Identification and Tracking of Multi-group Targets in Circular Formation under Multi-sensor Networks

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***Abstract*—To address the challenges posed by structure identification, data transmission and information fusion in distributed group target tracking, this paper proposes a novel distributed structure identification and tracking algorithm for resolvable group targets with circular formations. The proposed algorithm combines the Joint Probabilistic Data Association algorithm and the K-medoids clustering method within each sensor to estimate all target states and partition them into different subgroups. Then, the circular formation of each subgroup is identified based on its geometric features. In addition, the Consensus on Information is introduced to fuse each local information after matching the states of group targets across multi-sensor networks. Simulation results demonstrate the effectiveness of the proposed algorithm.**

***Index Terms*—Resolvable group target, joint probabilistic data association, circular formation, consensus, multi-sensor networks**

I. Introduction

With the development of sensor technology, multi-sensor information fusion has been widely used in various fields, including the field of group target tracking. A group target usually refers to a group of multiple targets that coordinate their movements or exhibit certain group characteristics.

Multi-group target tracking algorithm can be regarded as an extension of traditional multi-target tracking algorithms, which can be mainly divided into data association based methods and random finite set (RFS) based methods. Among data association based methods, the more commonly used ones are multiple hypothesis tracking (MHT) [1] and joint probabilistic data association (JPDA) [2]. MHT algorithm realizes multi-group target tracking by creating multiple possible target trajectory hypotheses and using measurements to verify and update them. JPDA algorithm uses the measurements in the current scanning period within the tracking threshold to calculate the correlation probability between measurement and the corresponding track, and uses the probabilities to calculate the target state.

Certain algorithms based on RFS do not require data association, because they are not mainly aimed at data association problems, but at seeking for optimal or suboptimal solutions to multi-target states. Mahler proposed a tracking algorithm based on probability hypothesis density [3], and later proposed a standard tracking algorithm based on cardinality probability hypothesis density (CPHD), which improves the tracking accuracy via effective situation assessment of targets [4]. Generalized labeled multi-Bernoulli (GLMB) filter can label the states and generate the target tracks while estimating the target states [5]. Labeled multi-Bernoulli (LMB) filter is proposed to reduce the computational complexity of GLMB [6], which can also obtain better tracking accuracy than CPHD algorithm under multi-group target tracking situations [7].

As for group targets with resolvable characteristics, JPDA algorithm not only considers the data association between measurements and tracks, but also holds better interpretability in environments with clutters and allows for a distributed algorithm with less communication overhead [8], making it easier to perform data association and information fusion under multi-sensor networks. Therefore, in this article, the JPDA algorithm will be used for data association and state estimation.

In addition, since group targets sometimes need to maintain a certain group structure in the process of moving, more accurate tracking results can be obtained if the constraint information is taken into account. By using the estimation projection method [9], Hao et al. achieved the structural identification and formation estimation of circular formation based on the local estimates obtained by a single sensor using LMB algorithm [10], thereby gaining better tracking accuracy. However, this study only focuses on the circular formation with a central group member under single sensor system, and was not extended to more group structures.

Multi-sensor fusion in wireless sensor networks generally refers to the process of combining sensory data, e.g., position, range, bearing angle, time of arrival, etc, from several local sensor nodes, such that the resulting perception is in some sense better than when these sensors are used individually for sensing [11]. In multi-sensor fusion methods, the distributed fusion can obtain better robustness against sensor failure and gain better flexibility while lowering the communication burden. In the distributed fusion algorithms, consensus [12] based estimator can be a powerful tool to guarantee global convergence, which has two existing approaches: consensus on information (CI) [13], [14] and consensus on measurements (CM) [8], [15], [16]. A CI based algorithm, called distributed cubature information filtering, is proposed in [14] by performing average consensus on information vectors and matrices. The algorithm not only has advantages such as easy initialization and less computation burden, but also possesses the guaranteed stability regardless of consensus steps. For the combination of consensus filtering and data association algorithm, Sandell et al. proposed a distributed data association for multi-target tracking in sensor networks for linear systems based on JPDA and CM approach [8]. Chen et al. proposed a multi-target square-root cubature information weighted consensus filter [16], which reduces the effect of clutter by using JPDA and CM approach, and gets better accuracy and stability than conventional multi-target tracking algorithms. However, CI guarantees the stability for any number of consensus steps while CM does not unless the number of consensus steps is sufficiently high [17]. In order to obtain better stability and achieve global convergence of group target tracking as quickly as possible, this paper combines CI to achieve multi-sensor consensus filtering.

To sum up, the motivations of this paper are as follows: the current circular formation constraint algorithm is only based on the assumption that there is a central member in each group, hence its application scenarios are limited; multi-sensor fusion can improve target tracking accuracy greatly, and there are few researches on circular formation group target tracking under multi-sensor networks, which needs to be further studied.

In this paper, we propose a novel distributed structure identification and tracking algorithm for resolvable group targets with circular formations under multi-sensor networks. Firstly, JPDA and K-medoids are used to obtain local group target estimation results. Then a structure identification method is constructed based on the geometric features of each subgroup, and circular formation constrained estimation algorithm is introduced to obtain more accurate tracking results for targets in circular formations with and without central members. Subsequently the predicted estimation information is considered, and the multi-sensor fusion method, namely CI, is introduced based on the state matching results of each sensor. Finally, a high-precision fusion estimation and group structure identification results are obtained.

This paper is organized as follows. Section II formulates the system model and the circular formation characteristic. Section III presents the circular formation identification and tracking algorithm for group targets with and without central members under multi-sensor networks. Section IV demonstrates a simulated example that proves the effectiveness of the proposed algorithm, and Section V concludes the paper.

II. Problem Formulation

A. System Model

This section builds the system model on the basic linear system. Consider a multi-sensor network with N sensors, in which each sensor can obtain measurements of targets at the current time, and exchange information with neighboring nodes. Assuming there is a multi-group target scene in the sensor detection range, and the motion model of the i-th target at time $k+1$ can be considered as

$$x_i\left(k+1\right) = F\left(k\right)x_i\left(k\right) + w_i\left(k\right) \tag{1}$$

where $x_i\left(k\right)$ is the state vector of the i-th target at time k, $F\left(k\right)$ is the state transition matrix at time k, and $w_i\left(k\right)$ is a zero-mean Gaussian noise with covariance matrix Q_i.

The linear sensing model made by the n-th sensor node for the i-th target at time k can be written as

$$z_i^n\left(k\right) = H^n x_i\left(k\right) + v^n\left(k\right) \tag{2}$$

where H^n is the observation matrix, and $v^n\left(k\right)$ is a zero-mean Gaussian measurement noise with covariance R^n.

B. Circular Formation

With reference to the target state characteristics in the circular formation in practice, the following expression can be obtained [10]

$$\left\| M_i x_{i,s}^n\left(k|k\right) - M_c \bar{x}_s^n\left(k\right)\right\|^2 = d_s^n\left(k\right)^2 \tag{3}$$

where $x_{i,s}^n\left(k|k\right)$ indicates the state estimation result of the i-th target from the s-th group on the n-th sensor node at time k, and $\bar{x}_s^n\left(k\right)$ indicates the state of the central member in the group, regardless of its existence. M_i and M_c are matrices help get target positions. $d_s^n\left(k\right)$ is a structure parameter that represents the radius of the s-th circular formation subgroup that needs to be calculated.

III. Group Targets Identification and Tracking Algorithm

In this section, we propose a new circular formation identification and tracking algorithm for group targets with and without a central member by combining the CI method under multi-sensor networks.

At each time instant k, the JPDA algorithm is firstly used to calculate the state of each target based on the measurements obtained by each sensor. Here, we briefly review the basic procedure of JPDA algorithm.

Assuming that the scene contains $m_t(k)$ targets in total at time k, the state and covariance prediction of target $i \in \{1,\ldots,m_t(k)\}$ at time $k+1$ on sensor n are calculated as follows

$$x_i^n(k+1|k) = F(k)x_i^n(k|k) \tag{4}$$

$$P_i^n(k+1|k) = F(k)P_i^n(k|k)[F(k)]^{\mathrm{T}} + Q_i \tag{5}$$

Accordingly, given that at time $k+1$, the n-th sensor node obtains $m_z(k+1)$ measurements: $Z^n(k+1) = \left\{z_1^n(k+1), z_2^n(k+1), \cdots, z_{m_z(k+1)}^n(k+1)\right\}$. By setting

$$V_i^n(k+1) = \sum_{\gamma=0}^{m_z(k+1)} \beta_{i,\gamma}^n V_{i,\gamma}^n(k+1) \tag{6}$$

$$V_{i,\gamma}^n(k+1) = z_\gamma^n(k+1) - H^n x_i^n(k+1|k) \tag{7}$$

in which $V_{i,\gamma}^n(k+1)$ indicates the innovation vector of target i for the γ-th measurement, and $V_i^n(k+1)$ indicates the innovation vector of target i after considering all measurements. $\beta_{i,\gamma}^n$ represents the probability of association between γ-th measurement and target i on sensor n, and $\beta_{i,0}^n$ represents the probability that no measurement is associated with target i on sensor n, then the state estimation can be updated as

$$x_i^n(k+1|k+1) = x_i^n(k+1|k) + K_i^n(k+1)V_i^n(k+1) \tag{8}$$

where $K_i^n(k+1)$ indicates the Kalman gain. The corresponding covariance is given by

$$\begin{aligned} P_i^n(k+1|k+1) = P_i^n(k+1|k) - (1-\beta_{i,0}^n) \\ \times K_i^n(k+1)S_i^n(k+1)[K_i^n(k+1)]^{\mathrm{T}} \\ + K_i^n(k+1)\tilde{V}_i^n(k+1)[K_i^n(k+1)]^{\mathrm{T}} \end{aligned} \tag{9}$$

in which

$$\begin{aligned} \tilde{V}_i^n(k+1) = \sum_{\gamma=1}^{m_z(k+1)} \beta_{i,\gamma}^n V_{i,\gamma}^n(k+1)[V_{i,\gamma}^n(k+1)]^{\mathrm{T}} \\ - V_i^n(k+1)[V_i^n(k+1)]^{\mathrm{T}} \end{aligned} \tag{10}$$

For the sake of brevity, explicit expressions for $K_i^n(k+1)$ and $S_i^n(k+1)$ can be found in [2].

According to the estimation results obtained by JPDA algorithm, a novel K-medoids algorithm from [18] is used to divide multi-group targets into several subgroups. Then, on the basis of each group, the subsequent structure identification, circular constraint and multi-sensor data matching and fusion work can be carried out.

A. Structure Identification

After obtaining the target states and clustering result, the estimation result of the i-th target from the s-th group on sensor n at time k can be denoted as $x_{i,s}^n(k|k)$. Since the circular formation constraint only applies to the corresponding group structure, in order to avoid introducing wrong structure information to the subgroup, the structure identification of each subgroup should be carried out before circular formation constraint, and only the subgroups conform to (3) should be solved. In order to further expand the applicability of circular formation constraint algorithm, two kinds of circular formations are discussed here.

For the s-th subgroup whose structure is unknown and consists of m_s targets, its state estimate result on sensor n can be expressed as

$$X_s^n(k) = \left[x_{1,s}^n(k|k), x_{2,s}^n(k|k), \cdots, x_{m_s,s}^n(k|k)\right]^{\mathrm{T}} \tag{11}$$

By averaging the target states in the group, we obtain the center of the group as

$$\bar{x}_s^n(k) = \frac{1}{m_s}\sum_{j=1}^{m_s} x_{j,s}^n(k|k) \tag{12}$$

Then calculate the distance between each member and the center of the group

$$D_s(i,c) = \left\|M_i x_{i,s}^n(k|k) - M_c \bar{x}_s^n(k)\right\|^2 \tag{13}$$

in which $M_i = M_c = \begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 0 & 1 & 0\end{bmatrix}$, since here only consider the position and velocity information of the target in a two-dimensional space. For $i = 1, 2, \cdots, m_s$, considering a predetermined threshold d_e. If $\exists D_s(i,c) \le d_e$, we make the $x_{i,s}^n(k|k)$ that achieves the smallest $D_s(i,c)$ the central member, and set $\bar{x}_s^n(k) = x_{i,s}^n(k|k)$, then we have

$$X_s^n(k) = \left[\bar{x}_s^n(k), x_{2,s}^n(k|k), \cdots, x_{m_s,s}^n(k|k)\right]^{\mathrm{T}} \tag{14}$$

in which $X_s^n(k) \in \mathbb{R}^{4m_s \times 1}$. If $\forall D_s(i,c) > d_e$, we consider that the subgroup has no group center. In this case, we use any three target positions that are not collinear in the subgroup, connect them in pairs and calculate the perpendicular bisector for each line, and set the intersection of perpendicular bisector as the virtual center $\bar{x}_s^n(k)$. Then we have

$$X_s^n(k) = \left[\bar{x}_s^n(k), x_{1,s}^n(k|k), \cdots, x_{m_s,s}^n(k|k)\right]^{\mathrm{T}} \tag{15}$$

in which $X_s^n(k) \in \mathbb{R}^{4(m_s+1)\times 1}$.

At this time, it is still difficult to distinguish whether the subgroup conforms to the circular formation, so a cost function representing the error between different members and the central member is proposed as follow

$$J_s(k) = \sum_{i,j=2,i\neq j}^{m_s} \left\|D_s(i,c) - D_s(j,c)\right\|^2 \tag{16}$$

If the structure of the s-th subgroup conforms to the circular formation, in the ideal case, it should be true that $D_s(i,c) = D_s(j,c) = d_s^n(k)^2$, which means the cost function $J_s(k) = 0$. If in the presence of noise, since the value of the cost function $J_s(k)$ should be relatively small and proportional to the number of members in the s-th subgroup, the following method is constructed

$$\begin{cases} J_s(k) \le m_s T_e & \Rightarrow \quad C_s(k) = 0 \\ J_s(k) > m_s T_e & \Rightarrow \quad C_s(k) = 1 \end{cases} \tag{17}$$

in which T_e is a predetermined parameter, and $C_s(k) = 1$ and $C_s(k) = 0$ represent the subgroup does and does not conform to the circular formation. If the subgroup conforms to the circular formation structure, which means $C_s(k) = 1$, then the constrained estimation can be applied on it.

B. Circular Formation Constraint

In this section, we take a subgroup with central member as an example, and for the subgroups without central group member, the parameters can be adjusted according to the estimation result $X_s^n(k)$.

For the s-th group that conforms to circular formation, there is $X_s^n(k) = \left[\bar{x}_s^n(k), x_{2,s}^n(k|k), \cdots, x_{m_s,s}^n(k|k)\right]^{\mathrm{T}}$. According to the estimation projection method, the following form can be obtained

$$\begin{aligned}&\hat{X}_s^n(k) = \arg\min_{X_s^n(k)} \frac{1}{2}\left\|X_s^n(k) - \hat{X}_s^n(k)\right\|^2 \\ &s.t. \left\|G_j X_s^n(k)\right\|^2 = d_s^n(k)^2, j = 2, 3, \cdots, m_s\end{aligned} \tag{18}$$

in which G_j means the first part in the matrix is $G_j^1 = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 \end{bmatrix}$, the j-th part $G_j^j = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$, and the rest are all zero matrix. For (18), after using the Lagrange multiplier method [19], the equation could be transformed as

$$\begin{aligned}\Gamma\left(X_s^n(k), \lambda, d_s^n(k)\right) = \frac{1}{2}\left\|X_s^n(k) - \hat{X}_s^n(k)\right\|^2 \\ + \sum_{i=2}^{m_s} \lambda_i \left(\left\|G_j X_s^n(k)\right\|^2 - d_s^n(k)^2\right)\end{aligned} \tag{19}$$

By solving (19), we obtain the following formations

$$X_s^n(k) = \left(I + \sum_{i=2}^{m_s} \lambda_i G_i^{\mathrm{T}} G_i\right)^{-1} \hat{X}_s^n(k) \tag{20}$$

$$l_1 = -2\sum_{i=2}^{m_s} \lambda_i d_s^n(k) \tag{21}$$

$$l_j = \left\|G_j \left(I + \sum_{i=2}^{m_s} \lambda_i G_i^{\mathrm{T}} G_i\right) \hat{X}_s^n(k)\right\|^2 - d_s^n(k)^2 \tag{22}$$

where $j = 2, 3, \cdots, m_s$, and I stands for identity matrix. In order to solve (21) and (22), Newton iteration method [19] is used to obtain the following iteration form

$$D^{t+1} = D^t - \left[L'\left(D^t\right)\right]^{-1} L\left(D^t\right) \tag{23}$$

in which t represents the number of iterations, and

$$D^{t+1} = \left[d_s^{n,t+1}(k), \lambda_2^{t+1}, \cdots, \lambda_{m_s}^{t+1}\right]^{\mathrm{T}} \tag{24}$$

$$D^t = \left[d_s^{n,t}(k), \lambda_2^t, \cdots, \lambda_{m_s}^t\right]^{\mathrm{T}} \tag{25}$$

$$L = \left[l_1, l_2, \cdots, l_{m_s}\right]^T \tag{26}$$

The Jacobian matrix can be written by

$$\left[L'\left(D^t\right)\right]^{-1} = \begin{bmatrix} \frac{\partial l_1}{\partial d_s^n(k)} & \frac{\partial l_1}{\partial \lambda_1} & \cdots & \frac{\partial l_1}{\partial \lambda_{m_s}} \\ \frac{\partial l_2}{\partial d_s^n(k)} & \frac{\partial l_2}{\partial \lambda_1} & & \frac{\partial l_2}{\partial \lambda_{m_s}} \\ \vdots & & \ddots & \vdots \\ \frac{\partial l_{m_s}}{\partial d_s^n(k)} & \frac{\partial l_{m_s}}{\partial \lambda_1} & \cdots & \frac{\partial l_{m_s}}{\partial \lambda_{m_s}} \end{bmatrix} \tag{27}$$

For $i = 2, 3, \cdots, m_s$ and $j = 2, 3, \cdots, m_s$, the derivatives of each element in D are, respectively,

$$\frac{\partial l_1}{\partial d_s^n(k)} = -2\sum_{i=2}^{m_s} \lambda_i \tag{28}$$

$$\frac{\partial l_1}{\partial \lambda_i} = \frac{\partial l_j}{\partial d_s^n(k)} = -2 d_s^n(k) \tag{29}$$

$$\frac{\partial l_j}{\partial \lambda_i} = -\phi^T\left(\eta_1 + \eta_2\right)\phi \tag{30}$$

in which

$$\phi = \left(I + \sum_{i=2}^{m_s} \lambda_i G_i^{\mathrm{T}} G_i\right)^{-1} \hat{X}_s^n(k) \tag{31}$$

$$\eta_1 = G_i^{\mathrm{T}} G_i \left(I + \sum_{i=2}^{m_s} \lambda_i G_i^{\mathrm{T}} G_i\right)^{-\mathrm{T}} G_j^{\mathrm{T}} G_j \tag{32}$$

$$\eta_2 = G_j^{\mathrm{T}} G_j \left(I + \sum_{i=2}^{m_s} \lambda_i G_i^{\mathrm{T}} G_i\right)^{-1} G_i^{\mathrm{T}} G_i \tag{33}$$

To solve (23), the initial value of $d_s^n(k)$ is set by $\frac{1}{m_s}\sum_{i=2}^{m_s}\left\|M_i x_{i,s}^n(k|k) - M_c \bar{x}_s^n(k)\right\|^2$, and the stop condition of iteration is set by the threshold τ. When $\left\|D^{t+1} - D^t\right\|^2 \leq \tau$, the iteration terminates.

After the iteration, the obtained $d_s^n(k)$ is the radius of subgroup s at time k, and $X_s^n(k)$ contains the modified estimation result of each target in subgroup s.

C. Multi-sensor Fusion Based on CI

After the previous sections, we obtained the modified tracking results on each sensor at time k, and therefore the predicted target states at time $k+1$ can be calculated. On the premise that each sensor node can exchange information with its neighbor nodes, CI approach can be used in the prediction period in order to exploit the distributed information spread through the network so as to obtain better tracking accuracy.

Let us assume that, at time k, each node n in multi-sensor network can provide local estimate results to other nodes, which contains the target state and covariance. Before the consensus step, data matching should be carried out. The steps are as follows: First, the K-medoids algorithm is used for the central members' coordinates of all the subgroups obtained at time k. By setting the number of clusters as the number of sensors in the sensor network, we can divide the estimation results of the same subgroup into the same cluster. Then for target states in the same subgroup, Munkres' algorithm [20] is used here to match the estimation results on each sensor that may represent the same target by introducing Jensen-Shannon (JS) divergence. After the matching step, the procedure of CI-based multi-sensor fusion algorithm can be constructed.

According to the local estimate results obtained by JPDA for each sensor such as $\left\{x_{i,s}^n(k|k), P_{i,s}^n(k|k)\right\}$, the corresponding information matrix and information vector are calculated by

$$\Omega_{i,s}^n(k|k) = \left[P_{i,s}^n(k|k)\right]^{-1} \tag{34}$$

$$q_{i,s}^n(k|k) = \Omega_{i,s}^n(k|k)\, x_{i,s}^n(k|k) \tag{35}$$

By setting $W_{i,s} = Q_{i,s}^{-1}$, at time $k+1$, the predicted information matrix and vector of the i-th target in the s-th subgroup on sensor node n can be calculated as follows

$$\Omega_{i,s}^{n}\left(k+1|k\right) = W_{i,s} - W_{i,s}F\left(k\right)\left[\varphi_{i,s}^{n}\left(k\right)\right]^{-1}\left[F\left(k\right)\right]^{\mathrm{T}}W_{i,s} \tag{36}$$

$$q_{i,s}^{n}\left(k+1|k\right) = \Omega_{i,s}^{n}\left(k+1|k\right)x_{i,s}^{n}\left(k+1|k\right) \tag{37}$$

where

$$\varphi_{i,s}^{n}\left(k\right) = \Omega_{i,s}^{n}\left(k|k\right) + \left[F\left(k\right)\right]^{\mathrm{T}}W_{i,s}F\left(k\right) \tag{38}$$

and $x_{i,s}^{n}\left(k+1|k\right)$ can be calculated according to (4). In order to simplify the statement, for each sensor node n at the beginning of the consensus step, we first set

$$\Omega_{i,s}^{n,(0)} = \Omega_{i,s}^{n}\left(k+1|k\right) \tag{39}$$

$$q_{i,s}^{n,(0)} = q_{i,s}^{n}\left(k+1|k\right) \tag{40}$$

For $\alpha = 0, 1, \cdots, A$, while A indicates the consensus step, we obtain

$$\Omega_{i,s}^{n,(\alpha+1)} = \sum_{\varsigma\in\mathcal{N}^{n}} \pi_{n,\varsigma}\Omega_{i,s}^{\varsigma,(\alpha)} \tag{41}$$

$$q_{i,s}^{n,(\alpha+1)} = \sum_{\varsigma\in\mathcal{N}^{n}} \pi_{n,\varsigma}q_{i,s}^{\varsigma,(\alpha)} \tag{42}$$

where $\mathcal{N}^{n}$ indicates a set of nodes containing node n and all the neighbor nodes of node n. The consensus weights $\pi_{n,\varsigma}$ are calculated according to the Metropolis rule, i.e.,

$$\pi_{n,\varsigma} = \begin{cases} \left(1+\max\left\{b_{n}, b_{\varsigma}\right\}\right)^{-1} & \text{if} \quad \varsigma\in\mathcal{N}^{n}\setminus\{n\} \\ 1-\sum_{\varsigma'\in\mathcal{N}^{n}}\pi_{n,\varsigma'} & \text{if} \quad n=\varsigma \\ 0 & \text{otherwise} \end{cases} \tag{43}$$

in which b_n and b_ς indicate the number of neighbor nodes connected to sensor n and sensor ς.

After the multi-sensor fusion algorithm, the predicted results on each sensor at time $k+1$ can be used to conduct data association and filtering estimation using JPDA algorithm. Then the structure identification and constraint can be carried out again in order to detect the change of subgroup formations and improve the tracking accuracy.

To sum up, the process of the proposed algorithm in this paper is shown in Fig. 1.

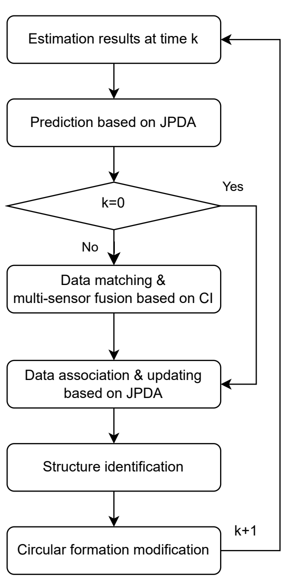

Fig. 1: The process of the proposed algorithm

IV. Numerical Simulation

In this section, an example of multi-group target tracking is presented to verify the proposed algorithm. Consider a scenario where there are three subgroups in the monitoring region $[-10000, 10000] \times [-10000, 10000]\, m^2$, in which subgroup 1 and subgroup 2 are circular formations without central member, and subgroup 3 is circular formation with a central member. The structure of three subgroups is shown in Fig. 2. The multi-sensor network contains 6 sensors, and the node connection is shown in Fig. 3. The radius of each subgroup is $d_1(0) = 80m$, $d_2(0) = d_3(0) = 100m$, which remain unchanged during tracking. The initial state of the center (or virtual center) of each subgroup is $\bar{x}_1(0) = [8000, -150, -5000, 0]^{\mathrm{T}}$, $\bar{x}_2(0) = [9000, -100, 9000, -100]^{\mathrm{T}}$, $\bar{x}_3(0) = [-6000, 100, -6000, 150]^{\mathrm{T}}$.

Clutter is uniformly distributed over the surveillance region with $\lambda_c = 50$. Other parameters' symbols and values are shown in Table I.

In this section, the effectiveness of circular formation constraint is mainly discussed, thus the group members are set strictly in accordance with the circular structure.

The average position root mean square error (RMSE) of all targets obtained by JPDA algorithm [2], constrained filter and the proposed algorithm over 100 Monte Carlo (MC) runs are shown in Fig. 4, where constrained filter represents the proposed algorithm without executing consensus on information. As shown in Fig. 4, compared with JPDA algorithm, the constrained filter reduces the average RMSE of all tracking targets on each sensor to basically the same extent. And the proposed algorithm further improves the average tracking

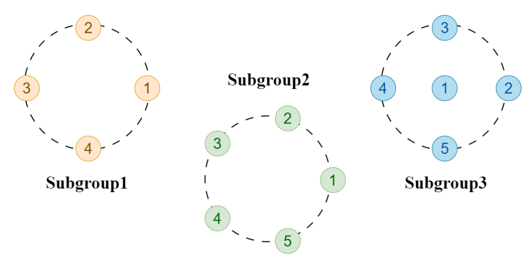

Fig. 2: The structure of three subgroups

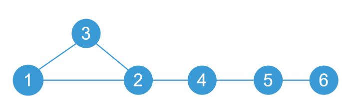

Fig. 3: Communication topology of the example sensor network

TABLE I: Parameter Settings

Parameter	Symbol	Value
Sampling period (s)	d_t	2
Detection probability	P_d	1
Measurement noise covariance (m)	R^n $(n = 1, \cdots, 6)$	$R^1 = \begin{bmatrix}100 & 0\\ 0 & 100\end{bmatrix}$ $R^2 = \begin{bmatrix}50 & 0\\ 0 & 100\end{bmatrix}$ $R^3 = \begin{bmatrix}64 & 0\\ 0 & 100\end{bmatrix}$ $R^4 = \begin{bmatrix}150 & 0\\ 0 & 150\end{bmatrix}$ $R^5 = \begin{bmatrix}144 & 0\\ 0 & 90\end{bmatrix}$ $R^6 = \begin{bmatrix}88 & 0\\ 0 & 169\end{bmatrix}$
State transition matrix	$F(k)$	$\begin{bmatrix}1 & d_t & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & d_t\\ 0 & 0 & 0 & 1\end{bmatrix}$
Measurement matrix	H^n $(n = 1, \cdots, 6)$	$\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 0 & 1 & 0\end{bmatrix}$
Initial value of covariance matrix	$P(0)$	$I \otimes \begin{bmatrix}100 & \frac{100}{d_t}\\ \frac{100}{d_t} & \frac{200}{d_t^2}\end{bmatrix}$
Group center detection threshold (m)	d_e	10^3
Circular formation identification threshold (m)	T_e	0.9×10^8
Iteration termination threshold	τ	0.01
Consensus step	A	2

accuracy to varying degrees according to the connections between sensors.

The RMSE of structure parameter d_1, d_2 and d_3 for each subgroup obtained by constrained filter and proposed algorithm over 100 MC runs are shown in Fig. 5, which shows that by combining multi-sensor fusion algorithm, the proposed algorithm can effectively reduce the RMSE of structure parameters for each subgroup.

The tracking accuracy of the constrained consensus filter is also affected by the consensus step A. By averaging the average position RMSE of targets in multi-sensor network, the effect of tracking accuracy changing with consensus step A is shown in Fig. 6. However, while the average tracking accuracy in multi-sensor network improves as the consensus step increases, the computational and communication burden increases as well. Hence, the consensus step should be selected appropriately.

V. Conclusion

This paper proposes a novel distributed structure identification and tracking algorithm for resolvable group targets with circular formation. Based on JPDA algorithm, this algorithm modifies the target results in circular formations with and without central members using circular formation identification and constrained estimation algorithm. According to the targets matching results between sensors, CI approach is leveraged to

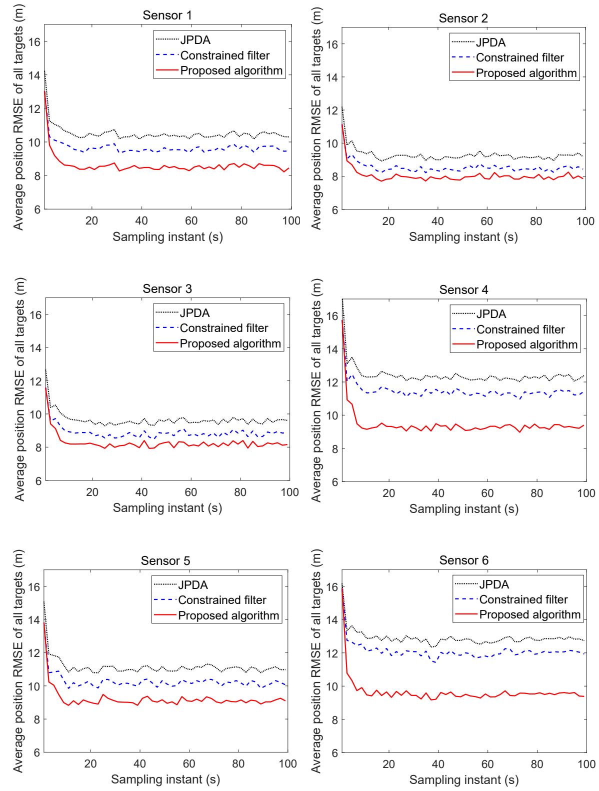

Fig. 4: Average position RMSE of all targets

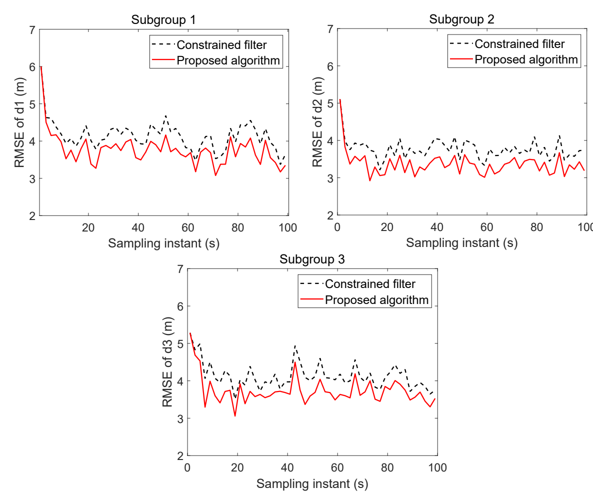

Fig. 5: RMSE of structure parameter for each subgroup

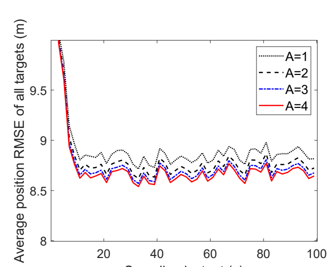

Fig. 6: Tracking accuracy with different consensus step A

reach agreement on estimation information over the distributed sensor network,thereby obtaining better tracking results. The simulation results show that the proposed algorithm can improve the accuracy of multi-group target tracking, and achieve better structure parameter estimation.

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