Occluded Target Tracking Method Based on Multi-feature JPDA

Man-liang LI, Xing-hao FENG*, Xue-hai TANG and Xiang-yang ZHAO

Mailbox 790-1, Korla, P.R. China

*Corresponding author

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Abstract. Aiming at the problem of tracking instability or misalignment when the target is occluded or disturbed by similar targets, this paper proposes an improved occluded target tracking method based on JPDA (Joint Probability Data Association) based on the analysis of JPDA algorithm which is prone to misalignment when the target is occluded. The algorithm judges by adding multi-dimensional attributes (area, gray level, location, etc.). Accurate correlation of inter-frame targets is achieved. the accuracy of occluded target position prediction is improved to enhance the anti-occlusion ability. The measurement image sequence is used to simulate at finally. The simulation results show that the accuracy of occluded target location extraction is significantly improved by using the improved multi-feature based algorithm JPDA, which can meet the target tracking requirements in most occluded scenarios.

Introduction

Target automatic tracking is a key technology in the field of measurement and control. It has very important applications in intelligent monitoring, national defense reconnaissance, military measurement and other field[1]. Although scholars at home and abroad have studied it for decades, there are still many problems to be solved, such as how to track the target smoothly and continuously under the condition of occlusion in the tracking process. Scholars at home and abroad have studied different data association algorithms for different application areas, such as NN algorithm for high SNR and low dense targets, PDA algorithm for low dense targets in clutter environment, JPDA and MHT algorithm for high dense maneuvering targets in clutter environment[2]. Among these algorithms, JPDA algorithm is widely used in practical engineering because it avoids the association failure caused by the uniqueness of NN algorithm and does not depend too much on the prior knowledge of target and clutter.

However, the number of joint events of JPDA is an exponential function of all candidate signals, and increases rapidly with the increase of signal density, resulting in the combination explosion of computing load. In engineering application, in order to effectively avoid the combined explosion problem of calculating load, it is necessary to reduce the signal density as far as possible and improve the accuracy of target matching. Aiming at the situation that the target is easily approximated when it is occluded, the characteristics of the target and the approximate target are studied. An improved JPDA (Joint Probability Data Association) algorithm based on the multi-feature information of the target (area, gray level, location, etc.) is proposed. By adding the judgment of multi-dimensional attributes, the accuracy of extracting the occluded target is improved. Finally, the simulation is carried out by using the measured image sequence. the simulation results show that the improved multi-feature JPDA algorithm can significantly improve the accuracy of target extraction and meet the tracking requirements of most occluded targets.

JPDA Algorithm

JPDA algorithm is developed on the basis of probabilistic data association (PDA) algorithm, which is only suitable for single target tracking. It can simultaneously track and process multiple targets. The following is a brief introduction.
**Associated Region**

The correlation region is a subspace of the measurement space, whose center is located at the prediction point of the target being tracked. Its size is determined by the detection probability $P_G$ of the target being observed. The specific method of selecting the value is referred to in reference [1]. The formation of correlation region is not only the key link to limit the amount of computation in the process of data association, but also the prerequisite to ensure the update of target track.

The correlation domain for calculating $k$-time is:

$$[Z_i^t - \hat{Z}_{i\cdot t}^k]S_i^k[Z_i^t - \hat{Z}_{i\cdot t}^k] \leq \gamma, \quad t = 1, 2, \ldots, T.$$  \hspace{1cm} (1)

In the formula, $\hat{Z}_{i\cdot t}^k$ represents the predicted value of target $T$ at $k$ time, and $S_i^k$ is the predicted covariance matrix of the target $T$ at $k$-time. $\gamma$ is the threshold value, which is determined by $P_G$, $Z_i^t$ is the measured value labeled $I$ for $k$ time.

Assuming that there are $m_k$ measuring points at $k$ time, it is recorded as $Z_{k, 1}, Z_{k, 2}, \ldots, Z_{k, m_k}$, the effective matrix of $k$-time is obtained as follows:

$$\Omega_k = \begin{pmatrix}
    0 & 1 & 2 & \ldots & T \\
    1 & o_{11} & o_{12} & \ldots & o_{1T} \\
    1 & o_{21} & o_{22} & \ldots & o_{2T} \\
    1 & \vdots & \vdots & \ddots & \vdots \\
    1 & o_{m_k, 1} & o_{m_k, 2} & \ldots & o_{m_k, T}
\end{pmatrix}.$$  \hspace{1cm} (2)

In the formula, $o_{ij}$ denotes whether the measurement point falls into the correlation domain, when it is 1, it denotes that the effective measurement point falls into the correlation domain, and when it is 0, it denotes that the measurement point does not fall into the correlation domain.

In the process of multi-target tracking correlation, Kalman filter is used to calculate the state estimation $\hat{X}_{i, k|k}$ of target $T$ at $k$-time recursively under the condition that all effective measurements at $k$ time are known.

**Splitting Efficient Matrix**

Effective matrix $\Omega_k$ is the key factor to determine the computational efficiency in Kalman filter recursive computation. Usually, effective matrix $A$ is split first by splitting it into several 0-1 matrices with only 1 in each row and only 1 in each column except column 1, these 0-1 matrices are called feasible matrices. Each feasible matrix corresponds to a joint association hypothesis event with respect to $m_k$ effective measurement points and targets. Feasible joint events are the basis of calculating association probability $\beta_{ij}$.

Principle of effective matrix splitting: Scanning effective matrix $\Omega_k$ row by row, only one element of feasible matrix is selected for each row; in feasible matrix, except for the first column, only one element can be found for each column. According to the splitting principle, an effective matrix can be divided into many feasible matrices, and $l$ is the number of feasible matrices. Generally speaking, the number of feasible matrices increases exponentially when the number of target $T$ and effective measurement $m_k$ are large. It is worth mentioning that $l$, the number of feasible matrices is also closely related to the degree of intersection of the target correlation regions, the more dense the intersection, the more feasible matrices there are.

**Computation of Association Probability**

Firstly, a correlation matrix of the aggregated target and candidate measurement points is established, and then a joint event is formed to obtain the probability of occurrence of the related event. Then, the correlation probability $\beta_{ij}$ of the target $T$ and candidate measurement points is calculated. Finally, the weight $\beta_{ij}$ is used to predict the track.
Let $P_D$ be the detection probability of the measurement system, indicating the probability that the correct measurement point falls into its tracking door. The clutter is uniformly distributed in the observation space and the number of clutter points obeys Poisson distribution. $Z^t$ is the total set of measurements for $T$ targets at time $k$. $Z_k$ is the vector set of candidate measurements at time $k$. Using Bayesian formula, the calculation formula of association probability of joint event $\chi$ can be deduced as follows:

$$\beta_{1,t} = \sum_{j,t} P(Z_{t,j} | Z^t)\cdot \beta_{1,0} = 1 - \beta_{1,1} \quad \text{ (3)}$$

In formula $P(Z_{t,j} | Z^t)$ is the conditional probability of joint event $\chi$ at $k$ time under total measurement conditions.

Multi-feature JPDA Improved Algorithm

Disadvantages of JPDA Algorithm

The main drawback of JPDA algorithm is that it only considers the target position correlation characteristics, that is to say, the target location can satisfy the tracking requirement without background interference, and it is easy to associate errors under the condition of background interference, which leads to the loss of target. The following analysis is an example of mid-wave infrared image sequence near several missing points when a device tracks a cloud-piercing target.

Through repeated studies of image sequences, it is found that there are two main phenomena in tracking cloud-piercing targets: one is jitter, the other is target loss. The cause of jitter is the alternation of right and wrong of target position correlation, while the missing target is the persistent error of target position correlation. The following are explained separately:

Example 1: Jitter

Fig. 1 is a binary image of four consecutive frames in the tracking gate when tracking jitter occurs. The target in the red circle represents the actual extracted target. In frame 7599, the target and background clouds are segmented correctly; in frame 7600, it is difficult to separate the target from the background cloud because of the adhesion between the target and the background cloud. In frame 7601, the target and the background cloud have adhesion, but there is a clutter similar to the target near the cloud. Although the correlation probability is low, it is also the highest among all the targets, so when the target is output, the target and the background cloud are segmented correctly in frame 7602 because of the previous one. The probability of target association in one frame is low (compared with frame 7599). After track association in frame 7599 and previous tracking target data, the correct target can be retrieved. Because the output positions of 7600 frames and 7601 frames are not the real position of the target, and the output positions of 7599 frames and 7602 frames are the real position of the target, the target will jitter in the whole field of view.

Example 2: Target loss

Fig. 2 is a binary image of four consecutive frames in the gate when tracking is lost. The target in the red circle represents the actual extracted target. Frame 12112 and previous targets and background clouds are segmented correctly, the target is correct, but there are clutters similar to the target features in the background; frame 12113 targets are not segmented, and clutter is taken as the target; in frame 12114, the target and background clouds are segmented correctly, but at the same time the clutter is also segmented correctly, so the clutter will still be the target; in frame 12115, the
clutter disappears, but because the clutter is taken as the real target in the first two frames, the correct target is discarded, so the target is lost.

Figure 2. Binarization of 4 consecutive frames in the target loss front gate.

Examples 1 and 2 arise because: In order to satisfy the stable tracking of the target under sudden changes such as target detonation and separation, the target association algorithm used by the tracker adopts a strategy with larger weight and larger threshold value for the moving target in track association, so it is easy to associate with the clutter in front of the moving target. In order to solve this problem, the JPDA algorithm is improved to increase the correlation between target gray level and target area.

**Increasing the Gray Level Relevance of the Target**

From the analysis process of Example 1 and Example 2, the gray level change of the target is a gradual process between successive frames. The gray value of the target in the next frame can be predicted by the least square method, and the gray correlation degree of the target can be established. Assuming that the set of gray-scale of target track confirmed before k-time is \( G_k \) and the latest measurement value of gray-scale of target is \( g(k) \), the second-order least squares method is used to calculate the predicted value \( \hat{g}(k) \) of gray scale at k-time:

\[
\hat{g}(k) = b_0 + b_1 k + b_2 k^2
\]

In the formula:

\[
\begin{bmatrix}
  b_0 \\
  b_1 \\
  b_2 \\
\end{bmatrix} = \frac{1}{|A|} \begin{bmatrix}
  c_{11} \sum_{i=1}^{N} g(i) + c_{12} \sum_{i=1}^{N} g(i)k + c_{13} \sum_{i=1}^{N} g(i)k^2 \\
  c_{12} \sum_{i=1}^{N} g(i) + c_{22} \sum_{i=1}^{N} g(i)k + c_{23} \sum_{i=1}^{N} g(i)k^2 \\
  c_{13} \sum_{i=1}^{N} g(i) + c_{23} \sum_{i=1}^{N} g(i)k + c_{33} \sum_{i=1}^{N} g(i)k^2 \\
\end{bmatrix}
\]

(5)

\[
A = \begin{bmatrix}
  N & \sum_{i=1}^{N} k & \sum_{i=1}^{N} k^2 & \sum_{i=1}^{N} k^3 \\
  \sum_{i=1}^{N} k & \sum_{i=1}^{N} k^2 & \sum_{i=1}^{N} k^3 & \sum_{i=1}^{N} k^4 \\
\end{bmatrix}
\]

(6)

Among them, \( c_{ij} \) is the remainder of determinant \( |A| \).

Then the prediction error between the gray-scale measurement value and the gray-scale prediction value of the i target at k-time is obtained.

\[
\Delta g_i^k = g_i^k - \hat{g}(k)
\]

(7)

Considering that the gray level of the target will not change abruptly in 2-3 consecutive frames in practical engineering applications, and the gray level of the false target formed in noise or abnormal images will change greatly, therefore, the gray correlation probability of the measured value with excessive gray prediction error can be set to 0 to increase the accuracy of gray correlation. Considering that there are some errors in image processing, the trapezoidal membership degree shown in Fig.3 is used to describe the gray level change. The gray level prediction value is 1/5 as
the decision threshold, the standard deviation of gray level change is \( \sigma_i^g = \frac{1}{10} \hat{g}(k) \), and the minimum threshold of gray level change is \( \varepsilon = \frac{1}{25} \hat{g}(k) \). Setting \( \varepsilon \) can ensure that the membership degree is 1 when the gray level of the target changes in a very small range, thus ignoring the influence of small deviation in image processing on the membership degree calculation results. The formulas for calculating the gray scale membership degree of each candidate target are as follows:

\[
\mu_i(g_i^g) = \begin{cases} 
1 & |\Delta g_i^g| \leq \varepsilon \\
\frac{\Delta g_i^g + 2\sigma_i^g}{2\sigma_i^g - \varepsilon} & \varepsilon < |\Delta g_i^g| \leq 2\sigma_i^g \\
0 & |\Delta g_i^g| > 2\sigma_i^g
\end{cases}
\]

(8)

Figure 3. Gray scale membership.

**Increase Target Area Correlation**

In addition to the gradual change of the gray level of the target, the target area will not change abruptly in 2-3 frames. Its value is mainly affected by the characteristics of the target itself, the complexity of the image background and the image extraction algorithm. In order to reduce the computational complexity, combined with the actual situation of the previous infrared image sequence, it is found that the average area of the target in the first three frames can be used as a method to predict the area of the target in the next frame.

Assuming that the target track area set confirmed before k-time is \( S^k \), the latest target area extraction value is \( S(k) \), and the target area prediction value at k-time is \( \hat{s}(k) \):

\[
\hat{s}(k) = \frac{1}{3}(s_{k-3} + s_{k-1} + s_{k-1}) 
\]

(9)

Then the area extraction value of the i target at k-time and the prediction error value of the target area prediction value are obtained, that is:

\[
\Delta s_k^i = s_k^i - \hat{s}(k) .
\]

(10)

Because the frame frequencies of detectors in ground-based optical measurement equipment are 50 Hz or even higher, the target area varies little in successive frames and is usually larger than the area of most noise, while the area of noise varies greatly due to its distribution characteristics. Therefore, the area correlation probability of the measured value with excessive area prediction error can be set to 0 to increase the accuracy of area correlation. The trapezoidal membership degree similar to Figure 3 is used to describe the change of target area. The threshold is 1/3 of the predicted area, the standard deviation of area change is \( \sigma_i^s = \frac{1}{6} \hat{s}(k) \), and the minimum threshold of area change is \( \varepsilon = \frac{1}{9} \hat{s}(k) \). The formulas for calculating the membership degree of the area change of each candidate target are as follows:
\[
\mu_i(s'_j) = \begin{cases} 
1 & |\Delta s'_j| \leq \varepsilon \\
\frac{|\Delta s'_j| + 2\sigma'_i}{2\sigma'_i - \varepsilon} & \varepsilon < |\Delta s'_j| \leq 2\sigma'_i \\
0 & |\Delta s'_j| > 2\sigma'_i
\end{cases}
\]

(11)

**Computation of Multi-feature JPDA Association Degree**

Multi-feature JPDA is to synthetically correlate target gray level features and target area features on the basis of original position features. Compared with track correlation using a single feature, JPDA can improve the accuracy and stability of correlation. The calculation method of comprehensive correlation degree is as follows:

Let there be \( n \) targets to be identified, \( n = m_k \), i.e., fuzzy identification object set \( A = \{A_1, A_2, \ldots, A_k\} \). Fuzzy factor variables \( X = \{x_1, x_2, x_3\} \), \( x_1, x_2 \) and \( x_3 \) represent the position, gray level and area of the characteristic parameters obtained by the sensor respectively. According to formula (3), formula (8) and formula (11), the membership function \( \mu_{A_j}(x_j) \) of each candidate target can be obtained. Let \( r_{ij} = \mu_{A_j}(x_j) \) represent the membership function of the \( j \) feature of the \( i \) target, the fuzzy evaluation matrix \( R \):

\[
R = \begin{bmatrix}
A_1 & r_{11} & r_{12} & r_{13} \\
& r_{21} & r_{22} & r_{23} \\
& & \vdots & \vdots & \vdots \\
A_k & r_{m1} & r_{m2} & r_{m3}
\end{bmatrix}
\]

(12)

Because the importance of various features of the target is different, different normalized weight vectors \( A \) are allocated to the correlation degree of different features, so the weighted comprehensive evaluation function is obtained:

\[
D_i = \sum_{j=1}^{m} w_j r_{ij}.
\]

(13)

Then the weighted correlation degree is normalized to get the comprehensive correlation degree of each candidate target:

\[
\beta_i(k) = D_i / \sum_{i=1}^{m} D_i, \quad i = 1, 2, \ldots, m_k.
\]

(14)

Then, the target state updates are obtained by using the comprehensive correlation degree of candidate targets:

\[
\hat{X}(k|k) = \sum_{i=0}^{m} \hat{X}_i(k|k) \cdot \beta_i(k).
\]

(15)

After the improvement of the algorithm, the accuracy of target association is improved by introducing more stringent Association conditions. In example 1, the correlation between frame 7600 and frame 7601 is directly invalid, the extrapolation prediction of target position is entered, and the extrapolation prediction of frame 7602 is invalid. Then the extrapolation prediction of target position is entered again. The target correlation of frame 7603 is correct, so that the target position of each frame output is closer to the real position of target, thus reducing the target jitter amplitude in tracking. In Example 2, frame 12113 is invalid (rather than incorrect), and when extrapolated into the target location prediction, frame 12114 can be associated with the correct target, and thus ensure the correct target association in frame 12115, so that the target is no longer lost.
Simulation and Analysis of Improvement Effect

Simulation

In order to fully verify the effectiveness of the improved multi-feature JPDA algorithm and ensure the reliability of Engineering application, the improved multi-feature JPDA algorithm is realized by VC programming, which can extract and reproduce the target association of the measured image sequence, thus realizing the comparison and analysis of the extracted results with the actual measurement.

Improvement Effect Analysis

In order to verify the tracking effect of the improved algorithm, a simulation program is used to test the mid-wave infrared image sequence of a device tracking ISS, and the tracking images corresponding to Example 1 and Example 2 are selected intentionally as the test image source.

Fig. 4 and 5 are the comparison of target extraction and tracking errors before and after the improvement of the algorithm in the case of large jitter respectively. It can be seen that the extracted position is closer to the real target after the adoption of the improved correlation algorithm, thus the jitter phenomenon in the tracking process can be reduced.

Fig. 6 and 7 are the comparison of target extraction and tracking errors before and after the improvement of the algorithm in the case of target loss respectively. It can be seen that the target extraction is accurate after the improvement of the algorithm, and the target will not be lost in the tracking process.
Based on the above analysis, the improved multi-feature JPDA algorithm can significantly improve the accuracy of target extraction, reduce the swaying range of the target in the tracking process when the target is occluded, and reduce the probability of target loss. It can be applied to the tracking requirements when most of the targets are occluded.

Concluding Remarks

Conventional JPDA algorithm only uses the location information of the target and takes whether the target falls into the prediction area as the correlation criterion. When the target is occluded, association errors easily occur, which results in the tracking jitter or the loss of the target. In this paper, an improved JPDA algorithm based on multi-feature is proposed, which increases the target gray level and target area, and establishes a comprehensive correlation degree as the criterion of correct target association, because the correlation conditions are more stringent and closer to engineering practice. Therefore, the false target can be eliminated, the extrapolation mode can be switched in time in the update of the target position, the dithering amplitude of the target and the probability of losing the target can be reduced effectively, and the self-tracking of the target when it is occluded can be well adapted. The effectiveness of the improved algorithm is proved by the simulation of the measured image sequence.

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