2013 IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing

# Fuzzy Double-Threshold Track Association Algorithm Using Adaptive Threshold in Distributed Multisensor-Multitarget Tracking Systems

Wei Du, Huansheng Ning, Yuan Wei and Jun Wang
School of Electronic and Information Engineering
Beihang University
Beijing, China
e-mail: dwbuaa@163.com

***Abstract*—The fuzzy double-threshold track association algorithm using the adaptive threshold (AT-FDTTA) is presented in this paper. The AT-FDTTA is described in detail at first. Then, the simulations of two different cases are designed to illustrate the improved performance caused by the adaptive threshold. Both the simulation results show that the correct association rate of the AF-FDTTA proposed here is higher than that of the fuzzy double-threshold track association algorithm with the fixed threshold (FT-FDTTA) algorithm, Besides, the AT-FDTTA is with lower missing association rate. Moreover, the high performance of the AT-FDTTA is not sensitive to other parameter values in the algorithm, which are usually chosen empirically by the users.**

**Keywords- track-to-track association; adaptive threshold; fuzzy track association**

## I. INTRODUCTION

Internet of Things (IoT) can be regarded as an extension of today's Internet to the Physical Space [1].As a crucial part in IoT, the distributed sensor network is widely used to track the statues of things in Physical Space, such as, the temperature, location or movements [2]. For such network, fusion is necessary to integrate data from different sensors and collect the relevant information of the targets [3]. This paper is focused on the track association in distributed multisensor-multitarget tracking systems, where each sensor node is able to make the noisy measurements of the targets' position, conduct the on-board computation, and transmit information to the fusion center. In these systems, the track association is an essential step to determine whether the tracks from different sensors belong to the same target.

Two kinds of track association algorithms including the statistic method and the fuzzy method are introduced in [4]. The statistic method is based on hypothesis verification, such as the weighted algorithm [5] and the nearest-neighbor algorithm [6]. This kind of method has clear concept, but it is affected by the measurement error and the tracks maneuver. Since the determine process of the track association is with fuzziness, the fuzzy track association method is introduced, which is based on the fuzzy modeling of the target statues. Currently, there are some algorithms based on this kind of method, like the fuzzy double-threshold track association algorithm (FT-FDTTA) [7], the fuzzy inference correlation algorithm [8], and the fuzzy clustering means (FCM) algorithm [9]. The fuzzy method is robust to the noise, but it is hard to choose the suitable parameters to achieve the optimal performance. In [10], a fuzzy adaptive algorithm is proposed based on current statistical probabilistic data association.

In this paper, the fuzzy double-threshold track association algorithm with the adaptive threshold (AT-FDTTA) is presented. Firstly, the procedure of the AT-FDTTA is provided. To compare the fuzzy double-threshold track association algorithm using the fixed threshold (FT-FDTTA) with the AT-FDTTA, two different simulation cases are considered. The first one is how the threshold affects the performance of the FT-FDTTA and the AT-FDTTA, while the second one is how the performance of the FT-FDTTA and the AT-FDTTA changes as other parameter values of the algorithm varies. Through the above simulations, the effect of the presented adaptive threshold may be demonstrated.

## II. FUZZY ADAPTIVE THRESHOLD ALGORITHM

Suppose sensor 1 and sensor 2 are two nodes in multisensor-multitarget tracking system. The two nodes are with their own local information processing system and their own set of targets in track.

Suppose, $N_1 = \{1, 2, ..., i, ..., n_1\}$ is the tracks from sensor 1, while $N_2 = \{1, 2, ..., j, ..., n_2\}$ is the tracks from sensor 2.

In the fuzzy track association algorithm, it is essential to determine the composition of fuzzy element sets, selection of membership function and assignment of weight vectors. In this paper, the Gaussian membership functions is chosen, and the selection of membership based on the *kth* parameter is

$$\mu_k = \mu(u_k) = \exp(-\tau_k(u_k^2 / \sigma_k^2)); k = 1, 2, ..., n \tag{1}$$

Where $\tau_k$ is the adjustment degree, $u_k$ is the fuzzy element set of the *kth* parameter, $\sigma_k$ is the latitude degree of the *kth* parameter.

978-0-7695-5046-6/13 $26.00 © 2013 IEEE
DOI 10.1109/GreenCom-iThings-CPSCom.2013.197

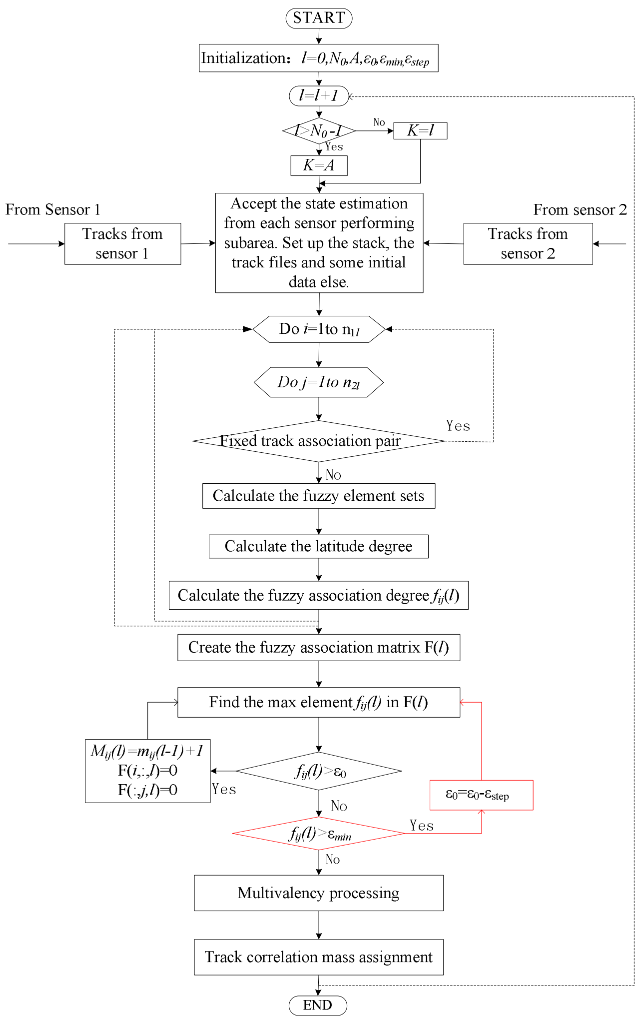


Figure 1. System flow chart of the fuzzy double-threshold track association algorithm with adaptive threshold.

As shown in Figure 1, the fuzzy double-threshold association algorithm with adaptive threshold is worked as follows.

- Initialize parameters, at first, some parameters need to be initialized, such as the sample moment l, the first threshold $N_0$, the second threshold A, the original threshold $\varepsilon_0$, the minimum threshold $\varepsilon_{\min}$ ($\varepsilon_0 > \varepsilon_{\min}$), the threshold step $\varepsilon_{step}$.
- Determine whether the track $i$ and the track $j$ are fixed track association pair. After the processing center accepts the state estimation from different nodes, it needs to determine whether the two tracks are fixed track association pair. If two tracks are fixed track association pair, the two tracks are track association pair and will not make track association test any more. In this paper, a dynamic method is applied to determine whether two tracks are fixed track association pair. For track $i$ and track $j$, in the case of $l > N_0$, if the total number of correct track association pair during the period from $l-N_0+1$ to $l$ is large than $K$, track $i$ and track $j$ are fixed track association pair; in the case of $l < N_0$, it will calculate the total number of correct association pair of all the $K$ times.
- Calculate the selection of membership of all the parameters, the comprehensive similarity is confirmed by the method of weighted mean as

$$f_{ij}(l) = \sum_{k=1}^{n} a_k(l)\mu_k; i \in N_1, j \in N_2 \qquad (2)$$

where $a_k(l)$ is the assignment of weight vectors at moment $l$.

- Build the fuzzy association matrix of the tracks from sensor i and sensor j which can be described as

$$F(l) = \begin{bmatrix} f_{11}(l) & f_{12}(l) & \cdots & f_{1n_2}(l) \\ f_{21}(l) & f_{22}(l) & \cdots & f_{2n_2}(l) \\ \vdots & \vdots & \cdots & \vdots \\ f_{n_1 1}(l) & f_{n_1 1}(l) & \cdots & f_{n_1 n_2}(l) \end{bmatrix} \qquad (3)$$

- The most comprehensive similarity and judging principles [11] are adopted to make the track association test. This process is to find the maximum parameters $f_{ij}$ in $F(l)$, if $f_{ij} > \varepsilon_0$ ($\varepsilon_0$ is the original threshold), track $i$ and track $j$ are associated. And assign zeros to row $i$ and column $j$. Then repeat the process until the max parameter in $F(l)$ is less than $\varepsilon_0$.
- As the gate in fuzzy track association algorithm is determined by people, it is hard to choose the best gate. If the gate is too low, it will increase the false track rate. If the gate is too high, it will increase the missed track rate. In this algorithm, as shown in the red part of Figure 1, after the above steps, if the max element in $F(l)$ is larger than $\varepsilon_{\min}$, decrease the gate ε0 by $\varepsilon_{step}$ to achieve a better correct track rate. Repeat this process until the max element in $F(l)$ is less than $\varepsilon_{\min}$. By this step, it can increase the correct track rate, decrease the missed track rate. As more tracks are included, it may increase the false track rate.
- If track $i$ from sensor $1$ are associated to more than one tracks from sensor $2$, the multivalency processing will be made for track $i$.
- Make the track association pair assignment.

## III. SIMULATION

The mathematic model describing the target dynamic is given as

$$X(k+1) = \Phi(k)X(k) + G(k)V(k) \qquad (4)$$

where $X(k)$ the target state vector with dimension n, the input noise $V(k)$ is assumed to be Gaussian. $\Phi(k)$ is the state transition matrix. G(k) is process noise distributed matrix. Its mean and variance can be described as

$$E[V(k)]=0 \tag{5}$$

$$E[V(k)V'(l)]=Q(k)\delta_{kl} \tag{6}$$

Furthermore, the general sensor observation measurement model is described as follows

$$Z(k)=H(k)X(k)+W(k) \tag{7}$$

Where $Z(k)$ is sensor measurement vector, $H(k)$ is the observation matrix, $W(k)$ is assumed to be Gaussian with dimension m. Its mean and variance can be described as

$$E[W(k)]=0 \tag{8}$$

$$E[W(k)W'(l)]=R(k)\delta_{kl} \tag{9}$$

And the state estimate is based on Kalman filter algorithm. $\hat{X}(l|l)=[\hat{x}(l),\hat{y}(l),\hat{\dot{x}}(l),\hat{\dot{y}}(l)]$ is the state estimate.

In this section, the sample period T is 1s.

In this section, the first fuzzy element sets are chosen, in this section n=3, which can be described as follows:

$$\begin{cases} u_1(l)=[(\hat{x}_i(l)-\hat{x}_j(l))^2+(\hat{y}_i(l)-\hat{y}_j(l))^2]^{1/2} \\ u_2(l)=|[(\hat{\dot{x}}_i(l))^2+(\hat{\dot{y}}_i(l))^2]^{1/2}-[(\hat{\dot{x}}_j(l))^2+ \\ \qquad (\hat{\dot{y}}_j(l))^2]^{1/2}|;i\in U_1, j\in U_2 \\ u_3(l)=\theta_{ij}(l)=|\tan^{-1}[\hat{\dot{y}}_i(l)/\hat{\dot{x}}_i(l)]- \\ \qquad \tan^{-1}[\hat{\dot{y}}_j(l)/\hat{\dot{x}}_j(l)]| \end{cases} \tag{10}$$

The latitude degree is as follows

$$\begin{cases} \sigma_1^2=P_{11}(i)+P_{11}(j)+P_{33}(i)+P_{33}(j) \\ \sigma_2^2=P_{22}(i)+P_{22}(j)+P_{44}(i)+P_{44}(j) \\ \sigma_3^2=\pi^2/12 \end{cases} \tag{11}$$

The assignment of weight vectors are as follows

$$a_1=0.55, a_2=0.35, a_3=0.1 \tag{12}$$

In this paper the algorithm is investigated based on 50 Monte Carlo simulations while the number of targets in common place is 60.

*Case 1*

In case 1, it compares the association result between FT-FDTTA algorithm and the new algorithm, where the parameter group is set to $\tau_1=0.5, \tau_2=0.2, \tau_3=0.3$

Figure 2, Figure 3 and Figure 4 show the track association result of the FT-FDTTA and the ATDTTA, where the fixed threshold and the original threshold in adaptive algorithm are in the same value, threshold1 and adaptive threshold1, threshold2 and adaptive threshold2 are 0.6 and 0.8, and εmin, εstep are 0.5 and 0.05. The false track association result is shown in Figure 3, and the missed track association result is shown in Figure 5.

As illustrated in Figure 2, no matter the threshold is low or high, the AT-FDTTA achieves higher correct track percent than the FT-FDTTA ones especially for the case of the threshold is high. For the threshold is 0.6, using adaptive threshold the corrected track percent is increased almost 5%, while the threshold is 0.8, it increases almost 25%. As the threshold in AT-FDTTA is decreased by a step, it will achieve higher correct track percent than FT-FDTTA. Figure 3 shows that the lower threshold will increase the false track association percent. With the adaptive threshold, the threshold is decreased by a step, the number of tracks calculated by the system is more than the fixed ones, thus it will increase false track percent. Figure 4 shows that the adaptive threshold is with less missed track percent, as the higher threshold will increase leakage track association percent.

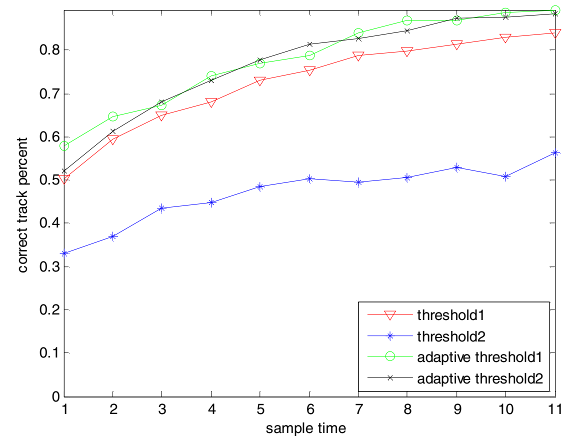


Figure 2. The correct track percent comparison of FT-FDTTA with different thresholds and AT-FDTTA.

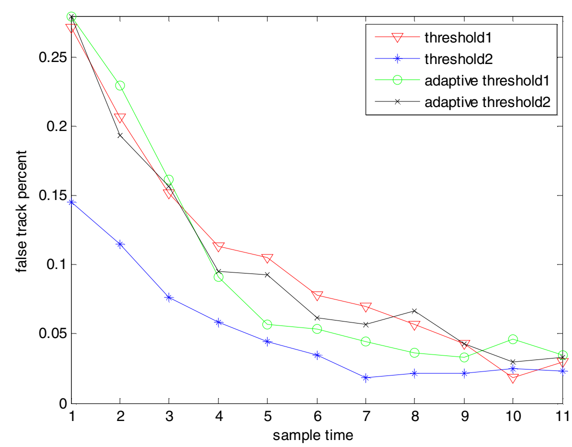


Figure 3. The false track percent comparison of FT-FDTTA with different thresholds and AT-FDTTA.

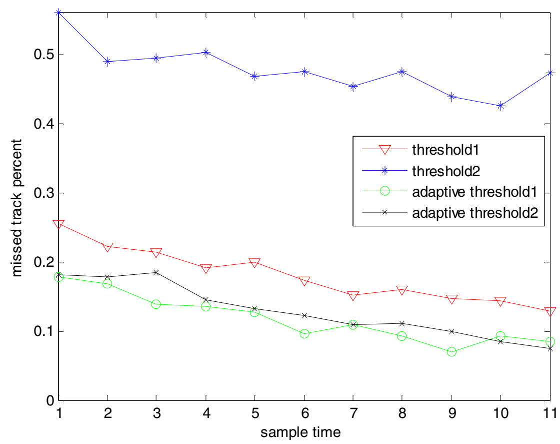


Figure 4. The missed track percent comparison of FT-FDTTA with different thresholds and AT-FDTTA.

*Case 2*

It is well known that the track association result is dependent on the parameter group which is subjective determined by people. Thus, in case 2, it compares the influence of the parameter group to association result of FT-FDTTA and the AT-FDTTA.

Figure 5, Figure 6 and Figure 7 depict the association results of the FT-FDTTA and the AT-FDTTA with two kinds of parameter groups. In Figure 5, Figure 6 and Figure 7, the parameter group1 is $\tau_1 = 0.8, \tau_2 = 0.1, \tau_3 = 0.1$, while the parameter group2 is $\tau_1 = 0.4, \tau_2 = 0.3, \tau_3 = 0.3$. The threshold in both FT-FDTTA and AT-FDTTA is 0.55. In Figure 5, it is shown that when the parameter group changes from group1 to group2, there is an improvement in the correct track association performance in both the FT-FDTTA and new algorithm. However, the AT-FDTTA is less dependent on the parameter group.

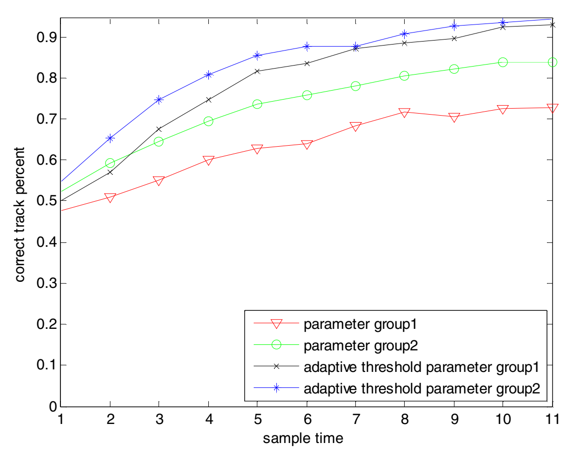


Figure 5. The correct track percent comparison of the FT-FDTTA and AT-FDTTA when parameter group changes.

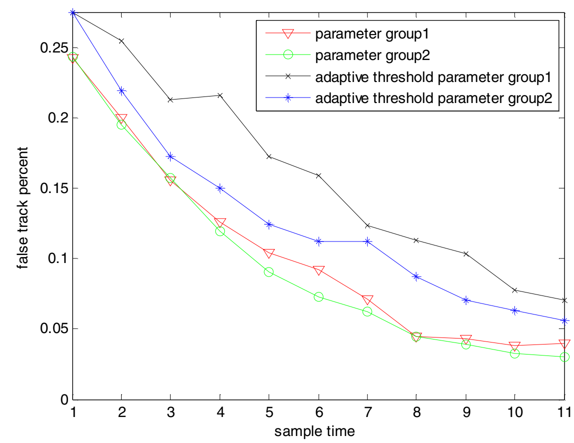


Figure 6. The false track percent comparison of the FT-FDTTA and AT-FDTTA when parameter group changes.

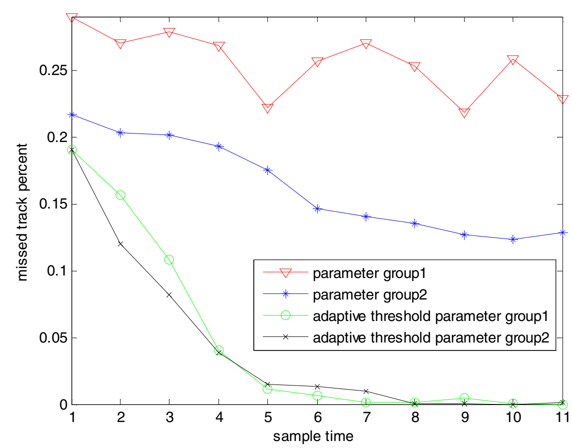


Figure 7. The missed track percent comparison of the FT-FDTTA and AT-FDTTA when parameter group changes.

## IV. CONCLUSION

An adaptive threshold based fuzzy track association algorithm is presented. By gradually adjusting the threshold in the FT-FDTTA, a higher correct association rate and a lower missed association rate can be obtained. The high performance of the presented AT-FDTTA is not sensitive to the initial threshold and other parameters values chosen empirically. This will make use of the AT-FDTTA in distributed multisensor-multitarget tracking systems more convenient and efficient.

## REFERENCES

[1] Z. Zhuo, D. Mendoza, S. W. Peng, Z. Qin, M. Jia, F. Jonsson, H. Tenhunen and et al., "A Low-Power and Flexible Energy Detection IR-UWB Receiver for RFID and Wireless Sensor Networks," IEEE Transactions on Circuits and Systems I: Regular Papers, vol.58, no.7,July 2011, pp.1470-1482.

[2] L. Atzori, A. Iera and G. Morabito, "The Internet of Things: A survey, " Computer Networks, vol. 54, Issue 15, 28 October 2010, pp. 2787-2805.

[3] M. E. Liggins, C. Chong, I. Kadar, M. G. Alford, V. Vannicola, and S. Thomopoulos, "Distributed fusion architectures and algorithms for target tracking," Proc. the IEEE , vol.85, no.1, Jan. 1997,pp.95-107.

[4] Y. Shalom and X. R. Li, “Multitarget multisensor tracking: principles and techniques” . YBS Publishing, 1995.

[5] A. Kanyuck and R. Singer, “Correlation of Multiple-site Track Data,” IEEE T-AES-6, vol. 2, 1970, pp. 180-187.

[6] M. Kosaka, S. Miyamoyo and H. Ihara, “A Track Correlation Algorithm for Multisensor Integration,” Proc. IEEE/AIAA 5th Digital Avionics System Conference, 1983, pp. 1-8.

[7] Y. He, G. Wang, D. Lu, and Y. Peng, Multisensor Information Fusion With Application, 2nd ed., Beijing,Publishing House of Electronics Industry, 2007, pp. 169-172, (in Chinese).

[8] E. Fan and W. Xie, “A Novel track -to -track association algorithm in distributed sensor network ” Signal processing , vol. 27, 2011,pp.1561 − 1565, ( in Chinese).

[9] A. M. Ashraf , "A new fuzzy clustering approach for data association and track fusion in multisensor-multitarget environment," Proc. IEEE Aerospace Conference, Mar. 2011, pp. 1-10.

[10] H. Yu, C. Fu, and L. Jiang "A fuzzy adaptive tracking algorithm based on current statistical probabilistic data association," Proc. 2nd International Conference on Signal Processing Systems (ICSPS), Jul. 2010, vol.2, pp.V2-757-V2-759, 5-7.

[11] S. Hu, Fuzzy Sets and Application, Chengdu: Sichuan University Industry, 1994.(in Chinese).