Multiple Group Target Tracking with Evolving Networks and Labeled Box Particle PHD Filter

Xuan Cheng, Liping Song, Zhibin Zou

Dept. of Electronic Engineering, Xidian University, Xi'an 710071
E-mail: chengxuanxd@163.com, lpsong@xidian.edu.cn, zbzou@stu.xidian.edu.cn

Abstract: This paper proposes a novel multiple group target tracking algorithm based on evolving networks and Labeled Box Particle Probability Hypothesis Density (LBP-PHD) filter. Firstly, it uses evolving networks to build group dynamic model. Secondly, LBP-PHD filter is proposed to estimate the number of targets and the targets state set. Adding different label to different box particle, it has ability to differentiate different tracks. Next, it uses established group dynamic models to update the group structure and estimate the number and the state set of group. Finally, it feeds group information back to the LBP-PHD filter's iterative process. The simulation results show that the proposed algorithm has a better performance in estimating precision and maintaining trajectory.

Key Words: group target tracking; evolving networks; labeled box particle filter; PHD filter

1 INTRODUCTION

In recent years, there has been an increasing interest in group targets tracking because of its significant role in military and civilian fields. The group targets are composed of a number of objects moving in a coordinated and interacting fashion [1]. Different from multiple targets, the group targets can get many measurements, even if one target only produces one measurement. According to the character of the group targets, multiple targets in a group should be seen as a whole. That is to say, a group can produce more than one measurement. Thus the conventional algorithms based on the assumption that one target only gives one measurement are no longer valid.

Gaussian Mixture Probability Hypothesis Density (GM-PHD) filter is used to track group targets under the linear condition [2]. In [3], Koch uses group centroid and its diffusion shape to describe the whole state of group, and proposes a new group targets tracking algorithm based on the classic Bayesian framework. But, the algorithm has not considered the clutter and only can realize a single group target tracking. Baum et al use elliptic random hypersurface model to model the measurements source and describe every group as an ellipse [4]. Combined with the random hypersurface theory, Zhang et al propose a GM-PHD filter for group targets tracking based on elliptic random hypersurface model in the literature [5]. In [6], the authors propose a partly resolvable group target tracking algorithm using SMC-PHD and realize the tracking of the centroid and shape of the group targets. However, the group structure information has not been mentioned in most algorithms above.

In [7], an evolving networks model is introduced for group targets, which can describe the merging, splitting and other motion patterns of groups well. But, it uses the traditional Joint Probabilistic Data Association (JPDA) algorithm to execute data association, so it can't handle the situation that the number of targets changes. What's more, particle filtering is used to estimate the state of the group targets in the algorithm, it can lead to a large operation load. In view of these problems, the literature [8] proposes a Box Particle Probability Hypothesis Density (BP-PHD) group targets tracking algorithm based on the evolving networks model. Compared with SMC-PHD group targets tracking algorithm, it greatly reduces the number of particles and decreases the amount of computation. And it also can deal with the varied number of targets. Unfortunately, it lacks the ability to distinguish different tracks from different groups and it is also easily affected by the instability of clustering. It inspires us to add labels to box particles and realize PHD filter based on labeled box particle.

In this paper, evolving networks model is used to establish group dynamic model and update the group structure. LBP-PHD filtering algorithm based on Random Finite Set (RFS) is proposed to estimate the number of targets and the targets state. And further, the number of group and the group state can be obtained. At the same time, it can also differentiate the tracks of targets.

2 EVOLVING NETWORKS MODEL

Group target tracking includes two aspects. One is to estimate the motion state of individual target in a group, the other is to describe the interaction relationship among different targets in a group. The evolving networks model uses the vertices to represent different targets, and uses the edges to represent the relationship among different targets. Thus, the group structure can be denoted by a graph $\boldsymbol{G}$ [7].

Consider N targets composing the set of vertices $\boldsymbol{V}=\{\boldsymbol{v}_1,\cdots,\boldsymbol{v}_N\}$, the relationship among different targets is represented by the edges denoted by $\boldsymbol{E}(i,j)=(\boldsymbol{v}_i,\boldsymbol{v}_j)$.Each vertex $\boldsymbol{v}_i$ is associated with the target state $\boldsymbol{x}_i$ and its corresponding variance $\boldsymbol{P}_i$. Then,

This work is supported by National Nature Science Foundation under Grant No. 61372003

the whole group structure can be denoted by $G = (\{v_1, \cdots, v_N\}, E)$. In order to quantitatively describe the presence or absence of an edge between two nodes, we calculate the Mahalanobis distance $d_k(i,j)$ which is computed from the estimated positions and the velocities of the targets between these two considered nodes and evaluate whether it exceeds a chosen decision threshold ε. If $d_k(i,j) \langle \varepsilon$, then $(v_i, v_j) \in E$. That means these two nodes are connected. In this representation, a group corresponds to a connected component of the graph structure. So the group structure also can be denoted by $G = \{g_1, \cdots, g_{n_G}\}$, where the group g_i are the connected components of G and n_G is the number of groups in G. In a word, the aim is to determine an evolution model $G_k = f(G_{k-1}, X_k)$ for group structure, where the vector $X_k = \{x_{k,1}, \cdots, x_{k,N}\}$ contains the state vectors of all the targets and f denotes the proposed evolution model.

In order to express more intuitively the relationship among every target in a group, the group information can be saved into an adjacency matrix. And it can be calculated by the following equation:

$$A_k = \begin{bmatrix} 0 & a_k(1,2) & \cdots & a_k(1,N_k) \\ a_k(2,1) & 0 & \cdots & a_k(2,N_k) \\ \vdots & \vdots & \ddots & \vdots \\ a_k(N_k,1) & a_k(N_k,2) & \cdots & 0 \end{bmatrix} \quad (1)$$

Where $a_k(i,j)$ is computed as follows:

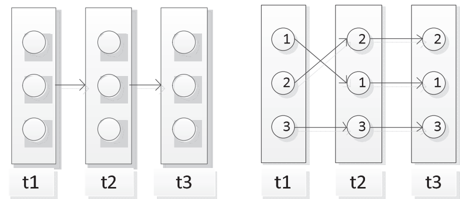
$$a_k(i,j) = \begin{cases} 1, d_k(i,j) \le \varepsilon, i \ne j \\ 0, \quad otherwise \end{cases} \quad (2)$$

Thus, the group structure estimation can be achieved by calculating a symmetric adjacency matrix A_k. In addition, we can get the number of group by computing the number of the connected components in adjacency matrix A_k.

3 LABELED BOX PARTICLE FILTER

Box particle filter [9] is a nonlinear filter combining particle filter and interval analysis. In the two-dimensional plane, a nonzero and controllable rectangular area with the maximum error known is defined as a box particle. Instead of the traditional point particle, it uses the box particle to approximate the posterior probability density function. However, box particle filter can only get the estimated state set of target. It fails to distinguish different target and obtain each target's track.

In view of the above problem, labeled box particle filter is proposed in this paper. It assigns a unique label for each box particle, and the box particles from the same target have the same label. Thus, each target can be resolved by different labels. Further, each target's track can be obtained by correlated the adjacent time estimated state according to the labels. The difference between box particle and labeled box particle filter is depicted in Fig.1 (a) and (b).



(a) (b)

Fig.1 box particle and labeled box particle

In Fig.1(a), three rectangles represent respectively the estimated state sets at $t1$、$t2$ and $t3$，three circles represent respectively the estimated states for three targets. It can be seen that the estimated states for three targets obtained by box particle filtering are unresolved and tracks for three targets can not be formed. Labeled box particle filtering solves this problem by adding a unique label to each box particle. The target state is extracted according to the labels. In Fig.1 (b), it is found that different targets can be distinguished by different labels, and tracks are formed by related the adjacent time estimated states which have the same labels. Last but not least, because labeled box particle filtering extracts the target state according to the different labels, unlike box particle filtering, it can avoid the influence caused by clustering instability.

4 GROUP TARGET TRACKING WITH EVOLVING NETWORKS MODEL AND LBP-PHD FILTER

Multiple group targets tracking algorithm based on the evolving networks model and LBP-PHD filter is summarized as follows.

4.1 Initialization

Supposing that there are N_0 targets at initial moment, their state set is $X_0 = \{x_0^1, \cdots, x_0^{N_0}\}$, and each target is sampled with N_{box} box particles. The box particles from the same target have the same labels, and the initialized labeled box particles set is $\{l_0^i, w_0^i, [x_0^i]\}_{i=1}^{N_0 \cdot N_{box}}$, $1 \le l_0^i \le N_0$. l_0^i and w_0^i are respectively the corresponding label and weight. Finally, according to the known initialized targets state set, initialized group structure G_0 is obtained by the evolving networks model.

4.2 Adding the new born labeled box particles

The labeled box particles set at time $k-1$ is denoted by $\{l_{k-1}^{per,i}, w_{k-1}^{per,i}, [x_{k-1}^{per,i}]\}_{i=1}^{N_p}$. The new born labeled box particles set $\{l_{k-1}^{bir,i}, w_{k-1}^{bir,i}, [x_{k-1}^{bir,i}]\}_{i=1}^{N_b}$ is got from the measurements set of the previous time, where $l_{k-1}^{bir,i} = 0$. More detailed introduction about new born box particles can refer to [10]. Then, the set composed of all labeled box particles is the following.

$$\{l_{k-1}^i, w_{k-1}^i, [\boldsymbol{x}_{k-1}^i]\}_{i=1}^{N'} =$$

$$\{l_{k-1}^{per,i}, w_{k-1}^{per,i}, [\boldsymbol{x}_{k-1}^{per,i}]\}_{i=1}^{N_p} \cup \{l_{k-1}^{bir,i}, w_{k-1}^{bir,i}, [\boldsymbol{x}_{k-1}^{bir,i}]\}_{i=1}^{N_b} \quad (3)$$

Where $N' = N_p + N_b$ and it is the whole number of labeled box particles. The box particle labels set is as follows.

$$L_{k-1} = \{l_{k-1}^{per,i}\}_{i=1}^{N_p} \cup \{l_{k-1}^{bir,i}\}_{i=1}^{N_b} = \{l_{k-1}^1, l_{k-1}^2, \cdots, l_{k-1}^{N'}\} \quad (4)$$

4.3 Prediction

All of the labeled box particles mentioned above are propagated by the motion equation.

$$[\boldsymbol{x}_{k|k-1}^i] = [f_{k|k-1}]([\boldsymbol{x}_{k-1}^i]), i = 1, \cdots, N' \quad (5)$$

$$w_{k|k-1}^i = P_s([\boldsymbol{x}_{k-1}^i]) w_{k-1}^i, i = 1, \cdots, N' \quad (6)$$

$$l_{k|k-1}^i = l_{k-1}^i, i = 1, \cdots, N' \quad (7)$$

Where P_s is the survival probability. The predicted labels set is denoted by $L_{k|k-1} = \{l_{k|k-1}^1, l_{k|k-1}^2, \cdots, l_{k|k-1}^{N'}\}$.

4.4 Updating

Supposing that the detection probability is P_d. The clutter modeled by a Poisson distribution with parameter λ distributes uniformly in the monitoring area. At time k, the updated weight and labels are respectively calculated as follows.

$$w_k^i = \left[\begin{array}{l} (1 - P_d([\boldsymbol{x}_{k|k-1}^i])) + \\ \sum_{j=1}^{m_k} \frac{g_k([\mathbf{z}_j] | [\boldsymbol{x}_{k|k-1}^i]) P_d([\boldsymbol{x}_{k|k-1}^i])}{\lambda_{k/k-1}([\mathbf{z}_j])} \end{array} \right] \cdot w_{k|k-1}^i \quad (8)$$

$$g_k([\mathbf{z}_j] | [\boldsymbol{x}_{k|k-1}^i]) = \frac{\left| [h_{cp}]([\boldsymbol{x}_{k|k-1}^i], [\mathbf{z}_j]) \right|}{\left| [\boldsymbol{x}_{k|k-1}^i] \right|} \quad (9)$$

$$\lambda_{k/k-1}([\mathbf{z}_j]) = \lambda c([\mathbf{z}_j]) + \sum_{i=1}^{N_p+N_b} g_k([\mathbf{z}_j] | [\boldsymbol{x}_{k|k-1}^i]) P_d([\boldsymbol{x}_{k|k-1}^i]) w_{k|k-1}^i \quad (10)$$

$$l_k^i = l_{k|k-1}^i, i = 1, \cdots, N' \quad (11)$$

Where $g_k([\mathbf{z}_j] | [\boldsymbol{x}_{k|k-1}^i])$ is a special likelihood function [10]. The function $[h_{cp}]([\boldsymbol{x}_{k|k-1}^i], [\mathbf{z}_j])$ returns a contracted version $[\boldsymbol{x}_{k|k-1}^i]$ and it is contracted by the corresponding measurement $[\mathbf{z}_j]$. The contraction method [9] is the following: $[\boldsymbol{x}] = [\boldsymbol{x}] \cap [\boldsymbol{x}_\mathbf{z}]$, $[\boldsymbol{y}] = [\boldsymbol{y}] \cap [\boldsymbol{y}_\mathbf{z}]$. The updated labels set is denoted by $L_k = \{l_k^1, l_k^2, \cdots, l_k^{N'}\}$.

4.5 Target number estimation and label processing

The estimated number of the targets is $\hat{N}_k$.

$$\hat{N}_k = \text{int}\left(\sum_{i=1}^{N'} w_k^i \right) \quad (12)$$

In order to simplify label processing, it is assumed that the new birth and disappearance of the target does not occur at the same time.

If $\hat{N}_k > \hat{N}_{k-1}$, it indicates that there are the new born targets, and the number of the new born targets is $N_{new} = \hat{N}_k - \hat{N}_{k-1}$. Search for the N_{new} box particles with the maximum weight in all labeled box particles which the label equals 0, and correct their labels as $(l_{max} + 1), \cdots, (l_{max} + N_{new})$, where l_{max} is the maximum label that has already appeared in all labeled box particles.

If $\hat{N}_k = \hat{N}_{k-1}$, it indicates that there are not the new born targets, the labels does not need to be changed.

If $\hat{N}_k < \hat{N}_{k-1}$, it indicates that partial targets have disappeared. According to the labels set L_k, the weight sum of the box particles with the same labels is computed as the number estimation of a single target. If the value is less than the threshold χ, it implies that the target dies. And correct the corresponding box particle's labels as 0.

The processed labels set is denoted by $L'_k = \{l'^1_k, l'^2_k, \cdots, l'^{N'}_k\}$.

4.6 Target state estimation and track continuity

Given the assumption that the box particles with the same labels are from the same target, the state and covariance of target j are estimated in the following.

$$\hat{\boldsymbol{x}}_k^j = \frac{1}{W_j} \sum_{i=1}^{N_j} mid\left(\left[\boldsymbol{x}_k^i \right] \right) \cdot w_k^i \quad (13)$$

$$\hat{\boldsymbol{P}}_k^j = \frac{1}{W_j} \sum_{i=1}^{N_j} w_k^i ((\hat{\boldsymbol{x}}_j - mid([\boldsymbol{x}_k^i])) \cdot (\hat{\boldsymbol{x}}_j - mid([\boldsymbol{x}_k^i]))^T) \quad (14)$$

$mid\left(\left[\boldsymbol{x}_k^i \right] \right)$ means finding the center of the box particle $[\cdot]$. N_j is the number of box particles with label j, $\left[\boldsymbol{x}_k^i \right]$ and w_k^i are respectively corresponding state and weight. W_j is normalized weight sum.

$$W_j = \sum_{i=1}^{N_j} w_k^i \quad (15)$$

Thus, we can get all $\hat{N}_k$ target state estimation. Consequently, each target track is formed by connecting the target state estimation with the same labels.

4.7 Resampling

For the box particles with the same label j and $j \neq 0$, we randomly pick a dimension to divide them into N_{box} equally weighted box particles to obtain the box particles set corresponding to the target j. By this way, we can get resampled box particles set $\{l_k'^i, w_k^i = 1/N_{box}, [\mathbf{x}_k^i]\}_{i=1}^{\hat{N}_k \cdot N_{box}}$. At the same time, in order to prevent the area degradation of the box particles, box particles after resampling need to be expanded appropriately.

4.8 Group state estimation and track continuity

The set of estimated target state at time k is $\hat{\boldsymbol{X}}_k$.

$$\hat{\boldsymbol{X}}_k = \left\{ \left(\hat{\boldsymbol{x}}_k^j, \hat{\boldsymbol{P}}_k^j \right) \right\}_{i=1}^{\hat{N}_k} \tag{16}$$

Based on the above estimation, we update group structure by using evolving networks model mentioned in Section 2. Then, the estimated target states set is divided into group state.

$$\hat{\boldsymbol{X}}_k = \bigcup_{g=1}^{G_k} \hat{\boldsymbol{X}}_k^g \tag{17}$$

Where G_k is the estimated group number and $\hat{\boldsymbol{X}}_k^g$ is the estimated target state within group g. In addition, we use group state to correct individual target state in a group to constrain group evolution.

Finally, we extend the label to group target. Each group g is added a label T_{k-1}^g at time $k-1$. If there is a group g' at time k that includes at least half of the targets from group g, then let $T_k^{g'} = T_{k-1}^g$, otherwise a new group label is assigned for $T_k^{g'}$.

5 SIMULATION RESULTS

In order to verify the performance of the proposed algorithm in this paper, we compare the performance of the LBP-PHD group targets tracking algorithm with BP-PHD group targets tracking algorithm in [8] with the same simulation scenario, and use the OSPA distance [11] to evaluate the tracking performance.

In our experiment, the group targets contain 4 groups, and move in a 2-dimension plane with constant velocity (CV). Dynamic model for each target in the group is established as follows.

$$\boldsymbol{x}_k = \boldsymbol{F}\boldsymbol{x}_{k-1} + \boldsymbol{\Gamma}\boldsymbol{\omega}_k \tag{18}$$

$$\boldsymbol{z}_k = \boldsymbol{H}\boldsymbol{x}_{k-1} + \boldsymbol{v}_k \tag{19}$$

$$\boldsymbol{F} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \boldsymbol{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

$$\boldsymbol{\Gamma} = \begin{bmatrix} T^2/2 & T & 0 & 0 \\ 0 & 0 & T^2/2 & T \end{bmatrix}^{\mathrm{T}}$$

Where $\boldsymbol{x}_k$ is the state vector for each target at time k, $\boldsymbol{F}$ is state transition matrix, $\boldsymbol{H}$ is measurement matrix, $\boldsymbol{\Gamma}$ is the transition matrix of state noise $\boldsymbol{\omega}_k$, $\boldsymbol{v}_k$ is measurement noise. What's more, the point measurement $\boldsymbol{z}_k$ needs to be converted into interval measurement $\left\|[\mathbf{z}_k]\right\|$ to process in this paper.

The range of surveillance is $[-1000,1000]\times[-1000,1000]m^2$, the duration of the scenario is $50s$, sampling interval is $T=1s$, the cluttered points in average is $r=2$, standard deviation of state noise is $\sigma_x = \sigma_y = 0.02m$, standard deviation of measurement noise is $\tilde{\sigma}_x = \tilde{\sigma}_y = 3m$. The probability of detection is $p_{\mathrm{d}} = 1$, and the surviving probability is $p_{\mathrm{s}} = 0.99$. The point measurement function is $h_k(\boldsymbol{x})$ at time k, so the interval measurement is defined as $[\mathbf{z}_k] = [h_k(\boldsymbol{x}) + \boldsymbol{v}_k - 0.5\Delta,\ \ h_k(\boldsymbol{x}) + \boldsymbol{v}_k + 0.5\Delta]$. Interval length is $\Delta = [18,18]^{\mathrm{T}}$. 30 labeled box particles are used in the filtering process, and 4 labeled box particles are added to detect newborn targets. The OSPA distance parameters are $p=2, c=200$.

The target true tracks are shown in Fig.2, different targets are represented by different colors in every group, and the starting position is denoted by the circles.

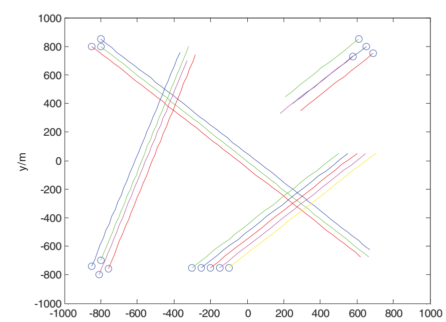


Fig.2 True tracks of group targets

Four groups give birth and disappear at different time. The group 1 is new born at $[-800,800]$ at $k=1s$, and dies at $k=50s$. The group 2 is new born at $[-800,-700]$ at $k=10s$, and dies at $k=40s$. The group 3 is new born at

$[-200,-750]$ at $k=15s$, and dies at $k=35s$. The group 4 is new born at $[580,730]$ at $k=20s$, and dies at $k=30s$. In our tracking process, we assume that four groups are independent, the number of targets and groups are unknown. Target and group tracks estimation by the LBP-PHD and BP-PHD filter are shown in Fig.3-6, respectively.

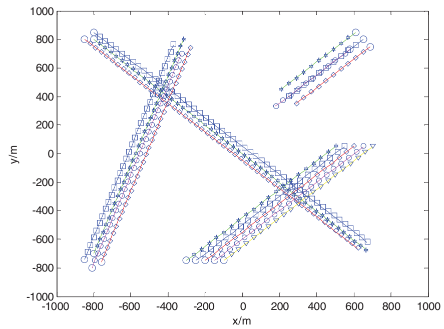


Fig.3 Target tracks estimation by LBP-PHD filter

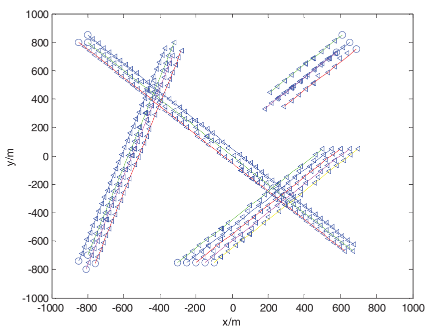


Fig.4 Target tracks estimation by BP-PHD filter

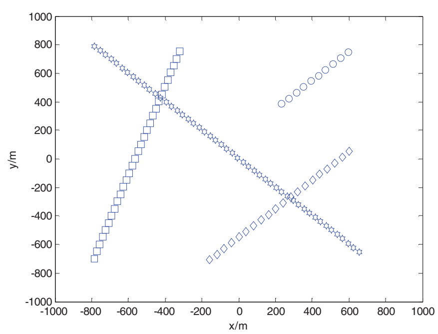


Fig.5 Group centroid tracks estimation by LBP-PHD filter

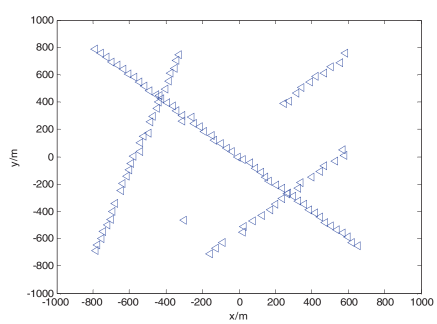


Fig.6 Group centroid tracks estimation by BP-PHD filter

From Fig.3-6, we can see that LBP-PHD filter is able to distinguish different targets and groups. It can also obtain each target and group centroid track denoted by different symbol. That's because a unique label is added to each target and group in LBP-PHD filter. However, BP-PHD filter can only get each target and group centroid state estimation. It is unable to distinguish different targets and groups.

After 30 Monte Carlo simulations, the estimated number of targets and groups by two algorithms are respectively shown in Fig.7 and Fig.8, It can be seen that two algorithms can get the accurate target number estimation. Fig.9 and Fig.10 show the OSPA distance for target and group centroid estimation. Because of the instability of k-means clustering, BP-PHD filter is far worse than LBP-PHD filter in the extraction of target state and group centroid state. It has a higher OSPA distance.

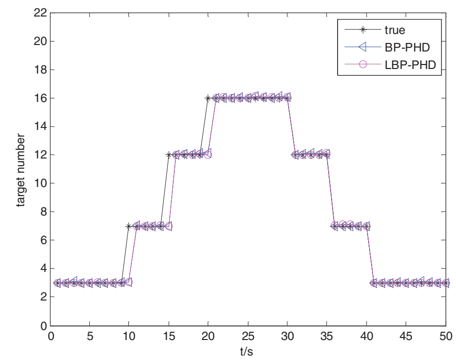


Fig.7 The estimated number of target

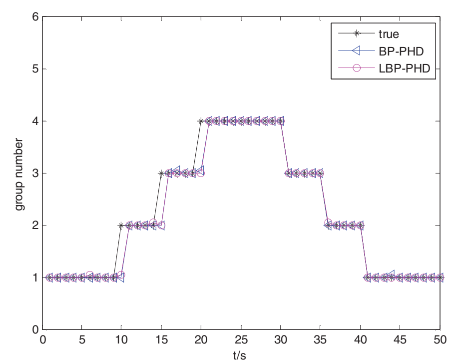


Fig.8 The estimated number of group

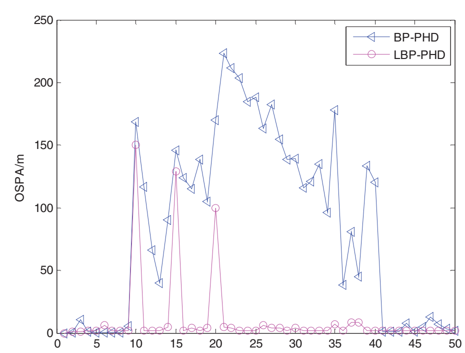


Fig.9 OSPA distance for target

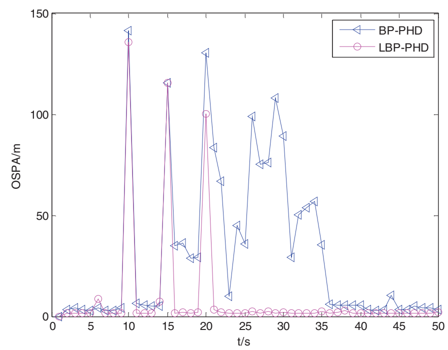


Fig.10 OSPA distance for group centroid

6 CONCLUSION

Different from the traditional multi-target tracking, group targets consist of many targets with a coordinated and interacting pattern. However, the target track and the group structure have not been considered in most of the exiting algorithm. We propose a novel multiple group target tracking algorithm based on evolving networks model and LBP-PHD filter in this paper. LBP-PHD filter has ability to differentiate different tracks by adding different labels to different box particles. Meanwhile, using evolving networks model to update group structure, we can obtain each target track and group centroid tracks. Further, the estimated number of targets and groups can also be obtained. The simulation results show that the proposed algorithm has a better performance than BP-PHD group targets tracking algorithm.

REFERENCES

[1] Mihaylova L, Carmi A Y, Septier F. Overview of Bayesian sequential Mote Carlo methods for group and extended object tracking[J]. Digital Signal Processing, 2014, 25: 1-16.

[2] Clark D, Godsill S. Group target tracking with the Gaussian mixture probability hypothesis density filter[C]. 2007 3rd International Conference on Intelligent Sensors, Sensor Networks and Information. Melbourne, Australia: IEEE, 2007: 149-154.

[3] Koch J W. Bayesian approach to extended object and cluster tracking using random matrices[J]. IEEE Transactions on Aerospace and Electronic Systems, 2008, 44(3): 1042~1059.

[4] M Baum, B Noack, U D Hanebeck. Extended object and group tracking with elliptic random hypersurface models[C]. 13th Conference on Information Fusion, 2010.

[5] Hui Zhang, Hui Xu, Xue-Ying Wang, et al. A PHD Filter for Tracking Closely Spaced Objects with Elliptic Random Hypersurface Models[C]. 16th International Conference on Information Fusion, 2013.

[6] Lian F, Han C Z, Liu W F, et al. Tracking partly resolvable group targets using SMC-PHDF[J]. ACTA Automatica Sinica, 2010,36(5): 732-741.

[7] Gning A, Mihaylova L, Maskell S, et al. Group object structure and state estimation with evolving networks and Monte Carlo methods[J]. IEEE Transactions on Signal Processing, 2011, 59(4): 1383-1395.

[8] SONG Li-ping, LIU Yu-hang, CHENG Xuan. Box-particle evolution network PHD filter for group targets tracking[J]. Control and Decision, 2018, 33(1): 74-80.

[9] Abdallah F, Gning A, Bonnifait P. Box particle filtering for nonlinear state estimation using interval analysis[J]. Automatica, 2008, 44(3): 807–815.

[10] Schikora M, Gning A, Mihaylova L, et al. Box-particle PHD filter for multi-target tracking[C]. 2012 15th International Conference on Information Fusion. Singapore: IEEE, 2012: 106-113.

[11] Schuhmacher D, Vo B T, Vo B N. A consistent metric for performance evaluation of multi-object filters[J]. IEEE Transactions on Signal Processing, 2008, 56(8): 3447-3457.