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A New Improvement Algorithm for Multiple Target Tracking

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Abstract: Data association technology is the key part in multi-sensor target tracking system and has a great significance for research. The efficiency of target tracking should be guaranteed first and the improvement of target tracking precision and reduction of the computation complexity are the key points. In the multiple clutters and multiple targets environment, due to the influence of such factors as measurement noise and sensor precision, the phenomenon of tracking precision error is so large that mistakenly tracking and tracking lost prone to happen. We put forward by using maximum fuzzy entropy to solve the computing dimension about the joint matrix and through the DS evidence theory on estimation measurement to improve the estimation precision of the target. The simulation results verify that the algorithm has advantages in terms of target tracking precision and computational complexity and has a certain practical value.

Key words: Information fusion, target tracking, DS evidence theory, joint data association, maximum entropy fuzzy, joint matrix

INTRODUCTION

In multiple targets, many interference, much clutter, cross and bifurcate environment, target tracking problem becomes very difficult to deal. Reasonable data association algorithm can avoid the influence of noise with the target tracking objective. The traditional methods such as nearest neighbor standard filter (Li and Bar-Shalom, 1996), probability data association filter (Yaakov *et al*., 2001), interacting multiple model probability data association filter (Abolmaesumi and Sirouspour, 2004), joint probabilistic data association filter (Musicki and Evans, 2004) and multiple hypothesis tracking filter (Oussalah and De Schutter, 2002) have been invested before.

Recently, domestic and foreign scholars did lots of researches about data association algorithm. On the idea of NNF (nearest neighbor filter) is represented by (Song *et al*., 2005; Petsios *et al*., 2008), the nearest data association algorithm used in the environment with high signal-to-noise ratio and low clutters, when confront the high density with clutters, the anti-interference ability of NNF is poor and easy to produce associated mistake. PDAF (probability data association filter) algorithm has a good performance in single target tracking in high clutter environment (Bethel *et al*., 2010; Aslan and Saranli, 2011; Zhou *et al*., 2011; Sathyan *et al*., 2012) however, when the measured interval has different targets, it is a must to consider the original of each measurement and it is difficult to track the target effectively with excessive interference. Some researchers have put forward the IMMPDAF (interacting multiple model probability data association filter) algorithm to cope with the target tracking problems (Blom and Bloem, 2006; Mohammed *et al*., 2010; Ho, 2011; Gao *et al*., 2012). Interactive multiple models data association algorithm is suitable for high clutter environment but the target tracking precision is sensitive to the model selection and the algorithm has a large amount of computation. JPDAF (joint probability data association filter) algorithm has a good performance in the low clutter environment. Joint probability data association algorithm has attracted a high attention owing to its excellent performance (Jian *et al*., 2012; Honqxin *et al*., 2008; Lei *et al*., 2008; Yang *et al*., 2011; Aziz, 2011). But because the method requires exponential function involves all the echo candidates, therefore, once the density of the echo is increasing, the complexity of the algorithm will increase in an explosive manner.

We put forward an algorithm to solve the computing dimension about the joint matrix by utilizing the maximum fuzzy entropy theory and improve the estimation precision of the target by utilizing the DS evidence theory.

JOINT PROBABILITY DATA ASSOCIATION

Joint probability data association was proposed by Bar-Shalom and the algorithm has been applied in multi-objectives situation.

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In the JPDA algorithm, the targets are divided into several clusters firstly in accordance with the geometric relationship between the multi-objectives. In order to express the complex relationship between the measurement and multi-target tracking gate, the confirm matrix is introduced:

$$\Omega = \left\{\omega_j^t\right\}_{j=1,2,\ldots,m_k}^{t=0,1,\ldots,N} \tag{1}$$

where, N denotes the number of target, m_k denotes the number of measurement.

The set of all possible events at kth moment can be expressed as follows:

$$\theta_{k,i} = \bigcap_{j=1}^{m_k} \theta_{k,i}^{j,t_j} \tag{2}$$

$\theta_{k,i}^{j,t_j}$ denotes the event that the jth measurement of the ith joint event originates from the target t_j.

Based on the two assumptions of the JPDA algorithm, the events connected with target t at the kth moment should have the following characteristics:

$$\text{Incompatibility: } \theta_k^{i,t} \cap \theta_k^{j,t} = \varnothing \quad i \neq j \tag{3}$$

$$\text{Completeness: } P\left(\bigcup_{j=0}^{m_k} \theta_k^{j,t} \mid Z^k\right) = 1 \quad t = 0,1,\ldots N \tag{4}$$

Thus, the state estimation for target t is:

$$\begin{aligned} \hat{x}_{k|k}^t &= E\left(x_k^t \mid \boldsymbol{Z}^k\right) = E\left(x_k^t, \bigcup_{j=0}^{m_k} \theta_k^{j,t} \mid \boldsymbol{Z}^k\right) \\ &= \sum_{j=0}^{m_k} E\left(x_k^t \mid \theta_k^{j,t}, \boldsymbol{Z}^k\right) P\left(\theta_k^{j,t} \mid \boldsymbol{Z}^k\right) = \sum_{j=0}^{m_k} \beta_k^{j,t} \hat{x}_{k|k,j}^t \end{aligned} \tag{5}$$

where, $\hat{x}_{k|k,j}^t = E\left(x_k^t \mid \theta_k^{j,t}, \boldsymbol{Z}^k\right) \quad j = 0,1,\ldots m_k$.

The covariance matrix of state estimate is:

$$\begin{aligned} P_{k|k}^t &= E\left(\left(x_k^t - \hat{x}_{k|k}^t\right)\left(x_k^t - \hat{x}_{k|k}^t\right)^T \mid Z^k\right) \\ &= P_{k|k-1}^t - \left(1 - \beta_k^{0,t}\right) K_k^t S_k^t \left(K_k^t\right)^T + \sum_{j=0}^{m_k} \beta_k^{j,t} \left[\hat{x}_{k|k,j}^t \left(\hat{x}_{k|k,j}^t\right)^T - \hat{x}_{k|k}^t \left(\hat{x}_{k|k}^t\right)^T\right] \end{aligned} \tag{6}$$

The problem of JPDA algorithm is the difficulty in getting the exact probability of joint events and related events, for in this method, the number of joint events is the exponential function of the number of all echo candidates. Furthermore, the combinatorial explosion phenomenon will happen as the increase of the echo density. In this study we will overcome this problem by utilizing the modified maximum fuzzy entropy method.

IMPROVING DS EVIDENCE THEORY

DS evidence theory can deal with the uncertainty problem well and improve the estimation accuracy when applied in JPDA algorithm. However, there are some defects such as the great conflict of evidence and one-vote veto phenomenon in this algorithm. This study presents an improved method to solve the defects of DS evidence theory effectively and make it combined with JPDA algorithm to improve the stability and the tracking accuracy of system.

Set Θ is the distinguish framework, $m:2^\Theta \rightarrow [0, 1]$ is the basic probability assignment, the elements of which are mass function in Θ. These functions need to meet the following conditions:

$$\begin{cases} m(\varnothing) = 0 \\ \sum_{A \subseteq \Theta} m(A) = 1 \\ m(A) > 0 \end{cases} \tag{7}$$

The synthesis law of two reliabilities:

$$m(A) = m_1 \oplus m_2(A) = \frac{\sum_{A_i \cap B_j = A} m_1(A_i) m_2(B_j)}{1 - \sum_{A_i \cap B_j = \varnothing} m_1(A_i) m_2(B_j)} \tag{8}$$

Actually the utilization of DS evidence theory may cause some problems. We often use examples to analyze the insufficient of DS evidence theory.

Example 1: Two groups of BPA evidence reports are shown in Table 1. In the Table 1, A-E is the focal of the evidence and m_i means different evidence. After evidence combination formula, we can obtain the fusion results and conflict factor:

m(A) = 0.0001, m(B) = 0.4996, m(C) = 0.0002, m(D) = 0.4996, m(E) = 0.0005 and K = 0.9997

For the data results above, DS evidence theory fusion results can't reflect the real situation between the evidence effectively and the main reason is that when focal element of the evidence appear 0, the final fusion result will always be 0 no matter how this group support the focal element and that is what we call one-vote veto phenomenon. The great computed conflict factor leads to

Table 1: The probability basic allocation about two groups of evidence

Evidence	A	B	C	D	E
m_1	0.01	0.00	0.01	0.97	0.01
M_2	0.00	0.97	0.01	0.00	0.02

the unefficient combination of the two sets evidence. The method proposed in this paper is as follows:

- Use the Camberra distance to measure the distance between two vectors (Wu *et al*., 2009):

$$d(m_1,m_2)=\sum_{i=1}^{n}\left|\frac{p_i-q_i}{p_i+q_i}\right| \tag{9}$$

- Define two evidence vectors m_1 and m_2, the similarity measure as:

$$S(m_1,m_2)=1-\frac{1}{n}\sum_{i=1}^{n}\left|\frac{p_i-q_i}{p_i+q_i}\right| \tag{10}$$

- The degree of support for the body of evidence m_i as:

$$Sup(m_i)=\sum_{j\neq i}^{n}S(m_i,m_j) \tag{11}$$

- Then the weight of evidence m_i can be defined as:

$$Wet(m_i)=\frac{Sup(m_i)}{\sum_{j=1}^{n}Sup(m_j)} \tag{12}$$

- Use the weight of evidence to make the weighted average and get the new evidence m^f:

$$m^f=\sum_{i=1}^{n}Wet(m_i)\times m_i \tag{13}$$

- Finally, use the synthesis formula of DS evidence theory to fusion new evidence m^f

Utilize the above method to re-calculated the data of Example 1 again and get the fusion result as:

m(A) = 0.0001 m(B) = 0.1996 m(C) = 0.0002
m(D) = 0.4996 m(E) = 0.0005

The obtained evidence can be truly reflecting the supporting degree of evidence for the focal element. With the increase of the evidence, the supporting degree of evidence for focal element varies and reflects the supporting degree much more efficiently (Chen, 2006; Yi-Bing *et al*., 2011).

MAXIMUM ENTROPY FUZZY WITH DS-JPDA

The JPDA algorithm exist the problem of great computational complexity and main reason is that when target number and measure number increase, the number of feasibility matrix will increase with geometry multiple and that will result in the increasing amount of computation work due to the computation of association probability. In this study, the maximum fuzzy entropy idea is utilized for solving the problem of great amount of combination when the number feasibility matrix increases.

Ensuring the basic structure of the JPDA algorithm unchanged, replace the associated probability with the fuzzy membership obtained by clustering with the modified maximum fuzzy entropy algorithm.

Given a finite data set Z = $\{z_1, z_2,..., z_{mk}\}$, c is the cluster number, Assume that the cluster centers for each cluster is Vj_j(j = 1, 2,..., c) and the membership matrix is $U_{mk\times c}$:

$$U=\begin{bmatrix}\beta_1^1 & \beta_2^1 & \cdots & \beta_{m_k}^1\\ \beta_1^2 & \beta_2^2 & \cdots & \beta_{m_k}^2\\ \vdots & \vdots & \ddots & \vdots\\ \beta_1^T & \beta_2^T & \cdots & \beta_{m_k}^T\end{bmatrix} \tag{14}$$

If the observation z_i is a valid observation of the target t(t = 1,2,..., T), we can get $\beta_i^t = u_t^i$ and in other situations, the value of β_i^t is zero.

The new objective function can be written as:

$$J(U,V)=-\sum_{i=1}^{m_k}\sum_{j=1}^{c}u_{ij}\ln u_{ij}-\sum_{i=1}^{m_k}\alpha_i\sum_{j=1}^{c}u_{ij}\cdot d(x_i,c_j)+\sum_{i=1}^{m_k}\lambda_i\left(\sum_{j=1}^{c}u_{ij}-1\right) \tag{15}$$

Maximizing the above objective function, it can obtained that the degree of membership between point x_i and cluster c_j as follows:

$$u_{ij}=\frac{e^{-\alpha_i d(x_i,c_j)}}{\sum_{k=1}^{c}e^{-\alpha_i d(x_i,c_k)}} \tag{16}$$

where, α_i denotes the difference coefficient and the selection of its value is usually dependent on the specific application. In the target tracking, α_i relate to the measurement distance and the clutter density. The value of difference coefficient can be defined as:

$$\alpha_i=\frac{\eta}{\lambda\cdot d(x_i,c_j)_{min}} \tag{17}$$

where, λ is the clutter density, η is a constant.

In summary, the flow chart of the proposed algorithm can be shown as Fig. 1.

The S_i^{mk} is defined to express the set of the data which come from sensor i and m_k is the number of measurement, X_{k-1}^j means the initial value of target j. P_{k-1}^j is the prediction covariance of target j. The threshold is expressed as γ_0.

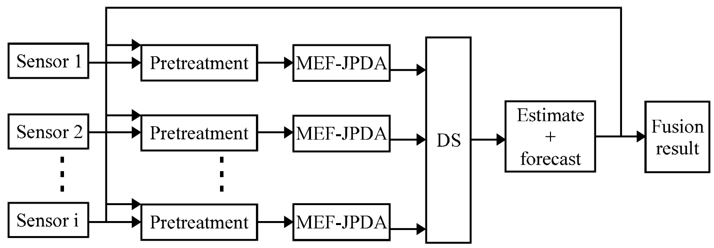

Fig. 1: The flow chart of DS-MEFJPDA algorithm

Step 1: Data pretreatment. Make sure that the sensor data is in the tracking door and the data should meet the following condition:

$$\left(S_i^{m_i} - X_{k-1}^j\right)^T \left(HP_{k-1}^j H^T\right)\left(S_i^{m_i} - X_{k-1}^j\right) \le \gamma_0 \tag{18}$$

where, H is the measurement matrix. Get the data set Y_i^m and m is the number of the measurement which fulfills the condition by Eq. 18.

Step 2: Use MEF algorithm from Eq. 14-17. Calculate the joint association probability u_{ij} by Eq. 16. Combine it with the JPDA algorithm to obtain the state estimate value $\hat{x}_i^j$

Step 3: After we get the state estimate value by different sensors. We can obtain the accurate estimate through Eq. 9-13

Step 4: The data which we get from step 3 can be regarded as the initial value and return to step 1

So we can make a brief summary. First of all, the data received by sensors are preprocessed, secondly, do fuzzy cluster for each target by applying the MEF-JPDA (maximum entropy fuzzy-joint probability data association) method and then combine the obtained target membership interconnected matrix with JPDA algorithm to estimate and predict the target state. Thirdly, apply the improved DS algorithm into the fusion process to get a more accurate estimate result. Finally, treat the obtained state value as the initial value of the next moment and output the fusion results.

THE SIMULATION EXPERIMENT

The simulation experiment for multi-targets tracking: Tracking threshold $\lambda = 9.21$, the probability of correct echo falling into tracking gate is $P_g = 0.99$, clutter in the radar surveillance area obeys to uniform distribution. Probability of detection is $P_d = 1$. Sensor sampling period is T = 1 second. State transition matrix model is:

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

the initial position of the multi-targets are:

$$x_5 = \begin{bmatrix} 2000m \\ 200\,m/s \\ 1500m \\ 100m/s \end{bmatrix},\ x_2 = \begin{bmatrix} 500m \\ 400\,m/s \\ 1500m \\ 300m/s \end{bmatrix},\ x_3 = \begin{bmatrix} 500m \\ 300\,m/s \\ 500m \\ 400m/s \end{bmatrix},\ x_4 = \begin{bmatrix} 800m \\ 200\,m/s \\ 800m \\ 300m/s \end{bmatrix},\ x_5 = \begin{bmatrix} 2000m \\ 200\,m/s \\ 1500m \\ 100m/s \end{bmatrix}$$

Randomly add clutter sequence near the track, the covariance of measurement noise is:

$$R = \begin{bmatrix} 300m & 0 \\ 0 & 300m \end{bmatrix}$$

the number of Monte Carlo simulation is 100 times.

Simulate with the JPDA algorithm and the DS-MEFJPDA algorithm, respectively. The situation of track obtained is shown in Fig. 2. We can use one target to illustrate the tracking accuracy problem. For target 1, Fig. 3 and 4 represent the position root mean square error(RMSE) and velocity RMSE, respectively.

While, the 'blue line' indicate the true tracking of the target and the 'black line' indicate the tracking result by JPDA algorithm. The blue '•' indicate the tracking result by DS-MEFJPDA algorithm. From Fig. 2, we can see that the DS-MEFJPDA algorithm make a higher tracking accuracy than the JPDA algorithm. The JPDA algorithm has a relatively large error when the targets cross each other, but the DS-MEFJPDA algorithm has solved this problem very well.

In the Fig. 3, we can get the position RMSE by JPDA and DS-MEFJPDA, respectively. And the accuracy by DS-MEFJPDA is higher than the JPDA which is shown in the picture.

In the Fig. 4, we can get the velocity RMSE by JPDA and DS-MEFJPDA, respectively. The velocity RMSE by DS-MEFJPDA is nearly 5 meters in different time and this is lesser than the JPDA.

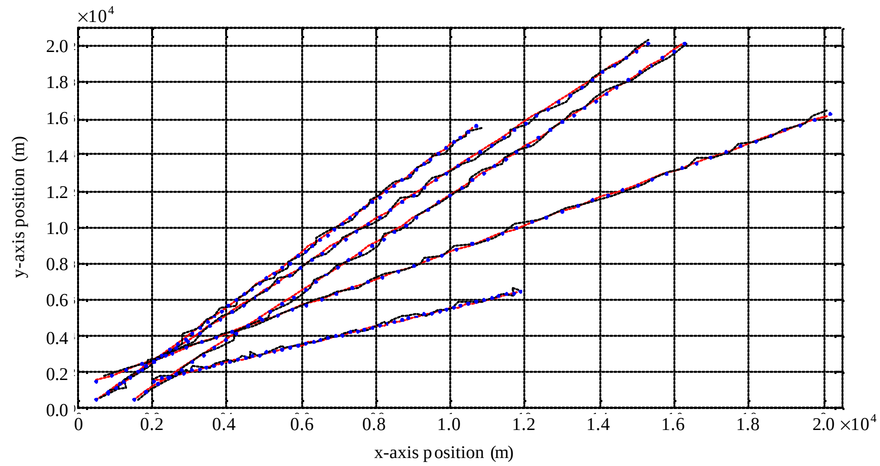

Fig. 2: Target tracking situation of JPDA and DS-MEFJPDA

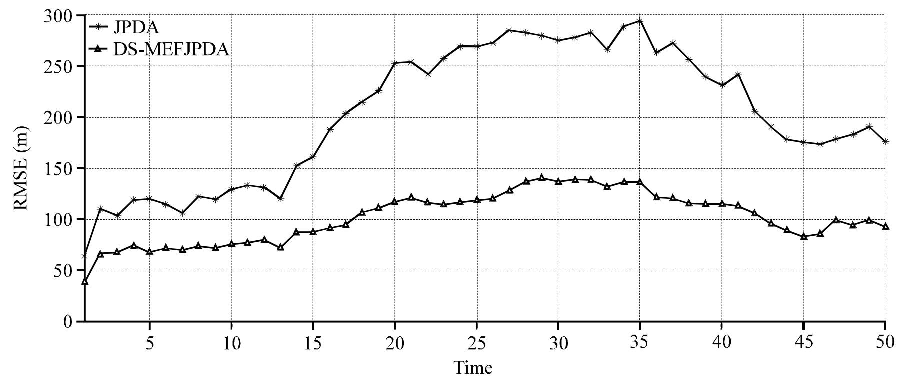

Fig. 3: Position RMSE by JPDA and DS-MEFJPDA

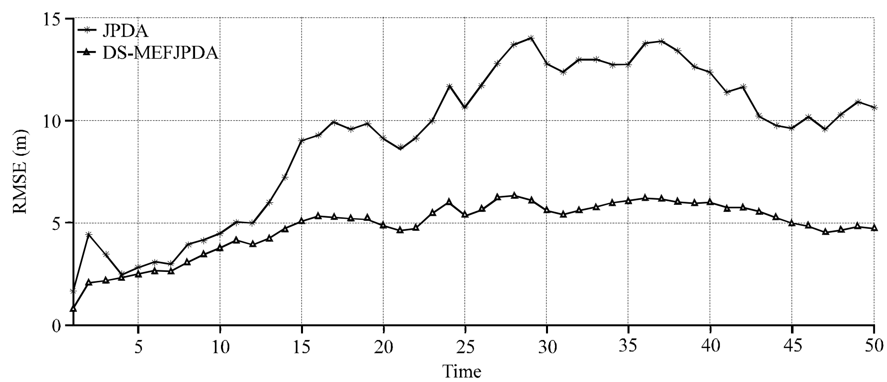

Fig. 4: Velocity RMSE by JPDA and DS-MEFJPDA

From Fig. 3 and 4, we can get the basic situation of the target 1 and the other target's accuracy problem are nearly the same as target 1. We will use Table 2 to reflect the different tracking accuracy of the different algorithm for the multi-targets.

It can be seen from Table 2 that the root mean square error of the DS-MEFJPDA algorithm is less than which of JPDA algorithm obviously. That is to say the proposed algorithm has improved the estimation accuracy of the target significantly.

From Table 3 we can obtain that the running time of the two algorithms is almost the same when the number of target is 1. With the increase of the number of targets, the number of measurements

Table 2: RMSE of position and velocity about JPDA and DS-MEFJPDA

	Target				
RMSE (m) target	1	2	3	4	5
x-axis position					
JPDA	380.8935	403.0711	381.0645	379.5903	400.9342
DS-MEFJPDA	153.3946	143.1567	164.8650	151.4001	175.8980
x-axis velocity					
JPDA	6.4972	8.5219	11.0724	10.6831	9.0402
DS-MEFJPDA	3.2087	4.7963	3.1097	4.1312	4.0728
y-axis position					
JPDA	336.8822	382.3129	365.5562	426.5800	384.3867
DS-MEFJPDA	158.0694	144.2866	138.6586	174.2222	160.9505
y-axis velocity					
JPDA	6.2743	7.2300	15.0247	7.5632	4.9478
DS-MEFJPDA	3.2887	3.0352	4.8105	4.0126	4.3432

Table 3: Running time of JPDA and DS-MEFJPDA algorithm

	Target					
Running time (sec)	1	2	3	4	5	6
JPDA	0.107617	1.214566	0.151401	2.555300	9.731523	23.064714
DS-MEFJPDA	0.087071	0.249414	0.259701	0.359317	0.511642	0.888405

is inevitable to increase and result in the feasibility matrix into a geometrically sharp increase. This makes the computation amount of the JPDA algorithm has increased dramatically. The DS-MEFJPDA algorithm proposed in this paper is effective to solve the problem of computationally intensive by JPDA algorithm.

CONCLUSIONS

The data association technique is the most important aspects of the multi-target tracking system. Firstly, we utilize the idea of maximum entropy fuzzy to replace the feasibility matrix of JPDA algorithm and save much computing time. Secondly, we utilize the improved DS evidence theory in the fusion of the multi-sensor's measurement information and improve the estimation accuracy of the target. Experimental results show that compared with the traditional JPDA method, the proposed DS-MEFJPDA method in this paper has a low computation and a good performance in anti-jamming capability. It can also avoid the interference of invalid measurements with the target and track the multi-targets effectively and accurately under the environment of large density of clutter.

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