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Tracklet-Global Track Association and Fusion Methods in Distributed Sensor Networks

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Abstract

In distributed sensor networks, track association and track fusion become difficult due to the existence of various uncertainties in multiple target tracking (MTT). In an actual tracking system, state estimates of a local track are usually transmitted from local nodes to the global node by message, and each message generally contains single state estimate. Based on this fact, one can define two state estimates of a local track in continuous times as a tracklet. Then, local track-global track association can be divided into tracklet-global track (T2GT) association in real time. Hence, a T2GT association method based on Hough transform (HT-T2GT) is proposed. By Hough transform, all the tracklets in the same interval can be mapped into a set of points in Hough space, and the track association problem can be transformed as one of point clustering in Hough space. The maximum entropy fuzzy c-mean (ME-FCM) clustering method is used to realize T2GT association. In addition, a T2GT fusion method based on the support degree function (SDF-T2GT) is developed for track fusion. The experimental results illustrate that the proposed methods can respectively realize T2GT association and track fusion in the situations with multiple local nodes, reduce the average time of updating global tracks and satisfy the requirement of real-time processing in the global node. It achieves higher association processing rate than other two track association methods.

Keywords*: multiple target tracking; track association; track fusion; maximum entropy fuzzy clustering; Hough transform*

1. Introduction

Information fusion is usually utilized in multiple target tracking (MTT) for its better performance on estimation and decision by using different kinds of measurements or information from various sensors or multiple sources [1-4]. Track association is the prerequisite of MTT [5]. Generally, designing a track association method is closely related to system structures and sensor types. The distributed structure is widely utilized in various applications. Compared with the centralized structure, it generally consumes lower costs to obtain better performances in reliability, availability and expansibility, and meanwhile relaxes the requirements of frequency bandwidths and process abilities for different nodes in sensor networks. According to the transmission paths of data flow, the

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distributed structure can be also divided into two types, namely the fully distributed and hierarchical structure [4]. In addition, track association can be classified into local track-local track (LT2LT) association and local track-global track (LT2GT) association, which relies on whether the state estimates of global tracks are utilized in association judgments. In large-scale sensor network, each node needs to process a growing number of data due to its wide distribution and mass sensors. Especially, its performance in processing rate and communication capability is limited in battlefields. Therefore, it is necessary to improve the capacity of data processing for track association in actual sensor networks.

A key issue in track association is to quickly determine which local tracks observed by different sensors or platforms are from the same target. The traditional track association methods can be divided into two categories: statistical and fuzzy track association methods [5-6]. In the recent years, the former mainly focus on the problems related to the actual noise and bias of measurements, high dimensional state information and attribute information [5-7]. Due to the existence of both the great uncertainty in association judgments and correlated noises or errors in actual situations, their computational complexities become increasing large. Considered the advantages of the fuzzy theory on processing the uncertainty problems, the fuzzy association methods possess the good performances in processing rate, storage capacity and communication capability, and they are suitable to apply in an actual system with large errors [3]. Generally, the traditional track association methods handle with two state estimates from a pair of tracks in single judgment. Consequently, they need execution of several judgments for updating global tracks. Based on this fact, the update time of global tracks is not only constrained, but also these methods are difficult to satisfy the requirements of actual tracking systems with multiple local nodes [8]. Gao *et al* in [9] mapped the tracks associated as a set of points in high dimensional space, and utilize the weighted fuzzy clustering method to resolve the track association problem in the situations with multiple local nodes. Unfortunately, because processing whole tracks in single judgment increases the update time of global tracks, it is hard to meet the requirement of an actual system in real-time processing. If LT2GT association is divided into local state estimate-track association, then it can be regarded as a generalized measurement-track association. Li *et al* in [10] proposed a two-scan data association (TSDT) method, which utilizes two measurements observed in continuous scans to calculate the associated probabilities on a target. Due to the increasing information content of associated objects in single judgment, it can improve the performance in association accuracy. The TSDT method provides an idea for track association. In addition, signal transforming and processing in different spaces can also provide a theoretical basis for track association according to the information theory [9-11].

In actual hierarchical sensor networks, the state estimates of local tracks are sequentially transmitted to the global node from each local node by message. Based on this fact, one can define two local state estimates in continuous times on the same target as a tracklet. Hence, LT2GT association can be divided into tracklet-global track (T2GT) association. Then a T2GT association method based on Hough transform (HT-T2GT) is developed. In the proposed method, all the tracklets in the same interval are mapped as a set of points in Hough space by Hough transform (HT), and then T2GT association is realized through the maximum entropy fuzzy c-means (ME-FCM) clustering algorithm. In addition, a T2GT fusion method using the support degree function (SDF-T2GT) is proposed. Finally, two experiments by using simulational and real data are applied to evaluate the performance of the HT-T2GT association method, compared with the traditional track association methods.

The remainder of this paper is organized as follows: in Section 2, the definition of tracklets is given according to the transmitted mode of different tracks in an actual tracking system, and then these tracklets are mapped as the points in Hough space; in Section 3, the HT-T2GT association method is developed based on the ME-FCM clustering algorithm; in Section 4, SDF-T2GT fusion method is proposed. Section 5 presents the experiment results and the performance comparison with the other two track association methods; finally, conclusions are provided in Section 6.

2. Definition of tTracklet and its Mapping

2.1. Definition of Tracklets

It is assumed that there exist a global node $(\mathrm{N}_g, g = 1)$ and M local nodes $(\mathrm{N}_l, l = 1, 2, \cdots, M)$ in a hierarchical tracking system. In real situations, the global node needs to generate two types of tracks: global tracks applied for target tracking, and tracklets used for updating global tracks [12]. As mentioned in Section 1, the state estimates of local tracks are orderly transmitted to the global node by message in battlefields with limited bandwidth. Based on this fact, a tracklet is defined by two state estimates of a local track in continuous time. Concretely, a tracklet and a candidate tracklet are expressed respectively as follows:

$$\boldsymbol{t}_l^i(k) = \{\hat{\boldsymbol{x}}_{l,k-1}^i, \hat{\boldsymbol{x}}_{l,k}^i\}, i = 1, 2, \dots, n_l \tag{1}$$

$$\boldsymbol{t}_l^i(k) = \{\hat{\boldsymbol{x}}_{l,k}^i\}, i = 1, 2, \dots, n_l \tag{2}$$

where $\hat{x}_{l,k-1}^i$ and $\hat{x}_{l,k}^i$ are the state estimates of the local track $T_{l,k}^i$ at time k-1 and k transmitted from the local node N_l to the global node N_g.

The generated procedure of tracklets and candidate tracklets is given as follows: 1) when the global node N_g receives the message containing an estimate $\hat{x}_{l,k}^i$, then it determines if there exist a candidate tracklet from the same source in the sequence of candidate tracklets; 2) if there exists, generate a tracklet $t_{l,k}^i$; otherwise, if there doesn't, generate a candidate tracket $\tilde{t}_{l,k}^i$. Hence, utilizing the T2GT association are suitable for the transmission requirement and it can decrease the redundant information transmitted [10].

2.2. Tracklet Mapping by Using Hough Transform

Compared with single local state estimate, a tracklet including two local state estimates provides more associated information, and then it can reduce the uncertainty of track association. Hence, the traditional LT2GT association can be replaced by T2GT association. Generally, a target keeps moving for a long time, and its trajectory can be regarded as non-linear. Relatively, a trackltet keeps moving for a short time, and it can be regarded as linear due to the small change rate between two state estimates. In addition, the height on a moving target will be transmitted only in the phrase of track initialization or its change. As a result, all the tracklets in the same interval can be seemed as a sequence of straight lines in a plane. The rest of this paper mainly discusses the situations with the height change on a moving target less than the given threshold. Therefore, the T2GT association problem can be transformed as that of point distribution if the tracklets in the same interval are mapped into a set of points in Hough space. Furthermore, the geometrical features and clustering analysis of mapped points in Hough space provides a new thought for track association. According to Hough transform, one can obtain the following expression:

$$\rho(\theta) = \hat{x}_{l,k}^i \cos\theta + \hat{y}_{l,k}^i \sin\theta \tag{3}$$

Here, ρ and θ are the coordinates of the mapped point in Hough space corresponding to the state estimate $\hat{x}_{l,k}^i$; $\hat{x}_{l,k}^i$ and $\hat{y}_{l,k}^i$ are the corresponding components of $\hat{x}_{l,k}^i$ in the xaxis and y-axis directions. Hence, one can establish a mapping from the tracklet $\boldsymbol{t}^i_{l,k}$ to the point $\boldsymbol{p}^i_{l,k}$:

$$\boldsymbol{p}^i_{l,k} = f(\boldsymbol{t}^i_{l,k}) = (\rho^i_{l,k}, \theta^i_{l,k}) \tag{4}$$

Here, $f(\cdot)$ is the mapping function; $\rho^i_{l,k}$ and $\theta^i_{l,k}$ are the coordinates of the point $\boldsymbol{p}^i_{l,k}$

$$\rho^i_l = \left|\eta^i_l \hat{x}^i_{l,k} - \hat{y}^i_{l,k}\right| \Big/ \sqrt{(\eta^i_l)^2 + 1} \tag{5}$$

$$\theta^i_{l,k} = \arctan(-1/\eta^i_l) \tag{6}$$

$$\eta^i_l = (\hat{y}^i_{l,k} - \hat{y}^i_{l,k-1}) \big/ (\hat{x}^i_{l,k} - \hat{x}^i_{l,k-1}) \tag{7}$$

Hence, a sequence of tacklets can be mapped to a point set:

$$\{ p^i_{l,k} \mid (\rho^i_{l,k}, \theta^i_{l,k}) = f(t^i_{l,k}), l = 1, \ldots, M; i = 1, \ldots, M_l \} \tag{8}$$

If there exist several tracklets associated with the same target, their corresponding points mapped in Hough space can be clustered together. Then the T2GT association problem can be transformed into the clustering analysis of points in Hough space through Hough transform. For better clustering, it is necessary to normalize ρ and θ : $\rho' = \rho/\rho_{\max}$, $\theta' = \theta/\theta_{\max}$. Here, $\rho_{\max}$ and $\theta_{\max}$ are the corresponding maximum value of ρ and θ , and both of them are related to the spatial distribution and motion model of moving targets.

3. HT-T2GT Association Method

Because the ME-FCM clustering algorithm [13] can obtain the minimum unbiased estimates of membership degrees, and possess the advantages of good clustering effect, clear mathematical meaning and physical meaning, it is widely applied in various applications. This paper uses the ME-FCM clustering algorithm to solve the T2GT association problem.

3.1. Maximum Entropy fuzzy Clustering Based on Tracklets

At time k , suppose that there exist m local tracks $\{T^i_{l,k}\}$ from the local node N_l and c global tracks $\{T^i_{g,k-1}\}$ from the global node N_g , and m tracklets $\{\boldsymbol{t}^i_{l,k}\}$ generated in the global node N_g . By Hough transform, one can obtain a point set $P = \{\boldsymbol{p}_{j,k}\}^m_{j=1}$ and the clustering centers $V = [\boldsymbol{v}_{1,k}, \boldsymbol{v}_{2,k}, \cdots, \boldsymbol{v}_{c,k}]^{\mathrm{T}}$ in Hough space. Here, $\boldsymbol{v}_{i,k}$ is the clustering center of the class i ; $u_{li}(k) = u_l(\boldsymbol{p}_{i,k})$ is the membership degree of the point $\boldsymbol{p}_{i,k}$ for the cluster center $\boldsymbol{v}_{l,k}$; $U = \{u_{li}(k)\}$ is a $c \times m$ matrix. Hence, the T2GT association problem can be transformed as that of clustering analysis of points in Hough space, and the clustering procedure can be described as an optimization problem. The cost function is constructed as follow:

$$E = \sum_{i=1}^{n_k} \sum_{l=1}^{c} u_{li}(k) d(\boldsymbol{p}_{i,k}, \boldsymbol{v}_{l,k}) \tag{9}$$

Here, $d(\boldsymbol{p}_{i,k}, \boldsymbol{v}_{l,k}) = |\boldsymbol{p}_{i,k} - \boldsymbol{v}_{l,k}|^2$ is the Euclidean distance from the point $\boldsymbol{p}_{i,k}$ to the cluster center $\boldsymbol{v}_{l,k}$, $u_{li}(k)$ obeys the following constraints:

$$\sum_{l=1}^{c} u_{li}(k) = 1, \forall u_{li}(k) \in [0,1] \tag{10}$$

With the Shannon theorem, one can deduce the following equation:

$$H = H(u_{li}(k)) = -\sum_{i=1}^{n_k}\sum_{l=1}^{c} u_{li}(k)\ln u_{li}(k) \tag{11}$$

Under the restraints of Eqs. (9) and (10), maximize Eq. (11) to construct the objective function by the Lagrange multiplier algorithm:

$$J(\boldsymbol{U},\boldsymbol{V}) = -\sum_{i=1}^{n_k}\sum_{l=1}^{c} u_{li}(k)\ln u_{li}(k) - \sum_{i=1}^{n_k}\omega_i\sum_{l=1}^{c} u_{li}(k)d(\boldsymbol{p}_{i,k},\boldsymbol{v}_{l,k}) + \sum_{i=1}^{n_k}\mu_i\left(\sum_{l=1}^{c} u_{li}(k)-1\right) \tag{12}$$

where, ω_i and μ_i are the Lagrange multipliers. Thus, one can obtain the following formula:

$$u_{li}(k) = \exp[-\omega_i d(\boldsymbol{p}_{i,k},\boldsymbol{v}_{l,k})] \Big/ \sum_{k=1}^{c}\exp[-\omega_i d(\boldsymbol{p}_{i,k},\boldsymbol{v}_{l,k})] \tag{13}$$

Here, ω_i is also called the differential factor. By controlling ω_i, the membership degree $u_{li}(k)$ can be correspondingly adjusted. To reduce the iteration times, the set consisting of the current and the next predictive values of a global track are mapped as a clustering center in Hough space, namely $\boldsymbol{v}_{i,k} = f(\{\hat{\boldsymbol{x}}_{0,k-1}^{i}, \hat{\boldsymbol{x}}_{0,k|k-1}^{i}\})$. The prediction equation is given by:

$$\hat{\boldsymbol{x}}_{0,k|k-1}^{i} = H_{k-1}F_{k-1}\hat{\boldsymbol{x}}_{0,k-1}^{i} \tag{14}$$

where H_{k-1} and F_{k-1} are the observation transfer matrix and state transfer matrix at time $k-1$.

3.2. Difference Factor Analysis

From [13], the value of ω_i is related to the concrete application, and the common form of its optimal value can be expressed by

$$(\omega_i)_{opt} = -\ln(\varepsilon)\big/d_{l\min} \tag{15}$$

Here, $d_{l\min} = \min\{d(\boldsymbol{p}_{i,k},\boldsymbol{v}_{l,k})\}_{i=1}^{c}$, and ε is a positive constant. In the clustering procedure, while the distance from points to the clustering center becomes smaller, the association probability becomes greater between tracklets and global tracks. In addition, while the false alarm rate of the sensor is lower, and the reliability of the tracklets for the corresponding sensor is higher. In track association, ω_i can be defined as:

$$\omega_i = \eta\big/(\xi_i d_{l\min}) \tag{16}$$

Here, ξ_i is the false alarm rate of the corresponding sensor, and η is a positive constant. In the situations with dense targets and mass sensors, one can choose an appropriate threshold of membership degrees and then determine the threshold of distances: if the distance from a point to the clustering center is greater than the given threshold, the membership degree of the corresponding point can be neglected, and then the calculated amount of the EM-FCM

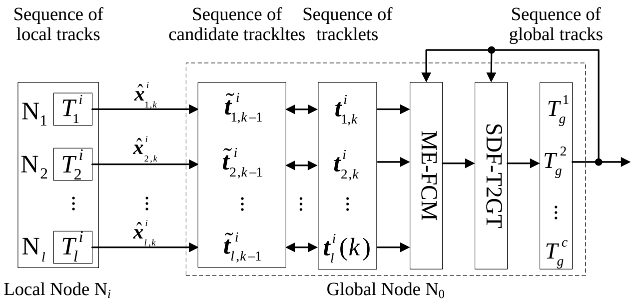

Figure 1. Flow Chart of HT-T2GT Method

Clustering algorithm is further reduced. The flow chart of the HT-T2GT association method is shown in Figure 1.

4. SDF-T2GT Fusion Method

Because local tracks from different local nodes possess unequal qualities, tracklets can't be directly utilized into track fusion. Meanwhile, considered modeling error in tracking systems and random disturbances from real environments, one can only estimate the qualities of different tracklets for determining their weights in fusion results according to the information hided in local state estimates of local tracks. By mapping tracklets as a set of points, a SDF-T2GT fusion method is developed to realize track fusion.

In Hough space, the distance of two mapped points can be defined as:

$$d_{ij} = |\boldsymbol{p}^i_{l,k} - \boldsymbol{p}^j_{g,k}| \tag{17}$$

Here, the point $\boldsymbol{p}^i_{l,k}$ is the mapped point corresponding to the tracklet $\boldsymbol{t}^i_{l,k}$; $\boldsymbol{p}^j_{g,k}$ can be calculated by

$$\boldsymbol{p}^j_{g,k} = f(\{\hat{\boldsymbol{x}}^j_{g,k-1}, \hat{\boldsymbol{x}}^j_{g,k|k-1}\}) \tag{18}$$

where $\hat{x}^j_{g,k-1}$ is the state estimate of the global track $T^j_{g,k}$ at time $k-1$ and $\hat{x}^j_g(k\,|\,k-1)$ is the predicted position at time k . The corresponding predicted equation can be expressed as:

$$\hat{\boldsymbol{x}}^j_{g,k|k-1} = F_{k-1}\hat{\boldsymbol{x}}^j_{g,k-1} \tag{19}$$

where F_{k-1} is the state transition matrix at time $k-1$.

As known in Eq. (17), the value of the distance d_{ij} becomes larger with the increase of the difference between $\boldsymbol{t}^i_{l,k}$ and $\boldsymbol{t}^j_{g,k}$, and then it shows that the relative support degree of these two tracklets is smaller. Then, one can define the support degree function by:

$$r_{ij} = -\frac{d_{ij}}{\max\{d_{ij}\}} + 1 \tag{20}$$

Here, $d_{ij} > 0$, $r_{ij} \in [0,1]$, $\max\{d_{ij}\}$ is the maximum value in all the distances for any two points.

From Eq. (20), r_{ij} only expresses the mutual support degree of two tracklets, but it can't reflect the support degree of the tracklet relative to all the other tracklets at time *k*. Then, r_{ij} is normalized as follow:

$$\omega_{ij} = \frac{r_{ij}}{r_{1j} + r_{2j} + \cdots + r_{mj}} \tag{21}$$

Based on the above analysis, the global estimate $\hat{x}_{g,k}^{j}$ of the global track $T_{g,k}^{j}$ at time k can be expressed by

$$\hat{\boldsymbol{x}}_{g,k}^{j} = \omega_{1j}\hat{\boldsymbol{x}}_{1,k}^{(1)} + \omega_{2j}\hat{\boldsymbol{x}}_{2,k}^{(2)} + \cdots + \omega_{mj}\hat{\boldsymbol{x}}_{m,k}^{(m)} \tag{22}$$

where m is the number of tracklets associated with the global track $T_{g,k}^{j}$.

5. Experimental Results and Analysis

Two experiments of simulational and real data have been carried out to evaluate the performance of the HT-T2GT association method in comparison with other two methods, including the weighted fuzzy clustering method (wFC) [9] and the fuzzy track association method (FTA, association quality $m = 6$) [3]. These experiments are conducted by using a computer with a dual-core CPU of Intel(R) 2.20 GHz, 8-GB RAM, and the programs are performed by using MATLAB 2009a version software.

5.1. Simulational Experiment

It is assumed that there exist four crossing targets moving with constant velocity and keeping the height of 1.0 km in the air surveillance of 2-D Cartesian xy-plane. The trajectories of four targets are given as shown in Figure 2. Their initial states are $(9.0\text{ km}, 200\text{ m/s}, 7.4\text{ km}, 200\text{ m/s})^{\mathrm{T}}$, $(9.0\text{ km}, 200\text{ m/s}, 7.3\text{ m}, 200\text{ m/s})^{\mathrm{T}}$, $(9.0\text{ km}, 200\text{ m/s}, 7.2\text{ km}, 200\text{ m/s})^{\mathrm{T}}$, and $(9.0\text{ km}, 200\text{ m/s}, 6.2\text{ km}, 200\text{ m/s})^{\mathrm{T}}$, respectively. Assumed there exists a global node and four local nodes in a distributed tracking system, these nodes above are located at $(15\text{ km}, 24\text{ km})$, $(8.5\text{ km}, 4.5\text{ km})$, $(21\text{ km}, 4.5\text{ km})$, $(8.5\text{ km}, 24\text{ km})$, and $(21\text{ km}, 24\text{ km})$, respectively. The performance parameters of four radars are as follows: range error $\sigma_r = 100\text{ m}$, angle error $\sigma_\theta = 0.1^{\circ}$, and sampling period $T = 3\text{ s}$. In addition, all radars work synchronously. The observed results are shown in Figure 2. The procedures of data processing in the system is as follows: 1) generate local tracks by the collected measurements in local nodes; 2) transform the state estimates of local tracks from polar coordinate system to global rectangular coordinate system; 3) transmit these estimates orderly to the global node; 4) generates tracklets in the global node; 5) utilize the proposed method to realize T2GT association; 6) apply the SDF-T2GT fusion method for track fusion.

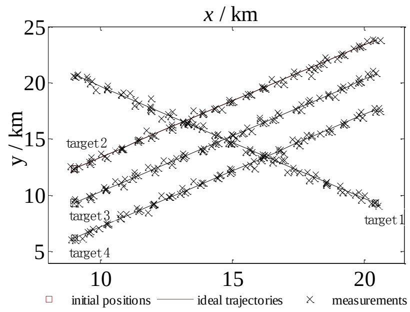

Figure 2. Ideal Tracks and Real Measurements

Figure 3 shows the distribution of the points in Hough space after by Hough transform in the second period. Figure 4 shows the fusion results of global tracks obtained by the HT-T2GT association method and the SDF-T2GT fusion method. Generally, the performance of the clustering algorithm is related to the number and distribution of targets in the measured space of each sensor [14]. It can be found from Figure 3 that the corresponding points in Hough space has obvious separabilities in the same period, because the tracklets on the same target has a large association probability in real situations. Therefore, it can be verified that it is feasible to realize T2GT association.

It can be found from Figure 4 that the SDF-T2GT fusion method obtained the good fusion results in accuracy, it is indirectly verified that the SDF-T2GT fusion method can correctly realize T2GT association. Table 1 provides the average time of updating global tracks and the capability of processing multiple local nodes problem using three methods for 100 times Monte Carlo simulation runs. It can be seem from Table 1 that the HT-T2GT association method does not only satisfy the processing requirement of multiple local nodes, but also its average time of updating global tracks is least in three methods, discussed as follows. In single judgment, the HT-T2GT association method can process all the tracklets in the same interval, and its associated objects are tracklets. Meanwhile, the mapping of the predicted positions into the initial values of the fuzzy clustering algorithm can reduce the iteration times. Similarly, in single judgment, the wFC method can process all the local tracks in the same interval, namely satisfying the processing requirement of multiple local nodes, but its associated objects are the whole local tracks. Hence, it consumes more time for updating global tracks than the HT-T2GT association method. In single judgment, the FTA method can only process two estimates of local state. To update global tracks, it is necessary to make several times of judgments for satisfying the processing requirement of associated quality. Thus, it can't satisfy the processing requirement of multiple local nodes and its time of updating global tracks is the longest.

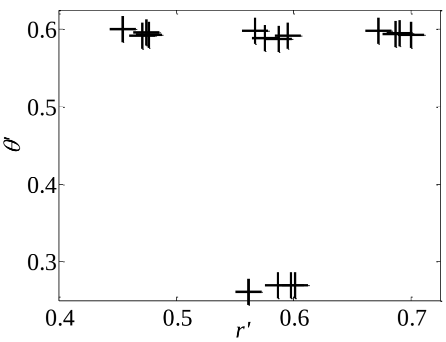

Figure 3. Clustering Results of HT-T2GT

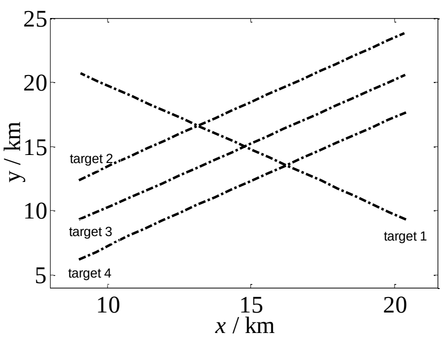

Figure 4. Fusion Results

Table 1. Performance of Three Methods

methods	average time of updating global track	processing capacity of multiple local nodes
HT-T2GT	0.000 8 s	yes
wFC	0.001 1 s	yes
FTA	0.002 0 s	no

5.2. Real-Data Experiment

As shown in Figure 5, a certain type of two radars was used to track six targets. The addresses of the radars and the global node are $(117.815\ 11^{\circ}, 33.537\ 26^{\circ}, 0\ \mathrm{m})$, $(120.999\ 49^{\circ}, 30.842\ 36^{\circ}, 0\ \mathrm{m})$ and $(119.407\ 30^{\circ}, 32.189\ 81^{\circ}, 0\ \mathrm{m})$, respectively. The performance parameters of two radars are given as follows: maximum detection range $r_{\max} = 230\ \mathrm{km}$, range error $\sigma_r = 100\ \mathrm{m}$, angle error $\sigma_{\theta} = 0.5^{\circ}$, and scan period $T = 3\ \mathrm{s}$. Table 2 shows the initial positions of real local tracks with the height of 1.0 km from the corresponding radars. The real procedure of data processing in the tracking system is as below: 1) align the time of each radar; 2) transform the state estimates of local tracks in each radar from the local coordinate system to the geographic coordinate system; 3) transmit these estimates to the global node; 4) transform local tracks from the geographic coordinate system to the global coordinate system through the inner earth coordinate system; 4) generate tracklets; 5) apply the HT-T2GT association method in T2GT association; 6) carry out track fusion by the SDF-T2GT fusion method. Figure 5 shows real local tracks of each radar in the geographic coordinates system. Figure 6 shows the fused results by the HT-T2GT association method and the SDF-T2GT fusion method, and it indirectly validates the feasibility of the proposed method.

Table 2. Initial Positions of Real Tracks

ID	initial positions	ID	initial positions
11	118.828 95°, 30.741 55°	21	118.828 06°, 30.741 81°
12	118.268 51°, 33.293 15°	22	119.911 59°, 33.147 78°
13	119.912 92°, 33.147 46°	23	120.859 33°, 32.837 50°
14	120.858 83°, 32.836 56°	24	117.046 23°, 33.650 14°
15	117.039 08°, 33.640 30°	25	118.291 72°, 33.278 58°
16	116.860 65°, 30.538 84°	26	117.051 13°, 31.508 67°

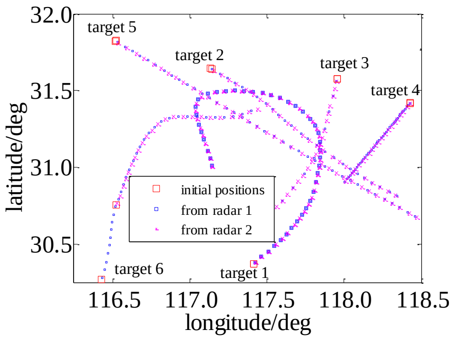

Figure 5. Real Tracks

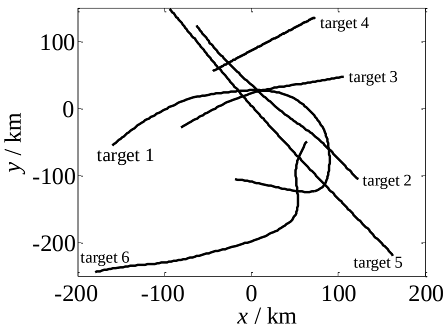

Figure 6. Fusion Results

6. Conclusion

To solve the MTT problem in the situations with multiple local nodes, the HT-T2GT association method and the SDF-T2GT fusion method are proposed respectively. In the global node, the HT-T2GT association method defines state estimates of local tracks as tracklets in continuous times, and then all the tracklets in the same interval are mapped as a set of points in Hough space by the Hough transform algorithm. Consequently, the track association problem can be solved by utilizing the maximum entropy fuzzy c-means clustering (ME-FCM) algorithm in Hough space. In single judgment, utilizing HT-T2GT association can reduce the average time of updating global tracks and meanwhile satisfy the requirements of real-time processing. In addition, incorporation of the ME-FCM algorithm in Hough space can realize parallel processing of track association, and classification accuracy is also improved with the increase of information content on associated targets. Finally, the SDF-T2GT fusion method is developed to realize track fusion. The results of simulational and real experiments show the proposed method can realize T2GT association correctly in situations with multiple local nodes, and it can achieve has better performance in processing rate than the traditional fuzzy track association algorithm and the weighted fuzzy clustering algorithm.

Acknowledgments

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