International Journal of Control and Automation
Vol. 9, No. 6 (2016), pp.127-136
http//dx.doi.org/10.14257/ijca.2016.9.6.12

Uncertainty Analysis of Multiple Target Tracking in Distributed Sensor Networks

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Abstract

The related theories and technologies on sensor networks are a hot research field. Due to great uncertainties existed in its data processing, multiple target tracking (MTT) has become a difficult problem in distributed sensor networks (DNWs). Hence, this paper mainly studies the uncertainty problems on MTT in the framework of DNW systems by using the fuzzy theory. According to its model structure, a DNW system can be divided into three layers according to its model structure: the data capture layer, data processing layer and data analysis layer. Based on data processing in different layers, the MTT process can be classified as three phrases: data association/fusion of measurement-measurement/sensor track, sensor track-local track, and local track-global track. It presents a complete procedure of data processing on MTT in a real tracking system. Then, the uncertainty problems on MTT are classified. After analyzing data characteristics, one can utilize the fuzzy information processing technology to solve these problems. Finally, the difficulties on MTT in real tracking systems are summarized.

Keywords: *distributed sensor network; information fusion; multiple target tracking; fuzzy information processing*

1. Introduction

In sensor networks, information fusion is used to reduce the uncertainties in tracking process by integrating different information for solving multiple target tracking (MTT) problems, and then one can obtain accurate estimates and correct decisions [1-3]. Because sensor networks can be seemed as a kind of complex information processing systems, and there exist great uncertainties in data inputs, data outputs and data processing at different nodes of these systems. To solve the uncertainty problems of MTT, the traditional tracking methods can be divided into two classes, namely the statistical and fuzzy tracking methods. In tracking processes, generally the statistical theory can be used to describe the whole probability distribution of target trajectories correlated with measurements or estimates in measured space. Unfortunately, because the continuous changes of motion models lead to the uncertainties of statistical characteristics, it is difficult to obtain accurate probability distribution. Moreover, great information in tracking process is hard to be described by statistical mathematics. Hence, these tracking methods based on statistical mathematics usually possess expensive calculation

ISSN: 2005-4297 IJCA

complexities, and they are not suitable for the real-timely processing requirements. Therefore, they are restrained in real situations with inadequate prior information [4-6].

The fuzzy information processing technology is a kind of intelligent information processing methods. They are concise and powerful in processing uncertainty problems. For the uncertainty problems with imprecise and incomplete information, it can provide an effective and accurate mathematical tool [7-11]. In the framework of fuzzy theories, fuzzy mathematics can describe or express different information, and then establish a relationship between them. Hence, it can provide a good thought for solving the uncertainty problems on MTT. To avoid the decrease of tracking methods or improve the quality of their tracking results, some researchers utilize fuzzy mathematics to make the characteristics of motion models and different type of attributes into fuzzy information, and then the fuzzy information is incorporated into tracking methods or fuzzy operators to track methods [12-15]. However, these tracking methods usually aim at single procedure of MTT, and they seldom focus on the whole process in hierarchical systems. For this reason, one can utilize the fuzzy information processing technology to systematically solve the uncertainty problems of MTT in the whole framework of sensor networks.

In real applications, the designs of MTT methods are not only relative with the fusion structure of a sensor network system, but also with the processing performance of each layer's nodes and data characteristics. Furthermore, data characteristics are relative with each node's type and the corresponding data fusion method utilized [16]. Therefore, we firstly analyze the structure model of sensor networks, and then establish a whole data processing flow of MTT. For different phrases of MTT, data characteristics in different nodes are analyzed, and their corresponding uncertainties are classified. Meanwhile, the influences of each node's performance at different layers on the design of MTT methods are analyzed. In addition, the difficulties of MTT in sensor networks are summarized for the characteristics of real tracking systems. Finally, the conclusions are given.

2. Data Processing in Distributed Sensor Networks

A distributed network is a usual structure model in real applications. In system performance, it consumes lower costs to obtain equal or approximate accuracy obtained by a centralized sensor network and even better performance in reliability and availability. In physical structure, it relaxes the requirements of communication bandwidths and processing abilities for a tracking system. In addition, a distributed network can be also classified as the hierarchical and full distributed sensor network (DSW). The former is usually applied in the military domain, and it generally consists of three layers according to the data stream [16, 17]: the data capture layer corresponding to sensor nodes, the data processing layer corresponding to local nodes, and the data analysis layer corresponding to the global node.

As shown in Figure 1, the procedures of data processing in hierarchical sensor network are given as follows: 1) in the data capture layer, each sensor node utilizes measurements to generate sensor tracks after track initialization, measurement-sensor track association and fusion; 2) in data processing layer, each local node utilizes sensor tracks to generate local tracks by sensor track-local track association and fusion; 3) in data analysis layer, the global node utilizes local tracks to generate global tracks and form a uniform situation. In real tracking systems, each node needs to process mass data, including measurements and tracks. In real situations, once a node receives a message, and then processes it immediately. Hence, the system increases the requirement of each node for data processing.

In the view of information fusion, data processing in DSW systems can be regarded as an information fusion process. It can processing multi-source or multi-node information as its inputs, and then utilizes data fusion methods to generate novel and superior information. In the view of signal processing, it is a data processing procedure at different nodes corresponding to different layers. Namely, it utilizes data fusion methods at different nodes to process mass information. In the view of information transmission, it is that information flows from low layers to high layers and meanwhile it becomes newer and better. Hence, the data processing in DSWs is a process of multi-source fusion and refinement, and it is a reasoning process of data-driven from below to above [18].

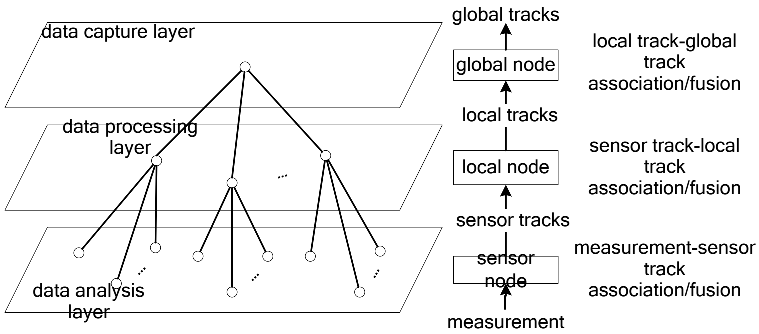


Figure 1. Procedure of Data Processing in DSWs

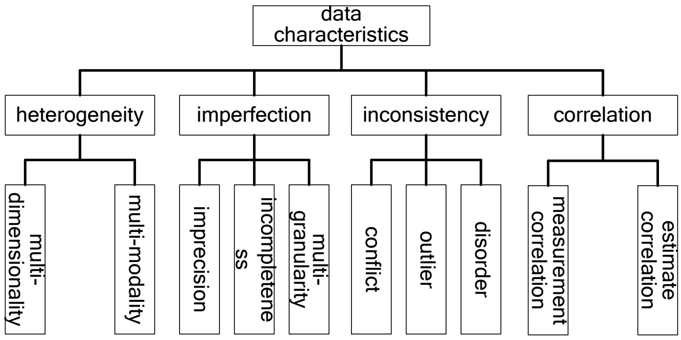


Figure 2. Data Characteristics in Sensor Network

3. Uncertainties Classification in MTT

The uncertainties in MTT can be generally divided into three categories as the uncertainties on observed targets, the uncertainties on measurements and track estimates, and the uncertainties on data processing at each node.

(1) the uncertainties on observed targets

The uncertainties on observed targets include those of target amounts and motion models. The correct amount of moving targets in real tracking situations is hard to obtain, and this leads to the uncertainties of target amounts. When tracking single target at a sensor node, there possibly exist several valid measurements associated with a target, and then one needs to design a rule on measurement-sensor track association. When tracking multiple targets at a sensor node, the designed rule becomes increasingly complicated. At a local node or global node, the amount of target tracks may change at any time, and one needs to design the rule on sensor track-local track association or local track-global track association. In addition, the uncertainties of motion models denotes the trajectory of a moving target changes continuously, and this leads to the complexity of the state equation on the motion model of a target.

(2) the uncertainties on measurements and track estimates

Due to the restraint of the nodes' performance and the environments' prior information, the obtained measurements are unavoidable to incorporate measuring errors and observed noises. The uncertainties on data processing at each node can be divided into three aspects [19]: random errors, system errors, and false errors. According to the structure model of tracking systems, target tracks can be divided into three categories: sensor tracks, local tracks and global tracks. The uncertainties of track data include that of quality and reliability. Considered the sources of local tracks, the performance of nodes and fusion algorithms are different, local tracks generated by different nodes possess unequal quality and reliability.

(3) the uncertainties on data processing at each node

As described above, measurements or tracks generally possess the uncertainties, and the performance of nodes is different. Based on this reason, it leads to the uncertainties of data fusion algorithms designed for different nodes. In real tracking systems, the messages transmitted between two nodes don't include the covariances of estimate errors due to limited bandwidths in battlefields. Hence, the traditional data fusion algorithms are unsuitable in real systems. Meanwhile, the uncertainties of measurements or local estimates destroy the associated relationship of measurement-measurement/sensor track, sensor track-local track, and local track-local track, and it increases the complexity of data fusion algorithms.

4. Uncertainty Analysis in MTT

To realize MTT, one needs to establish the models for different phrases of target tracking, namely data processing at different nodes. Its aim is to obtain the better performance in estimation and decision. Considered the advantages of the fuzzy theory on uncertainty problems, the fuzzy information processing technology is applied to solve the uncertainty problems on MTT in DSWs. The related technologies are given as Figure 3 [16].

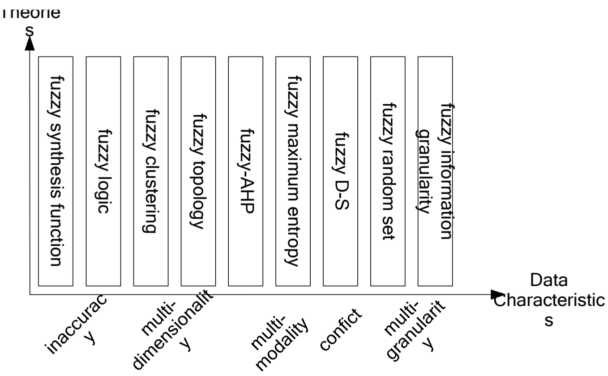


Figure 3. Common Technologies in Fuzzy Information Processing

4.1. Uncertainties in Observed Data

The uncertainties of observed data can be modeled as statistical and fuzzy measurements according to the statistical and fuzzy theories. The uncertainty measures of these two measurements are given as follow [20]:

Definition 1: The uncertainty measure of the *l*th type's statistical measurements at time *k* is defined by:

$$\alpha_k^l = H(p_k^l) / \sigma_k^l \tag{1}$$

Here, σ_k^l and $H(p_k^l)$ denote the standard deviation and the statistical entropy, calculated by

$$\sigma_k^l = \sum_{i=1}^{m} \sqrt{(\mathbf{z}_{i,k}^l - \overline{\mathbf{z}}_{c,k}^l)^{\mathrm{T}} (\mathbf{z}_{i,k}^l - \overline{\mathbf{z}}_{c,k}^l)} \Big/ m\, g_{\mathbf{z}^l} \tag{2}$$

$$H(p_k^l) = -\sum_{i=1}^{m} p_k^l(\mathbf{z}_{k,i}^l) \ln p_k^l(\mathbf{z}_{k,i}^l) \tag{3}$$

where $\mathbf{z}_{k,i}^l$ and $p^l(\mathbf{z}_{k,i}^l)$ denote the ith statistical observation and its statistical probability, $\mathbf{z}_{k,c}^l$ and m_k^l denote the center and the amount of statistical observations, $g_{\mathbf{z}^l}$ is the association gate. In Equation (1), σ_k^l describes the clustering feature, $H(p_k^l)$ describes the distribution of statistical probabilities assigned to the statistical observations.

Definition 2: The uncertainty measure of the lth type's fuzzy measurements at time k is defined by:

$$\tilde{\alpha}_k^l = \tilde{H}(u_k^l) \big/ \tilde{\sigma}_k^l \tag{4}$$

Here, $\tilde{\sigma}_k^l$ and $\tilde{H}(u_k^l)$ denote the standard deviation and the fuzzy entropy, calculated by

$$\tilde{\sigma}_k^l = \sum_{i=1}^{n} \sqrt{(\mathbf{s}_{i,k}^l - \overline{\mathbf{s}}_{c,k}^l)^{\mathrm{T}} (\mathbf{s}_{i,k}^l - \mathbf{s}_{c,k}^l)} \Big/ n\, g_{\mathbf{s}^l} \tag{5}$$

$$\tilde{H}(u_k^l) = -\sum_{i=1}^{n} u_k^l(\mathbf{s}_{i,k}^l) \ln u_k^l(\mathbf{s}_{i,k}^l) \tag{6}$$

where $\mathbf{s}_{k,i}^l$ and $u^l(\mathbf{s}_{k,i}^l)$ denote the ith observation and its membership degree, $\mathbf{s}_c^l(k)$ and n_k^l denote the center and the amount of fuzzy observations, $g_{\mathbf{s}^l}$ is the association gate. In Equation (4), $\tilde{\sigma}_k^l$ describes the clustering feature of the fuzzy observations, $\tilde{H}(u_k^l)$ describes the distribution of membership degrees assigned to the fuzzy observations.

Based on these facts, to process the statistical and fuzzy measurements in a uniform frame, a new additive fusion strategy is proposed as following in [20]:

$$\rho(\mathbf{z}_{i,k}^1, \ldots, \mathbf{z}_{i,k}^m, \mathbf{s}_{i,k}^1, \ldots, \mathbf{s}_{i,k}^n \mid \mathbf{x}_k^t) = \sum_{l=1}^{m} \alpha_k^l p_k^l(\mathbf{z}_{i,k}^l \mid \mathbf{x}_k^t) + \sum_{l=1}^{n} \tilde{\alpha}_k^l u_k^l(\mathbf{s}_{i,k}^l \mid \mathbf{x}_k^t) \tag{7}$$

where $p_k^l(\mathbf{z}_{i,k}^l \mid \mathbf{x}_k^t)$ and $u_k^l(\mathbf{s}_{i,k}^l \mid \mathbf{x}_k^t)$ are the corresponding statistic associated probabilities and fuzzy associated probabilities, m and n are the amounts of statistical and fuzzy measurements, respectively. Hence, the proposed strategy can keep the consistency of tracking results with statistic and fuzzy measurements.

4.2. Uncertainties in Target Motion Model

In maneuvering target tracking, the motion models of targets possess great uncertainties, and meanwhile maneuvering information is also unknown in real applications. To solve the problem of maneuvering target tracking, there exist two thoughts for the above situation: describe a trajectory as several typical motion models with known parameters or their combination or incorporate control variables in the motion equation as the random variables with the certain possibility distribution function. However, the prior information of motion models or the possibility distribution functions of input variables are difficult to obtain real-timely. Due to its universal approximation, fuzzy systems can utilize the simple fuzzy linguistic terms to describe various uncertainties flexibly. Therefore, a good idea is to utilize fuzzy systems to adjust the parameters of tracking filter based on the maneuvering changes of moving targets.

Because data characteristics are generally unknown, the Kalman filter (KF) is limited in real applications. The recursive least squares (RLS) filter doesn't only tracks a moving target with constant velocity, but also possesses small calculated complexity. Unfortunately, its performance seriously degrades when tracking a maneuvering target. A fuzzy RLS filter in [21] describes the maneuvering process as a combination of several different uniform models and utilizes fuzzy systems to adjust the factor. The fuzzy RLS filter can be expressed as:

$$\hat{\boldsymbol{x}}_k = \Phi_k H_k \hat{\boldsymbol{x}}_{k-1} + P_k H_k^{\mathrm{T}} (\boldsymbol{z}_k - H_k \Phi_k \hat{\boldsymbol{x}}_{k-1}) \tag{8}$$

$$P_k = \tilde{\lambda}_k^{-1} \Phi_k P_{k\text{-}1} \Phi_k^{\mathrm{T}} - \tilde{\lambda}_k^{-2} \Phi_k P_{k-1} \Phi_k^{\mathrm{T}} H_k^{\mathrm{T}} (I + \tilde{\lambda}_k^{-1} H_k \Phi_k P_{k\text{-}1} \Phi_k^{\mathrm{T}} H_k^{\mathrm{T}})^{-1} H_k \Phi_k P_{k\text{-}1} \Phi_k^{\mathrm{T}} \tag{9}$$

Here, $\tilde{\lambda}_k$ is the fuzzy fading factor, Φ_k, H_k and P_k are the state transition matrix, observation matrix and covariance matrix of estimate errors, respectively.

Based on this fact, Fan *et al* proposed a probabilistic data association-fuzzy recursive least squares filter (PDA-FRLSF) in [22] and generalized joint data association-fuzzy recursive least squares filter (GJPDA-FRLSF) [20] for single target tracking and multiple target tracking respectively in cluttered environments.

4.3. Uncertainties in Data Processing for Nodes

According to the model structure, one can analyze the uncertainties at different nodes from three respects:

(1) the uncertainties of data processing at sensor node

At sensor node, track initialization (namely measurement-measurement association) is the primary problem in MTT. The track initialization method based on Hough transform (HT-TI) is a representative of batching methods and is widely applied in strong clutter environments. Due to the effects of noises and clutters, track initialization possesses great uncertainties, and it leads to the diffusion of a cumulative function's peaks [23]. Hence, one can utilize the fuzzy cumulative function [23-26] to describe the uncertainties of track initialization:

$$\tilde{F}(\rho_l, \theta_l) = \sum_{t=k}^{k+n-1} \sum_{i,j} u(\rho_{i,t}, \theta_{j,t}),\ (\rho_{i,t}, \theta_{j,t}) \in \sigma(\rho_{l,t}, \theta_{l,t}) \tag{10}$$

Here, $\tilde{F}(\rho_l, \theta_l)$ is the fuzzy cumulative matrix, $u(\rho_i, \theta_j)$ is the membership function, namely

$$u(\rho_i, \theta_j) = \exp\left(-\frac{(\rho_i - \rho_l)^2}{2\sigma_r^2} - \frac{(q_j - q_l)^2}{2\sigma_\beta^2} \right), (r_i, q_j) \in \tilde{\boldsymbol{A}}_l(\rho_l, \theta_l) \tag{11}$$

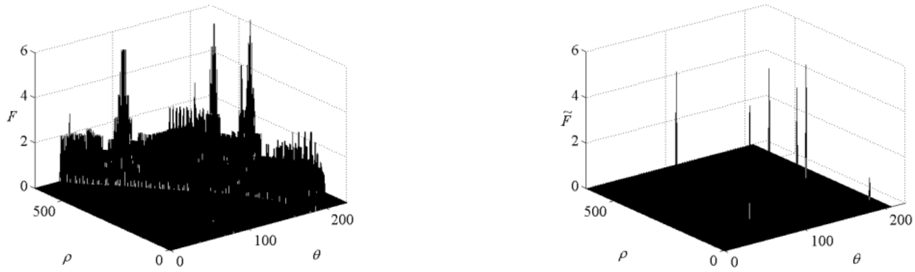
where, σ_r and σ_β are measured errors, the point (ρ_i, θ_j) is the mapping of the measurement $\boldsymbol{z}_l$ in parameter space, $\tilde{\boldsymbol{A}}_l(\rho_i, \theta_j)$ is the fuzzy set. To reduce the uncertainties of detected results, Fan *et al* in [26] incorporate the temporal information of measurement sequences and motion information of moving targets into track detection. Considered the possibilities of the occurrence of new targets generated by the points out the neighbor region, the membership can be further rewrote as

$$u(r_{i,k+1}, q_{j,k+1}) = \begin{cases} \exp\left(-\dfrac{(\rho_i - \rho_l)^2}{2\sigma_r^2} - \dfrac{(q_j - q_l)^2}{2\sigma_\beta^2} \right), (\rho_{i,k+1}, \theta_{j,k+1}) \in \sigma(\rho_{l,k}, \theta_{l,k}) \\ 1, \quad (\rho_{i,k+1}, \theta_{j,k+1}) \notin \sigma(\rho_{l,k}, \theta_{l,k}) \end{cases} \tag{12}$$

Here, $(r_{i,k+1}, q_{j,k+1})$ is the mapping generated at time $k+1$, $\sigma(\rho_{l,k}, \theta_{l,k})$ is the neighbour region of the kernel element $(\rho_{l,k}, \theta_{l,k})$ at time k

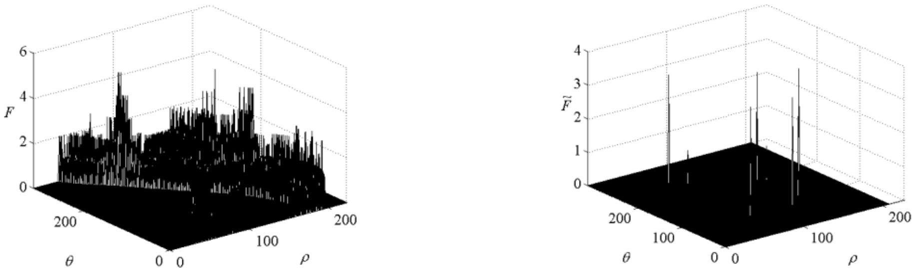
$$\sigma(\rho_l,\theta_l) = [\rho_l - 2\sigma_r, \rho_l + 2\sigma_r] \times [\theta_l - 2\sigma_\beta, \theta_l + 2\sigma_\beta] \quad (13)$$

Figures. 4 and 5 show the detected results in ideal and clutter environments by the HT-TI method and FHT-TI method in [26]. It is can be found that the FHT-HI method doesn't only enhance the peak of the cumulative matrix, but also reduces the calculated complexity.



(a) HT-TI Algorithm (b) FHT-TI Algorithm

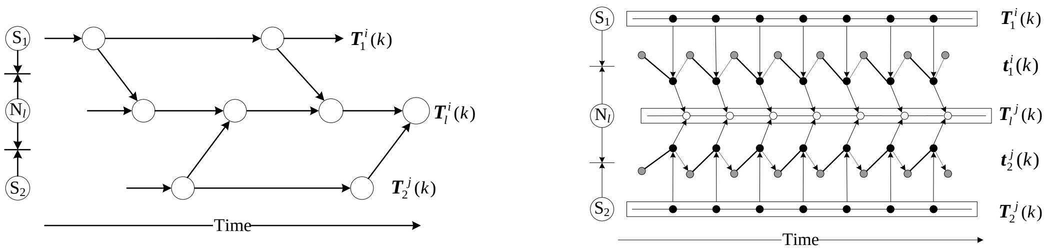
Figure 4. Detected Results in Ideal Situation



(a) HT-TI Algorithm (b) FHT-TI Algorithm

Figure 5. Detected Results in Cluttered Situation

(2) the uncertainties of data processing at local node



(a) structure of sensor track-local track association (b) structure of tracklet-local track association

Figure 6. Structure of Track Association

In real tracking systems, the estimates of local tracks are orderly transmitted from local nodes to the global node by message due to the restraint of communication bandwidth in battlefields. Furthermore, each message only contains single estimate of local tracks. In addition, there exist two types of tracks in local nodes: local tracks utilized for target tracking, tracklets used for updating global tracks. Due to single estimate without the direction information of a moving target, one defines two state estimates of a local track in continuous times as a tracklet in [27] as follow:

$$\boldsymbol{t}_{l,k}^{i} = [\hat{\boldsymbol{x}}_{s,k-1}^{i}, \hat{\boldsymbol{x}}_{s,k}^{i}]^{\mathrm{T}} \quad (14)$$

Here, $\hat{\boldsymbol{x}}_{s,k-1}^{i}$ and $\hat{\boldsymbol{x}}_{s,k}^{i}$ are the state estimates of the sensor track $T_{s,k}^{i}$ at time $k-1$ and k, respectively.

For the above reasons, sensor track-local track association can be real-timely divided into tracklet-local track association, shown as Figure 6. It can reduce the uncertainties in association judgment by increasing information amount in single associated object. Based on this fact, one can map tracklets into the points in parameter space according to Hough transform as follow in [27]:

$$\boldsymbol{p}_{si} = f(\boldsymbol{t}_{s,k}^{i}) = (\rho_{si}, \theta_{si}) \tag{15}$$

Hence, the track association problem can be transformed as that of point distribution. Here, $f(\cdot)$ is the mapping function of the tracklet $\boldsymbol{t}_{s,k}^{i}$ transformed as the point $\boldsymbol{p}_{si}$, ρ_{si} and θ_{si} are the coordinates of the point $\boldsymbol{p}_{si}$. Furthermore, the sequence of tracklets can mapped as a set of points:

$$\{\boldsymbol{p}_{si} \mid (\rho_{si}, \theta_{si}) = f(\boldsymbol{t}_{s,k}^{i}), s = 1, \cdots, n, i = 1, \cdots, n_s\} \tag{16}$$

Then, one utilizes the fuzzy maximum entropy cluttering method to calculate the fuzzy association degree on tracklet-local tracks (or predicted centers).

$$u_{li} = \exp(-\omega_l d(\boldsymbol{p}_i, \boldsymbol{v}_l)) \Big/ \sum_{k=1}^{c} \exp(-\omega_l d(\boldsymbol{p}_i, \boldsymbol{v}_k)) \tag{17}$$

where $\boldsymbol{v}_i = f([\hat{\boldsymbol{x}}_l^i(k-1), \hat{\boldsymbol{x}}_l^i(k \mid k-1)]^{\mathrm{T}})$, and ω_i is the difference factor, which can adjust the membership degree u_{li}.

(3) the uncertainties of data processing at global node

Considered the reliabilities of tracks from different local nodes, firstly one can define the reliabilities of local nodes, and then utilize the fuzzy analytical hierarchy process (AHP) method to calculate them. Based on these facts, a reliability-weighted nearest neighbor track association (wNNTA) method is proposed in [28]. In the proposed method, the association degrees of tracklet-global track can be calculated by:

$$u(\boldsymbol{t}_{l,k}^{i}, \boldsymbol{T}_{0,k}^{j}) = w_l \mu(\boldsymbol{t}_{l,k}^{i}, \boldsymbol{T}_{0,k}^{j}) \tag{18}$$

where, $\boldsymbol{t}_{l,k}^{i}$ is a tracklet, $\boldsymbol{T}_{0,k}^{j}$ is a global track, w_l is a weighted reliability coefficient, μ is the nearest neighbor operator. To solve the uncertainty problem on local estimates, the weighted fuzzy track association (FTA) operator is utilized to replace the nearest neighbor operator [29]:

$$u(M_i) = \sum_{l=1}^{n} a_l d_i(m_l) \tag{19}$$

Here, u and d_i are the fuzzy synthetic function and distance function, M_i is the fuzzy factor set, m_l is the lth factor in the set M_i, a_l is the weight of the factor m_l. In the situation that there exist many types of local nodes and different accuracies of local tracks, the weighted FTA method can increase the weight of tracklets with a larger reliabilities through reliability-weighting, and then improve the performance of fusion results.

5. Difficulties of MTT in real situations

Although the related MTT theories have achieved certain development, there still exist great difficulties in real applications, particularly for sensor networks. According to the characteristics of real tracking systems and related MTT problems, the existing tracking systems generally include two requirements for MTT methods: one is how to improve the rate of data processing for different levels' nodes, and the other is how to improve the performance of tracking results. For the uncertainties in MTT, here list some usual problems:

(1) In data processing of different nodes at the corresponding levels, there exist great uncertainties and relative prior information. Hence, we still need to further study the unit processing methods for different information in tracking systems.

(2) Due to the difference in geographical positions, processing performance and sampling periods for different nodes, we need to develop the track initialization methods for asynchronous measurements under consideration of the influences of different errors.

(3) In real applications, there is great information on relative motion models, how to dig fuzzy rules and adjust the parameters of filters is an urgent problem.

(4) For the situations with unknown qualities of local tracks, how to improve the performance of track fusion is a key issue in sensor networks.

6. Conclusion

Due to the existence of different uncertainties in DSWs, MTT has become a difficult problem in the information fusion field. Considered the framework of a sensor network and its data processing of the whole system, the uncertainties on different phrases of MTT has been fully analyzed and studied by the fuzzy information processing technology, and then the whole processing flow for MTT can be established. Meanwhile, one can further extend the applications of the fuzzy information processing technology in the MTT field. Additionally, for the design of MTT methods, one needs to consider the model structure of sensor networks, the types and performance of different nodes, and the modes of data processing. Based on these, we can design better MTT methods, which are suitable for real tracking systems.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (No. 61301074), the Startup Project of Doctor Science Research of Shaoxing University (No. 20155015), the Science Project of Shaoxing University (No. 2015LG1006), and the Natural Science Foundation of Shenzhen Polytechnic (No. 601522K21017).

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