Track Association for Dynamic Target Tracking System Based on AP Algorithm

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Abstract: Track association of multi-target has been recognized as one of the key technologies in distributed multiple-sensor data fusion system, and its accuracy directly impacts on the performance of the whole tracking system. A multi-sensor data association is proposed based on aftinity propagation (AP) algorithm. The proposed method needs an initial similarity, a distance between any two points, as a parameter, therefore, the similarity matrix is calculated by track position, velocity and azimuth of track data. The approach can automatically obtain the optimal classification of uncertain target based on clustering validity index. Furthermore, the same kind of data are fused based on the variance of measured data and the fusion result can be taken as a new measured data of the target. Finally, the measured data are classified to a certain target based on the nearest neighbor ideas and its characteristics, then filtering and target tracking are conducted. The experimental results show that the proposed method can effectively achieve multi-sensor and multi-target track association.

Key words: affinity propagation algorithm; data fusion; target tracking; track association

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1 Introduction

Multi-target tracking (MTT) is one of the most important research issues in both civilian and military. The sensors of space surveillance systems mainly include radar, infrared and sonar. In a distributed multi-sensor environment, although each sensor has its own information processing system, the tracking accuracy of single sensor is not enough, and multi-sensor working mode is required to form a distributed monitoring system. In this case, an important problem is how to determine whether the multiple tracks from different systems represent the same target, which is the track and the track association. Track association is the core problem of multi-target tracking system. Scholars have presented a lot of track association algorithms. The nearest neighbor data association (NNDA) algorithm was first proposed by Singer[1]. Bar-Shalom, et al. proposed a probabilistic data association (PDA) algorithm[2] and the joint probabilistic data association (JPDA) algorithm[3]. JPDA is now recognized as one of the best ways in clutter environment for multi-target tracking, but its computational load is too heavy.

Habtemariam, et al.[4] proposed a multiple-detection joint probabilistic data association filter (MD-JPDAF) for multitarget tracking, which was capable of handling multiple detections from targets per scan in the presence of clutter and missed detection. MD-JPDAF is applied to a multi-target tracking scenario with an over-the horizon radar (OTHR), which improves the state estimation accuracy. It is needed to know the location rather than the identity of the targets has brought out an increasingly popular estimate based on minimum mean optimal sub pattern as-

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signment (MMOSPA), known as set JPDA (SJPDA)[4]. SJPDA deals with target state estimation and identity maintenance (track labeling) as separate problems. Laet, et al. [5] proposed a novel online two-level multitarget tracking and detection (MTTD) algorithm, using clustering and JPDAF to overcome occlusions. The algorithm focuses on multi-target detection and tracking for multiple measurements per target, an unknown and varying number of targets.

In fact, the pursuit for optimal solution is not conducive to real-time tracking because of great computational load, so many scholars proposed a number of sub-optimal algorithms. Fuzzy data association (FDA) based on fuzzy clustering[6] is the most representative one. However, these algorithms need input of cluster number first, which is not practical. In the actual target tracking, the number of targets in the surveillance spatial tends to be dynamic. And some of them are false targets, e. g. advanced intelligent weapons release false targets to avoid being tracked . While in monitoring period, some targets may be out of monitoring scope. These factors destroy the corresponding relationship between the measured data and the targets, which is difficult to determine.

The proposed algorithm based on affinity propagation (AP) clustering can dynamically determine the clusters of targets, and track the target trajectories by data fusion and filter. And feature judgment and global search ideas are used to ensure the association precision in the track association process.

2 Track Association of Multi-target

In a clutter environment, measured data of different sensors in multi-target tracking system may come from the target and the clutter. Tracks come from the same sensor are not relevant with each other. The task of multi-target tracking is to extract measured data from specific targets or clutter according to track association algorithm. Subsequently, these measured data are fused and filtered, thereby the target state estimation is obtained. A multi-sensor fusion system is shown in Fig. 1.

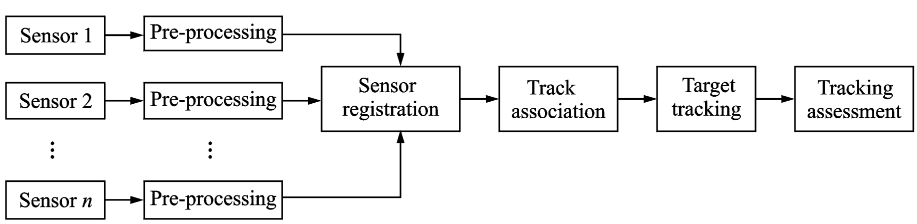

Fig. 1 Multi-sensor fusion system

Multi-sensor system receives a number of tracks in surveillance spatial, assuming the measured data synchronized in time, and it has been converted into the same coordinate system in space, but the number of targets within it is unknown. A lot of track association algorithms need to input the number of clusters in advance, but it is not practical in many cases. Therefore, there are two key problems in the track association algorithm. First, tracks need to be distinguished effectively in clutter environment. Second, tracks need to be classified correctly and the number of clusters need to be close to the number of targets. On this basis, target track is achieved by combining fusion technology and filtering technology, and the next state of the target can be predicted.

The dynamical model of a target t is defined as

$$\boldsymbol{X}^t(k+1)=\boldsymbol{F}(k)\boldsymbol{X}^t(k)+\boldsymbol{v}(k) \qquad (1)$$

and the corresponding measurement model is

$$\boldsymbol{Z}^t(k)=\boldsymbol{H}(k)\boldsymbol{X}^t(k)+\boldsymbol{w}(k) \qquad (2)$$

where $\boldsymbol{X}^t(k)$ is an n-dimensional target state vector at scan k, $\boldsymbol{Z}^t(k)$ an m-dimensional measurement vector at scan k, $\boldsymbol{F}$ an $n\times n$ state transition matrix, $\boldsymbol{H}$ an $m\times n$ measurement matrix, $\boldsymbol{v}(k)$ a process noise vector, and $\boldsymbol{w}(k)$ a measurement noise vector. $\boldsymbol{v}(k)$ and $\boldsymbol{w}(k)$ are assumed to be uncorrelated, zero mean Gaussian with covariance matrices are

$$\boldsymbol{Q}(k) = \mathrm{Cov}(\boldsymbol{v}(k)) \tag{3}$$

$$\boldsymbol{R}(k) = \mathrm{Cov}(\boldsymbol{w}(k)) \tag{4}$$

3 Track Data Classification Algorithm Based on AP Algorithm

3.1 Problem formulation of AP clustering algorithm

Affinity propagation (AP) algorithm, proposed by Frey[7], is highly competitive in the field of data mining. The algorithm is based on the similarity matrix $\boldsymbol{S}$ of N data points. Each similarity is set to a negative squared error (Euclidean distance), for point x_i and x_k, $s(i,k) = -\|x_i - x_k\|^2$. To avoid clustering result being affected by the choice of the initial representative point, which happens in the traditional clustering algorithm, all data points are considered as potential exemplars. AP algorithm has no special requirements for the symmetry of similarity matrix. Information is propagated by calculating information between each data point and its nearest neighbor or the second nearest neighbor point, which is called affinity propagation algorithm. Compared with the traditional clustering algorithm, AP algorithm can complete large-scale clustering for multi-class datasets in a relatively short time, and also solve the problem of non-Euclidean space. The diagonal values of similarity matrix ($\boldsymbol{S}$) are bias parameter (p), the initial value of which is usually the median of the input similarities. The number of clusters is influenced by the value of p. Initially, all data points are treated as potential exemplars, varied p can produce different numbers of clusters. The possibility of point i becoming cluster center can be increased as the similarity $\boldsymbol{S}[i, i]$ become greater[8].

AP algorithm calculates the exemplar combined availabilities ($a(i,k)$) with responsibilities ($r(i,k)$), and terminates the algorithm when the result does not change for a certain time of iteration. Then, responsibilities ($r(i,k)$) are sent from data points to candidate exemplars and indicate to how strongly each data point favors the candidate exemplars over other candidate exemplars (Fig. 2(a)). Availabilities ($a(i,k)$) are sent from candidate exemplars to data points and indicate to what degree each candidate exemplars is available as a cluster center for the data point (Fig. 2(b))[6].

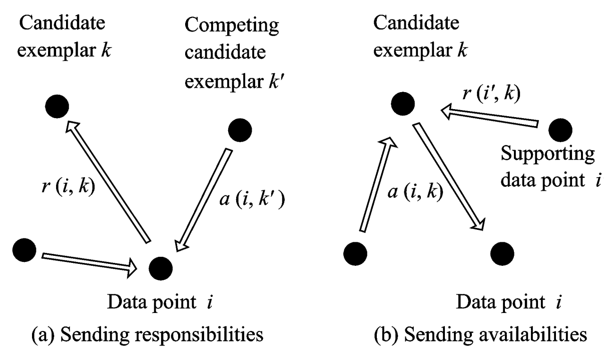

Fig. 2 Exchange of real-valued messages between data points

The availabilities are computed as

$$r(i,k) = s(i,k) - \max\{a(i,j) + s(i,j)\}$$
$$j = 1,2,\cdots,N;\ j \neq k \tag{5}$$

and the responsibilities are computed as

$$a(i,k) = \min\{0, r(k,k) + \sum_j \{\max(0, r(j,k))\}\}$$
$$j = 1,2,\cdots,N;\ j \neq i;\ j \neq k;\ i \neq k \tag{6}$$

$$a(k,k) = \sum_j \{\max(0, r(j,k))\}$$
$$j = 1,2,\cdots,N;\ j \neq k \tag{7}$$

When iteration is terminated, data point k is treated as exemplar if $r(k,k) + a(k,k) > 0$. And iteration will be rerun with another p value if the clustering result does not meet the requirements.

A key issue in AP algorithm is how to select a suitable bias parameter p for determining the optimal number of clusters in a dataset. We use indicators of effectiveness based on the sample geometry to assess the effectiveness of AP clustering algorithm and determine the optimal number of clusters of datasets[9].

Lets X be the set of validated measurement, i.e., $X = \{x_1, x_2, \cdots, x_n\}$, which is a dataset to be divided into k classes by AP algorithm with initial bias parameters. We define dividing indicator of the i-th sample within the j-th class as

$$\mathrm{BWP}(j,i)=\frac{bswd(j,i)}{bawd(j,i)}=\frac{bd(j,i)-wd(j,i)}{bd(j,i)+wd(j,i)} \tag{8}$$

where $bd(j,i)$ denotes the minimum distance of the i-th sample in the j-th class, and its value represents the minimum average distance between this sample to other class; $wd(j,i)$ the distance within the j-th class, and its value represents the average distance between the i-th sample to other sample of the j-th class; $bawd(j,i)$ the clustering distance, and its value represents the sum of $bd(j,i)$ and $wd(j,i)$; $bswd(j,i)$ the clustering deviation distance, and its value equals to the deviation of $bd(j,i)$ and $wd(j,i)$. $\mathrm{BWP}(j,i)$ is the ratio of clustering deviation distance and clustering distance, which is the evaluation of the clustering of each sample. When its value is larger, the clustering effect is getting better, and it indicates density is within the cluster and sparse is out of the cluster. If we want to evaluate the clustering result of all samples in dataset, we can choose the average of BWP index of all samples which reflects the effect of clustering by AP algorithm, so the number of clusters can be regarded as the best number of clusters when the average of BWP index reaches to the maximum.

In summary, we can combine Eq. (9) with Eq. (10) to determine the optimal number of clusters[10]

$$A_{\mathrm{BWP}}(k)=\frac{1}{n}\sum_{j=1}^{k}\sum_{i=1}^{n_j}\mathrm{BWP}(j,i) \tag{9}$$

$$k_{\mathrm{opt}}=\underset{2\leqslant k<\sqrt{n}}{\arg\max}\{A_{\mathrm{BWP}}(k)\} \tag{10}$$

where n denotes the total number of samples of dataset; n_j the total number of samples of each class; $A_{\mathrm{BWP}}(k)$ the average of BWP index of all samples when dataset is classified into k classes by AP algorithm; k_{opt} the optimal number of clusters. It should explain that the AP algorithm obtains different clusters by adjusting the value of p. If the dataset wants to be classified into k classes, we usually use the search method. Experimental result shows that, the number of clusters of dataset will increase while the value of p increasing, and vice versa. Therefore, we can get different AP clustering results by changing the value of p. For the convenience of description, we called the proposed method BWP-AP.

3.2 Track classification based on BWP-AP

In multiple-sensor data collection system, each measurement can only belong to one target or one clutter, and each target can only have one measurement from the same sensor in multi-target tracking system. Therefore, the measurement data of multi-sensor can convert to a lot of individual sensors. The information of the same target detected by different sensors must be relevant, but noise generally has not this property. Therefore, the fusion of the measured data can reduce the impact of clutter and improve the measurement accuracy of the information.

The number of targets in surveillance spatial is often uncertain. Most traditional clustering methods need to assume the initial target number, which is clearly not reasonable. AP algorithm is very suitable for dynamic data classification without assuming the initial number of categories. On the other hand, AP algorithm has been successfully applied to face image clustering and recognition, handwritten character recognition, and optimal air route determining. Therefore, the classification of target track data are automatically obtained by AP algorithm based on BWP validity index.

AP algorithm is based on similarity matrix. If we construct the similarity matrix of track points only according to their the position information and velocity information, it easily leads to erroneous association when the two tracks are intersecting, e. g. , a scene shown in Fig. 3. We can see clearly that point 1 associates with track 1, but point 1 associates with track 2 when only ac-

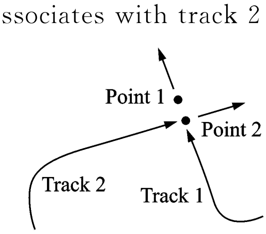

Fig. 3 Example of erroneous association

cording to the position information and the velocity information of track points[11]. Therefore, the heading information of track point also adds in similarity matrix in the algorithm. Similarity matrix is calculated as follows. Firstly, the position information (x, y, z) and the velocity (v_x, v_y, v_z) of track points are normalized into range $[0, 1]$. Secondly, the heading angle deviation $\Delta\theta$ $(0\leqslant\Delta\theta<180°)$ of the two track points is added to the calculation of Euclidean distance

$$d=\sqrt{(x_1-x_2)^2+(y_1-y_2)^2+(z_1-z_2)^2+(v_{x_1}-v_{x_2})^2+(v_{y_1}-v_{y_2})^2+(v_{z_1}-v_{z_2})^2+(\Delta\theta/180)^2} \tag{11}$$

Therefore, even if one track point is close to another, their movement directions are different, and they are not relevant in AP algorithm. We effectively eliminate wild-value in track points.

Assume that N tracks are formed from M sensors, the measurement of each sensor is synchronized in time, and has been converted to the same coordinate system in space. The attribute of measurement includs the track point position, speed, and azimuth. The procedure of data association algorithm based on AP algorithm and BWP validity index is described as follows. Table 1 shows the procedure of data association algorithm.

Tabel 1 Procedure of BWP-AP algorithm

BWP-AP algorithm
Input: Measurements of all sensors, $p\in[a,b]$, $k=1$, the maximum of scan $K_{\max}$.
Output: Trajectory of each target.
Step:
1. Calculate the similarity matrix of N data points at scan k, $\boldsymbol{S}_{N\times N}$.
2. Update all responsibilities $r(i,k)$ by Eq. (5).
3. Update all availabilities $a(i,k)$ by Eqs. (6,7).
4. Calculate exemplar of point i by combining availabilities with responsibilities.
5. Calculate the optimal number of clusters by Eqs. (9, 10). Each data point has its own exemlar, and the points with the same exemplar belong to the measurement of the same target.
6. Fuse the measurement of target t by Eq. (12).
7. Update the measurement of target t with Kalman filtering.
8. Repeat Steps 1 to 7 $K_{\max}$ times.

(1) At k scan, measurement of all sensors within the monitoring is normalized to $[0, 1]$. Based on track point position, speed and heading information, Euclidean distance between all measurements is calculated using Eq. (11), and similarity matrix $\boldsymbol{S}$ is formed with negative Euclidean distance.

(2) Initialize the variation range of p. AP algorithm is run based on similarity matrix $\boldsymbol{S}$, and the optimal number of clusters are determined by Eqs.(9,10), which is also the number of targets. If the number of clusters is varied compared with the previous scan, there may be new targets appearing or targets disappearing in the monitoring spatial, or it may be a noise.

(3) AP clustering process is also the data association process. Sample data from the same cluster must be interconnected. Let $Z_j(k)$ $(j=1, 2,\cdots, L)$ denotes L measurements from M sensors by data association process, and these L measurements are related with target t. To take full advantage of each measured data and reduce noise interference, furthermore, to improve tracking accuracy of target track, we need to fuse these L measurements. Let each sensor measurement error is a Gaussian white noise with zero mean and variance of δ^2, then the result of linear fusion is calculated by[12]

$$\boldsymbol{Z}_f^t(k)=f_1Z_1(k)+f_2Z_2(k)+\cdots+f_MZ_M(k) \tag{12}$$

$$f_i=\frac{\dfrac{1}{\delta_i^2}}{\displaystyle\sum_{j=1}^{M}\frac{1}{\delta_j^2}} \tag{13}$$

which is a measured data for the later filtering process. For the fusion result in scan $k-1$ and scan k, if a reasonable sampling period is chosen, the measurement value of current time belongs to a certain target based on its nearest neighbor ideas and data attributes, especially the direction of the track points. If it has not association with any targets, new target appears or disappears. The measured data from the same target are added to the target information. The heading information of the fusion value can assign the average heading angle of the measured data in the same cluster. If a clutter has not association with any targets in three consecutive scans, it will be discarded.

The fusion variance of the measurement is

$$\delta_f^2 = \frac{1}{\left(\frac{1}{\delta_1^2} + \frac{1}{\delta_2^2} + \cdots + \frac{1}{\delta_M^2}\right)} \tag{14}$$

It can be seen from Eq. (13) that if the i-th measurement variance is small, the i-th estimation accuracy is high, therefore, who plays a major role in fusion estimation, and vice versa.

(4) We can update measurement value with Kalman filtering when the target playing linear motion. We can choose extended Kalman filter (EKF), unscented Kalman filter (UKF) and particle filter (PF) to update measurement value for targets in non-linear motion.

3.3 Complexity analysis of BWP-AP algorithm

Let $X = \{x_1, x_2, \cdots, x_n\}$ is a dataset to be classified. The dataset is divided into c clusters by BWP-AP algorithm, and the average sample of each cluster is n/c. Therefore, the average time overhead for BWP index calculating of each cluster is $O\left(\frac{n^2}{c^2}\right)$ $(2 \leqslant c \leqslant \sqrt{n})$. We can get different classifications by changing p values. Once the number of clusters does not meet the range of c, algorithm will not calculate the average BWP index. The time complexity of AP algorithm is $O(n^2)$, and the iterations of AP algorithm is $k = (h - l)/s$ $(l \leqslant p \leqslant h)$, where s is the step of p. The time complexity of BWP-AP algorithm can be determined as $O(kn^2)$. Generally, p varies in a small range, for example, in subsequent experiments, $-50 \leqslant p \leqslant 0.1$, and $s=0.1$. Then $O(kn^2)$ will be close to $O(n^2)$.

4 Simulation Results

4.1 Experiment in artificial dataset

To visualize the effect of BWP-AP algorithm, we simulate an artificial dataset with four clusters in a plane coordinate system, the distribution is shown in Fig. 4. The range of horizontal and vertical coordinates are [0, 15], the total number of samples is 1 000, which include 50 noise data. p varies in [−50 0.1] and the step $s=0.1$.

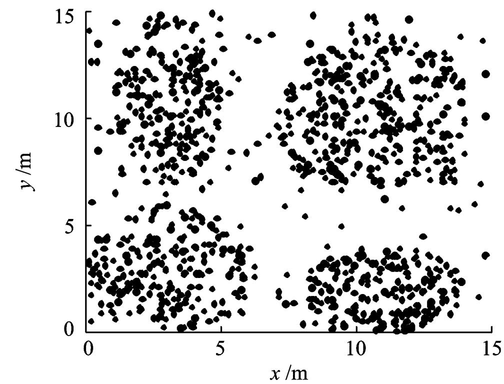

Fig. 4 Artificial dataset

For AP algorithm, we get four clusters by changing p between −5.4—−4.8. The classification results are shown in Fig. 5. For BWP-AP algorithm, we do not know the number of clusters in advance, but we can automatically searchs in a range. BWP clustering validity index gets the maximum 0.453 while $p=-5.1$. We obtain the right four clusters which are same as AP algorithm. BWP-AP algorithm is a unsupervised classification algorithm.

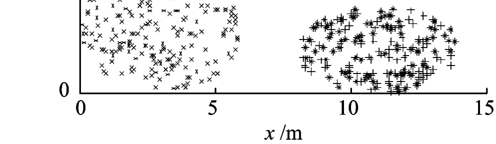

Fig. 5 Classification results

4.2 Data association performance simulation

In order to verify the performance of AP clustering algorithm based on BWP validity index in target track classification application, we design a set of tracking experiments[13]. A monitoring system consists of four radars which monitor spatial overlap. When coordinate conversion and time alignment problems are not considered, the sampling interval $T=1$ s. There are five targets within surveillance spatial, and the initial state of each target is shown in Table 2.

Tabel 2 Initial position, velocity and acceleration of five targets

Target	Initial position/km		Initial velocity/ (km · s^{-1})		Acceleration/ (m · s^{-2})	
T	x	y	V_x	V_y	a_x	a_y
1	23	7	0.2	0.04	−3.5	6
2	26	20	0.1	−0.3	6	3
3	23	20	0.1	−0.3	6	4
4	20	20	0.1	−0.3	6	5
5	17	20	0.1	−0.3	6	6

Assume the dynamic model of a target is

$$\boldsymbol{X}(k+1)=\boldsymbol{F}\boldsymbol{X}(k)+\boldsymbol{B}\boldsymbol{U}(k)+\boldsymbol{v}(k) \quad (15)$$

where $\boldsymbol{v}(k)$ is a process noise vector which is modeled as Gaussian, zero mean, with a certain standard deviation. The state vector $\boldsymbol{X}(k)$ contains the x- and y-target positions and velocities, i. e.

$$\boldsymbol{X}(k)=[x \quad \dot{x} \quad y \quad \dot{y}]^{\mathrm{T}} \quad (16)$$

and the control matrix $\boldsymbol{B}$ is given by

$$\boldsymbol{B}=\begin{bmatrix} \frac{T^2}{2} & 0 \\ T & 0 \\ 0 & \frac{T^2}{2} \\ 0 & T \end{bmatrix} \quad (17)$$

and the state transition matrix $\boldsymbol{F}$ is given by

$$\boldsymbol{F}=\begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (18)$$

where T is the sampling interval and $\boldsymbol{U}(k)$ is the power factor of target which contains horizontal acceleration and vertical acceleration, i. e.

$$\boldsymbol{U}(k)=[a_x \quad a_y]^{\mathrm{T}} \quad (19)$$

The measurement model is

$$\boldsymbol{Z}(k)=\boldsymbol{H}(k)\boldsymbol{X}(k)+\boldsymbol{w}(k) \quad (20)$$

where $\boldsymbol{w}(k)$ is a measurement noise vector which is also modeled as Gaussian, zero mean, with a certain standard deviation. The measurement matrix $\boldsymbol{H}$ is given by

$$\boldsymbol{H}(k)=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (21)$$

The process noise vector has a covariance matrix

$$\boldsymbol{Q}=\boldsymbol{E}\{\boldsymbol{v}(k)\boldsymbol{v}(j)^{\mathrm{T}}\}=q\boldsymbol{I}\boldsymbol{v}(k)\boldsymbol{\delta}(k-j) \quad (22)$$

where $q=2\times10^{-4}$, $\boldsymbol{I}=\mathrm{diag}[1,1]$. The measurement noise vector has a covariance matrix

$$\boldsymbol{R}=\boldsymbol{E}\{\boldsymbol{w}(k)\boldsymbol{w}(j)^{\mathrm{T}}\}=\boldsymbol{R}(k)\boldsymbol{\delta}(k-j) \quad (23)$$

The standard deviation of measurement noise of four radars are taken as $\sigma_1=100$ m, $\sigma_2=80$ m, $\sigma_3=120$ m and $\sigma_4=130$ m. The clutter distribution density is 0.5 km^{-2} in radar surveillance spatial. Since the targets are assumed linearly move, the fusion measurement is updated with Kalman filter in the experiment.

Even though we do not know the number of targets in the surveillance spatial, we can automatically determine the number of targets based on the BWP-AP algorithm. At the same time, we can accomplish target tracking depending on the result of fusion. The fusion trajectory and tracking trajectory are shown in Figs. 6, 7. The position tracking error of target 1 is shown in Fig. 8. Fig. 9 shows the tracking trajectory by single radar. It can be seen clearly that tracking accuracy of one radar is significantly not as good as multi-radar. This is mainly because multi-sensor system obtains more accurate information than a single sen-

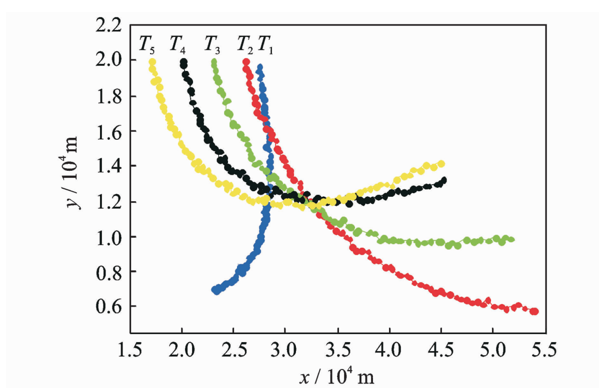

Fig. 6 Measured data fusion trajectory

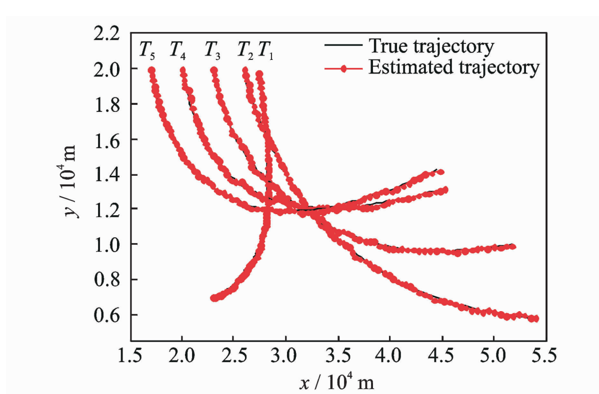

Fig. 7 Target trajectory and its estimates

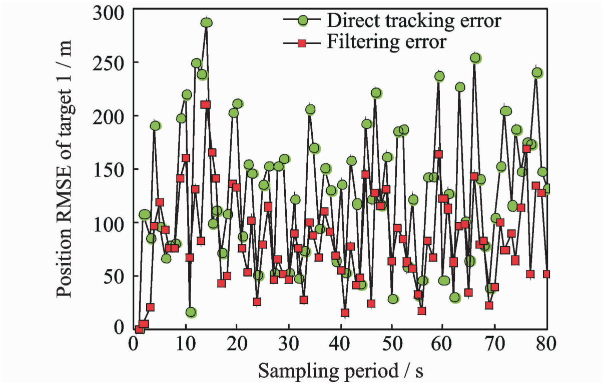

Fig. 8 Position RMSE of target 1

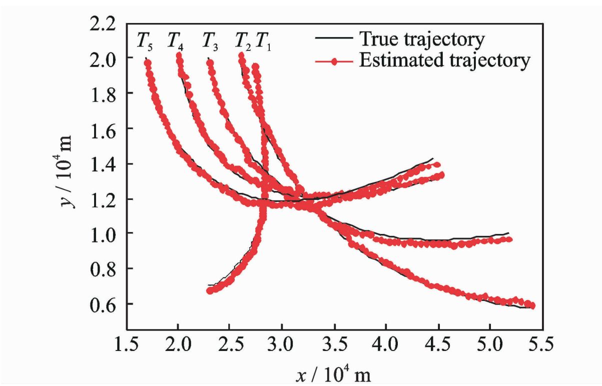

Fig. 9 Target trajectory of one radar

sor does. Since multi-sensor information fusion technology extends time and space coverage of the entire system, target tracking accuracy is bound to increase.

4.3 Performance comparison

For performace comparison, we select a few conventional target tracking data association algorithms, including fuzzy data association algorithm (FDA)[13], the improved fuzzy data association algorithm (IFDA)[14], the improved joint probabilistic data association algorithm (IJPDA)[15] and SJPDA[4]. These algorithms require the number of clusters in advance. IJPDA uses maximum likelihood estimation algorithm to divide multi-sensor measurements in order to achieve multi-target tracking. For convenience, we call the proposed algorithm BWP-APDA (data association based on BWP-AP algorithm) here. Experimental environment is the same with that in section 4.2.

We select the computing speed and the probability of error associated to compare the proposed algorithm with the traditional algorithms. The results are shown in Table 3. From Table 3, even though BWP-APDA does not need to set precise parameters, it can still ensure faster computing speed and lower probability of error associated, and automatically detect the target number in tracking range. The computing speed is close to IFDA while the probability of error associated is about the same as those of JPDA and Set JPDA.

Tabel 3 Performance comparison of multi-target tracking system association algorithms

Algorithm	Computing speed/s	Probability of error associated/%
BWP-APDA	7.586	4.25
FDA	8.903	7.44
IFDA	7.354	5.27
IJPDA	22.012	4.08
SJPDA	25.661	4.03

5 Conclusions

In a distributed multi-sensor fusion system, multi-target track association is not only a key problem, but also a difficult issue for current researches. Most of the algorithms have made an irrational assumption that the number of targets is known. Therefore, an automatic target classification algorithm based on AP algorithm and BWP validity index is proposed. Simulation results show that the proposed algorithm can effectively accomplish uncertain target track association, which is not only performs well, but also convenient for real time processing and implementation.

We assume that multi-sensor clock synchronization and the fusion is centralizing. For distributed asynchronous multi-sensor system, we can promote the proposed algorithm based on the idea of sequential discretization of the sampling points. This will be our next research.

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