Dim Targets Detection and Tracking by Self-adaptive Segmentation and Particle Filter in Starry Images

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Abstract

An effective method for dim and small multi-targets detection and tracking through successive CCD images in complex starry background is put forward in this paper. Optical starry background images contain a lot of interference noise besides the moving targets. Firstly, self-adaptive threshold segmentation can play an important role in eliminating noise and improving detection rate. Furthermore, back neighborhood frame correlation (BNFC) is proposed to detect and locate the target, which is sheltered by bigger interfered stars. After detection framework acquiring the location of moving targets, particle filter which has nonlinear filtering feature is applied to track the trajectories for multi-targets in real-time. Experimental results show that by using the adaptive target detection and improved particle filter, the trajectories could be achieved at a relative low signal to noise ratio (SNR ≥ 3.5) in the case of multi-targets detection and tracking in real time. The method has good prospect for engineering application.

Key Words: Complex Starry Background, Dim and Small Targets, Self-adaptive Target Detection, Particle Filter

1. Introduction

The detection and tracking of dim and small multi-targets in starry images is a hot and challenging issue in the field of targets tracking [1,2]. Since the first artificial satellite was sent into space in 1957 by the Soviet Union and it became space junk later. Today, the total number of different size space junk is countless. According to NASA’s 2013 report [3], there are more than 500,000 space junk whose diameter is more than the size of marble, 20,000 more than the size of softball by the end of 2013. Although the space junk is small, they have very high speed comparing to space vehicles and satellites and are threatening the normal operation of international space station and other spacecraft. It is of great significance to detect and track space junk to make surveillance of space safety and clear the junk in the future. Now the main instruments for observation of space junk are astronomic optical telescopes and radar imaging systems. But so far, the radar could not provide precise location information of all objects in space and tracking the trajectories of junk while optical image processing is developing rapidly. However, due to the size of junk in space is small and the distance is far from the imaging system, the targets on CCD images only have a few number of pixels. Moreover, the imaging system is interfered by cosmic rays, coupled with the image background clutter and singular highlights interference and the optical images’ SNR is very low. How to detect and track multiple small moving targets in starry images has become a challenging task.

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Generally, in terms of detection and tracking of targets, some useful algorithms are proposed on multi-frame image sequences, including dynamic programming algorithm [4], neural networks [5], sequential hypothesis testing [6] and optical-flow [7]. Dynamic programming algorithm could get trajectory of moving objects from continuous frame images through similar pixels but it couldn’t detect multiple targets and its large calculation is not suitable for real-time system. Neural networks, and sequential hypothesis testing have a good performance result for the image target detection, but they are more sensitive to the existence of noise and need a lot of computation and storage. They are not suitable for engineer application. Optical-flow is based on constant gradient value and target luminance, but the dim and small targets in star images haven’t enough features to meet the hypothesis.

Tracking for moving target’s trajectory is generally based on “filtering, data association” algorithm scheme, in other words state estimation. The motion model predicts a target’s location in a new frame of an image sequence using its motion history and other known movement characteristics, mainly comprising mean-shift [8], Kalman filter [9] and particle filter [10,11].

Mean-shift is a recursive estimation model. Firstly, an iterative process is used to calculate the mean deviation of the current point, and then the point is moved to offset average as a new starting point. Repeat this scheme until the condition is met. Kalman filter is a linear Gaussian tracking problem which is the optimal solution at minimum mean square error. It supports uniform linear motion model of the object and has a good convergence for tracking of uniform linear motion model. In the actual case, the state of moving target motion is often not uniform linear motion model, but more complex non-linear, non-Gaussian motion model. For nonlinear system, particle filter based on Monte Carlo has better performance. Therefore, particle filter is applied for tracking trajectories.

In order to meet the requirements of small targets detection and tracking under low SNR, this paper proposes a self-adaptive target detection and improved particle filter to track the trajectories. Firstly, considering the sequential frames correlation between the movement of targets, inter-frame correlation and self-adaptive threshold segmentation are applied to remove interfered noise and extract the moving targets from single frame. We take BNFC to improve detection rate. At last, the improved nonlinear particle filter is applied to track the moving targets. The experimental results show that the system could detect and track four targets accurately and the tracking error is less than 1.5 pixel.

2. CCD Optical Imaging Model in Star Background

Charge-coupled device (short for CCD) is a new type of semiconductor device, first proposed by Boyle and Smith in 1969 [12]. It is applied as detector for astrophysical research began in the late 1970s, mainly in observation from ground to space. In recent years, with the developing of outer space exploration, the CCD imaging system carried by satellite obtaining astronomical optical images begin to be used for space junk observation and early warning.

Space optical images consist of dark deep space background, the stars of various sizes, dim and small targets and noise caused by the imaging device and the space environment. The dim and small targets contain only a few pixels in optical images, usually 3*3 pixels, at most 5*5 pixels. For the moving targets, they have no fixed shape, size, color and texture features, but illumination, position and velocity information. Usually, we take sequential astronomical optical images acquired by CCD as three-dimensional image data, where \((x, y)\) represents the spatial position information and the other dimension is the time coordinate or frame number. Considering imaging detector-sensing noise is Gaussian white noise, the model of optical image could be expressed as follows:

\[
f(x, y, k) = f_t(x, y, k) + f_i(x, y, k) + f_j(x, y, k) + n(x, y, k)
\]

(1)

where \(f(x, y, k)\) is the optical CCD image intensity at position \((x, y)\) of the \(k\)-th image, \(f_i(x, y, k)\) is space junk ob-
ject image intensity, $f_S(x, y, k)$ is fixed star image intensity, $f_B(x, y, k)$ is background image intensity and $n(x, y, k)$ is the noise intensity in image.

Due to the small size of space junk, and far from the CCD imaging system, the targets follow Gaussian distribution in optical image. The reason is the diffraction and scattering of instrument and the disturbance of cosmic rays and particles, resulting that the junk targets aren’t no longer a point, but star image of flow intensity-point spread function (PSF) of cosmic target [13]. Using the method of measuring optics under PSF could obtain the precise location of small targets. The PSF models used currently are mainly function model, empirical model and the hybrid model. The analytic function PSF model proposed by King considering cosmic rays, the particles disturbance and scattering and diffraction of instruments could be described as two-dimensional Gaussian function approximately.

$$G(x, y) = \frac{I}{2\pi\sigma^2} \exp \left\{ -\frac{(x-x_0)^2 + (y-y_0)^2}{2\sigma^2} \right\}$$  \hspace{1cm} (2)$$

where $I$, $(x_0, y_0)$ and $\sigma$ are the illumination of center point, the center coordinates and dispersion rate respectively. Imaging model is shown in Figure 1:

According to the starry imaging model, we assume the model follows the Gaussian distribution. In order to obtain the target centroid more accurately, the gray weight average is used to get the mass center of continuous star point: $Z_k(n) = (x_{n}^k, y_{n}^k)$. Where $Z_k(n)$ represents the centroid coordinate of $n$-th target at time $k$, $x_{n}^k$ and $y_{n}^k$ are the two direction values. The detail equations are as follows:

$$x_{n}^k = \frac{\sum_{C_n} x \cdot I(x, y, k)}{\sum_{C_n} I(x, y, k)}$$  \hspace{1cm} (3)$$

$$y_{n}^k = \frac{\sum_{C_n} y \cdot I(x, y, k)}{\sum_{C_n} I(x, y, k)}$$  \hspace{1cm} (4)$$

The left picture in Figure 2 is an original space optical image. The right pictures are multiply dim and small targets, star noise image and space background image respectively. The Figure 3 is a three dimensional gray distribution picture. From the pictures, we could conclude two points: the moving targets and star noise are both gray points, gray distribution concentrated and meeting the PSF model; another one is that the target and star noise haven’t fixed morphological characteristics and texture features. Gray feature is similar. It is difficult to distinguish from each other.

![Figure 2. The target and noise in optical image.](image)

![Figure 3. Three-dimensional image of target.](image)

### 3. Self-adaptive Target Detection

The block diagram of detection and tracking algorithm is shown in Figure 4 below.

During the detection and tracking process, in each image frame, we need first to define a target region and
its background region in order to compute SNR and estimate tracking region. If a target is a rectangle whose area is \( h \times w \) pixels, then its background is defined as outline rectangle zone \((\sqrt{2}w \times \sqrt{2}h)\) around it. It’s shown in Figure 5.

### 3.1 Image Gray Transformation

The original optical astronomical images are 33 frames with 24 bit, 800*640 pixels size and there are 4 moving targets in them.

Since the star images with 24 bit have no difference in color feature, it’s useful to transform them to 8 bit images firstly. The 8 bit images have entire information of the original images and could reduce computation largely.

### 3.2 Interval Frame Subtraction and Background Noise Smoothing

The optical images acquired by CCD are related closely with each other. Generally, the moving targets in gray images and isolated noise could be extracted by interval frame subtraction without CCD shaking or other interfered factors. The equation is as follows:

\[
o(x, y, k+1) = |f(x, y, k+1) - f(x, y, k)|
\]  

where \( o(x, y, k+1) \) is the target in \( k+1 \) frame, \( f(x, y, k) \) and \( f(x, y, k+1) \) are \( k \) and \( k+1 \) original images.

The number of the pixels of the detected targets is small after interval frame subtraction. Due to the gray values of targets is larger than noises, the smoother filter could be used to suppress the noises. Considering the size of targets, the Gaussian filter of size 6*6 pixels could be applied.

### 3.3 Image Self-adaptive Threshold Segmentation

In order to distinguish moving junks from stars and noises, we take adaptive threshold segmentation to extract the moving junk. The principle is shown as follows:

\[
f(x, y, k) = \begin{cases} 1 & |f(x, y, k) - \mu| > \lambda \cdot \delta(x, y, k) \\ 0 & \text{else} \end{cases}
\]  

where \( \mu \) is the mean value of the \( f(x, y, k) \), \( \delta(x, y, k) \) is the variance of the image and \( \lambda \) is an empirical value related to image. In our experiments, we take \( \lambda = 20 \).

### 3.4 Objects Classification and BNFC to Estimate the Location of Target Interfered by Star

After image gray transformation, interval frame subtraction, background noise smoothing and self-adaptive threshold segmentation, the moving targets could be extracted. But sometimes, when a moving junk is covered
by a fix star noise, interval frame subtraction misses the target in the image. At the time, back neighborhood frame correlation is performed to estimate the centroid of the junk. The details of back neighborhood frame correlation method are illustrated in Figure 6:

(1) Due to the interference and shelter of the star noise, the moving star in the image which is got by interval frame subtraction disappears in one subtraction frame. \( f(x, y, k), f(x, y, k+1) \) and \( f(x, y, k+2) \) are 3 continuous frame images. \( o(x, y, k), o(x, y, k+1) \) and \( o(x, y, k+2) \) are images after subtraction related from original frames.

(2) The moving junk \( o(x, y, k+1) \) disappears for the shelter of star noise. Then we use cross projection of \( k \) and \( k+2 \) frames to acquire the location \( (x_k, y_k) \), \( (x_{k+2}, y_{k+2}) \) of the moving junk. The "□" represents fix star noise and "○" represents moving target.

(3) When we get the location \( (x_k, y_k) \) and \( (x_{k+2}, y_{k+2}) \), we could estimate the centroid \( (x_{k+1}, y_{k+1}) \) of the junk in \( f(x, y, k+1) \) through getting the location of interfered star.

3.5 Cross Projection and Gray Weight Value to Acquire the Coordinates of Targets

In terms of processed object image \( o(x, y, k) \), cross projection is performed to locate the target in vertical and horizontal axis. According to PSF model, gray weight value is applied to acquire the coordinates of moving targets in original images. The principle of cross projection is as follows:

\[
T(x) = \sum_{y=1}^{Y} T(x, y, k) \quad (7)
\]

\[
T(y) = \sum_{x=1}^{X} T(x, y, k) \quad (8)
\]

Comparing with the values of \( T(x) \) and \( T(y) \), we could get the centroid of the moving junk easily and quickly. According to CCD optical imaging model with equation (3) and (4), we could obtain the coordinates \((x, y)\) in original images.

4. Trajectories Tracked by Improved Particle Filter

Particle Filter is based on non-parametric Monte Carlo simulation method to achieve recursive Bayesian filter, which could be used for target tracking. This model uses a large number of particles to approximate the priori probability distribution.

The state space of dynamic system could be expressed as:

\[
X_k = f_k(X_{k-1}) + u_k \quad (9)
\]

\[
Z_k = h_k(X_k) + v_k \quad (10)
\]

where \( X_k \) is system state, \( u_k \) is the noise of the system, \( Z_k \) is observed value, \( v_k \) is noise of observation, \( f_k(\cdot) \) is the transfer function of the system and \( h_k(\cdot) \) is the observation function. \( u_k \) and \( v_k \) subject to Gaussian distribution.

With this model, the state \( X_k \) could be got by calculating the posterior probability \( P(X_k|Z_{1:k-1}) \) and observation value \( Z_k \). The main process is composed of two steps: prediction and update. The recursive process is as follows:

Prediction:

\[
P(X_k|Z_{1:k-1}) = \int P(X_k|X_{k-1})P(X_{k-1}|Z_{1:k-1}) \, dX_{k-1} \quad (11)
\]

Update:

\[
P(X_k|Z_{1:k}) = \frac{P(Z_k|X_k)P(X_k|Z_{1:k-1})}{P(Z_k|Z_{1:k-1})} \quad (12)
\]

Figure 6. The diagram of back neighborhood frame correlation.
We could get the new state from equation (11), (12) and (13):

\[ P(Z_k | Z_{k-1}) = \int P(Z_k | X_k) P(X_k | Z_{k-1}) dX_k \]  

(13)

Particle filter tracking algorithm:

(1) Initialization: \( N \) particles \( \{ w_i^0 = |i = 1, 2 \ldots N \} \) are established. The weights of all the initial particles are \( 1/N \).

(2) Weight update of every particle: \( k = 1, 2 \ldots n \)
   
   i) Extract \( N \) particles from distribution function:
   
   \[ X_i^t \sim q(X_i^t | X_{i-1}^t, Z_t), i = 1, 2 \ldots N \]
   
   ii) Update the weights of particles and normalization:
   
   \[ w_i^t = w_{i-1}^t p(Z_t | X_i^t) \]

   \[ \bar{w}_i^t = \frac{w_i^t}{\sum_{i=1}^{N} w_i^t} \]

(3) Resample:

   Calculate \( Neff = \frac{1}{\sum_{i=1}^{N} \bar{w}_i^t} \). If \( Neff < Nthr \) (\( Nthr \) is an assumed threshold), and then resample is performed to obtain new support particle collection. \( \{ \bar{X}_{i}^t, 1/N; j = 1, 2 \ldots N \} \)

(4) Calculate the output \( \bar{X}_i \) and let \( k = k+1 \). Go to step 2.

5. Experiment Results and Analysis

5.1 Experiment Platform

In this part, 33 original images are tested on a computer with i5 CPU, RAM 4 GB. The program is performed on MATLAB 2010 edition.

In order to estimate the experiment results and analysis the algorithm effects of dim and small targets, we take two effect indicators to evaluate the proposed method quantitatively:

(1) SNR [14] of target in partial zone:

\[ SNR = | \mu_T - \mu_B | \sigma_B \]

(15)

where \( \mu_T \) is mean value of target, \( \mu_B \) is mean value of target partial background, \( \sigma_B \) is the variance of target partial background.

(2) The detection rate (DR) and false alarm rate (FR)

In target image, when \( d \) represents detected targets, \( k \) represents false detected targets and \( b \) represents missed detected targets, the detection rate (DR) and false alarm rate (FR) are defined as follow:

\[ DR = \frac{d-k}{d-k+b}, \quad FR = \frac{k}{d-k+b} \]

(16)

5.2 The Experiment Results of Self-adaptive Target Detection are Shown as follow

In this experiment, there are 32 sequential original images. According to proposed algorithm flow of detection and tracking, gray transformation, interval frame subtraction, background noise smoothing and self-adaptive threshold segmentation are tested successively. The results are shown as follow (Taking the 6th frame and 19th frame as examples).

Figure 7 are the results of dim and small targets detection. (a) and (b) are original images of 6th and 9th frame. The 6th frame contains 4 moving targets illustrating as Number 1 2 3 and 4. The 19th frame contains 3 moving targets illustrating as Number 2 3 and 4. The Number 1 target moves outside of the image. (c) and (d) are images smoothed by Gaussian filter. The gray values of targets are different with each other and there is a lot of background noise. (e) and (f) are results after threshold segmentation and there is an interfered noise point in image (f). (g) is the four moving trajectories. From the image we could get that the trajectories are nearly linear but there are still some interfered random noise points.

The SNR of targets are different because the characteristics of targets and background differ largely. Com-
paring the SNR mean value of targets, the SNR value of target Number 4 is least and the signal frame least value is 3.56. The model could detect the moving targets and the DR is 1.00. Because of the existence of interference singularity points, the FM is 0.075. The detail parameters are shown in Table 1. It can be seen on the figure that the model could detect the dim and small targets under low SNR and guarantee low FM.

5.3 Location of Moving Targets

After self-adaptive target detection and cross projection, we will obtain the location of targets in images. The Number 1 target is no longer in optical images after 12th frame. The detail result is shown in Table 2 (taking 1th, 2th, 10th and 20th as examples).

Sequential optical images are related closely. Projection after threshold segmentation of four moving targets is shown on one picture where there are four sequential trajectories in Figure 8. From the picture, the four mov-

Table 1. The parameters of every target and model’s property

<table>
<thead>
<tr>
<th>Target number</th>
<th>Average SNR</th>
<th>Max SNR</th>
<th>Min SNR</th>
<th>DR</th>
<th>FM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target 1</td>
<td>5.13</td>
<td>6.16</td>
<td>4.40</td>
<td>1.00</td>
<td>0.075</td>
</tr>
<tr>
<td>Target 2</td>
<td>6.186</td>
<td>7.98</td>
<td>4.76</td>
<td>1.00</td>
<td>0.075</td>
</tr>
<tr>
<td>Target 3</td>
<td>8.83</td>
<td>13.08</td>
<td>6.39</td>
<td>1.00</td>
<td>0.075</td>
</tr>
<tr>
<td>Target 4</td>
<td>4.19</td>
<td>4.82</td>
<td>3.56</td>
<td>1.00</td>
<td>0.075</td>
</tr>
</tbody>
</table>

Table 2. Locations of the moving targets

<table>
<thead>
<tr>
<th>Target number</th>
<th>X direction</th>
<th>Y direction</th>
<th>Frame number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>89.00</td>
<td>128.75</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>80.50</td>
<td>126.00</td>
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<tr>
<td>1</td>
<td>14.22</td>
<td>105.22</td>
<td>10</td>
</tr>
<tr>
<td>1</td>
<td>166.00</td>
<td>340.5</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>160.67</td>
<td>340.75</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
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<td>340.00</td>
<td>10</td>
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<td>2</td>
<td>68.42</td>
<td>339.25</td>
<td>20</td>
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<tr>
<td>3</td>
<td>217.88</td>
<td>343.59</td>
<td>1</td>
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<td>3</td>
<td>212.65</td>
<td>343.47</td>
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<td>171.50</td>
<td>343.00</td>
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<td>120.22</td>
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<tr>
<td>4</td>
<td>267.00</td>
<td>332.00</td>
<td>20</td>
</tr>
</tbody>
</table>

Figure 7. Self-adaptive target detection of dim and small targets.

Figure 8. The trajectories of moving targets.
ing trajectories are nearly linear lines and target Number 1 exists on partial images.

5.4 Improved Particle Filter Tracking Results

In order to track the targets accurately and in real time, the observation values are taken into particle model to get every target’s tracking state. To quantize tracking accuracy, we take root mean square (RMS) to estimate tracking model. Figure 9 presents the tracking results that show the robustness of the model.

From Figure 9, (a), (d), (g) and (j) are the state result of targets which indicate the relation between the position of targets and results of particle filter. (b), (e), (h) and (k) are the velocity of every target and the velocity is non-uniform. (c), (f), (i) and (l) are tracking errors in experiments. It can be seen on the figure that the RMS is less than 1.5 pixels that show the robustness and accuracy of the tracking model.

Figure 9. The tracking results velocity and RMS of moving targets.
After experiments and the quantitative analysis of results, it can be concluded that this model could detect small targets effectively at low SNR. The DR is 1.00 while the FR is 0.075. Through analysis of particle filter results, the tracking error is less than 1.5 pixel, achieving tracking of dim and small targets in complex starry background.

6. Conclusions

Under the condition that detection and tracking of dim and small targets in complex starry background, we propose self-adaptive target detection and improved particle filter to track the targets in this paper. This method takes interval frame subtraction, Gaussian smoothing, self-adaptive threshold segmentation and cross projection to locate four moving targets. Considering interfac ing and sheltering of the fixed star noise, we propose BNFC to improve DR. Experiments show that this method is efficient and robust to noises, and could detect multi-targets effectively under a lot of interfered noise starry images and tracking error is less than 1.5 pixels. In the future work, the random noise should be decreased further and the method will be realized in DSP platform.

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