k + K_k(y_k - H_k \hat{x}_k) \tag{8}$$

$$\dot{P}_k = (I - K_k H_k)\hat{P}_k (I - K_k H_k)^T + K_K R_k K_k^T \tag{9}$$

8. Multi target continuous matching tracking strategy

The specific steps are as follows:

1. SIFT feature points of the object are extracted by sensor C_0, and the feature vector sequence S_0 is generated;
2. Frame image of the following sensor C_i is intercepted, the target position is predicted by Kalman target state prediction algorithm, and the feature point eigenvector sequence S_i is obtained by scale adaptive SIFT algorithm;
3. Match S_0 and S_i. If the number of feature point matches exceeds the threshold N, the matching tracking is successful, and step 4 is entered; otherwise, step 2 is returned;
4. Output and lock the matching target, and continue with step 2 for subsequent sensor C_{i+1}.

9. Experimental results and analysis comparison

In this experimental system, the outdoor monitoring scene without overlapping field of view is selected for simulation experiment. The video resolution is 440*360, and the frame rate of image acquisition is 26F/s. The experimental software environment: win10, OpenCV software, running on Corei5(3.2+3.2) GHz, 8G memory PC. In order to further verify the tracking performance of the algorithm in different scenes, we use literature [2], literature [3] algorithm and the algorithm in this paper to compare the same video in the public video library of PETS2008 offline simulation tracking, using these three algorithms to track this segment As for video, the number, time and accuracy of detection of matching points are shown in Table 1. It can be seen from the table that the algorithm in this paper extracts key points from pure targets and adopts adaptive SIFT algorithm, so the overall calculation is less, matching speed is fast and accuracy is high. Although the light intensity and viewing angle of the two viewing frequencies are quite different, there are often mutual occlusion between targets, but each of them follows the tracking index is better than other algorithms, and the tracking effect is ideal.

Table 1. Comparison of tracking accuracy and time of three algorithms.

Algorithm	**Check out matching points**	**Correctly match points**	**Accuracy %**	**Time consuming /s**
Literature [2] algorithm	1262	1021	82.8	12
Literature [3] algorithm	1303	932	68.2	24
Algorithm in this paper	460	311	96.5	3.5

Using laser to detect target has the characteristics of high speed and high precision. In this paper, multi-target recognition is carried out by using variable scale adaptive SIFT algorithm. By creating target scale space, determining target feature point position and main direction, target feature point feature vector is formed, multi-target scale adaptive algorithm is designed, tracking and predicting target state, so as to realize multi-target succession Match the tracking effect. The experimental results show that the method in this paper has strong adaptive ability, good real-time performance, strong multi-target remote tracking function, low environmental requirements, and easy to implement in engineering.

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