Multi-group target GM-PHD filter combined with rapid detection mechanism

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***Abstract*—A multi-group target Gaussian mixture probability hypothesis density (GM-PHD) filter algorithm combined with rapid detection mechanism is proposed for multi-group target tracking problem. The algorithm is based on the GM-PHD filter algorithm, using the characteristics of the group target, combined with the rapid detection mechanism to detect and track the new group. In order to effectively remove the clutter, after the prediction phase is completed, the correlation gates of all predicted Gaussian components are used to screen the measurements. In order to avoid missing new groups, a cyclic threshold aggregation method is used to detect whether a new group target appears in the measurement set at each moment. Simulation experiments show that the proposed method can track multi-group targets quickly and effectively, and has better ability to cope with sudden changes.**

Keywords—multi-group target, GM-PHD filter, rapid detection mechanism, correlation gates, cyclic threshold aggregation

I. Introduction

Group target tracking is a special multi-target tracking problem. It consists of some targets with similar motion states and relatively stable structure within the team. Since the number of measurements of group targets has been changing, traditional multi-target tracking techniques [1] are often difficult to effectively track group targets. As the joint probability data interconnection method used in the literature [1], this method needs to correlate the target and the measurement, and the distance between the targets within the group target is relatively close, which causes the clutter and the target to generate the true measurement. The accuracy of data association is reduced, the amount of calculation is increased, and the tracking effect is not good.

With the introduction of the random finite set (RFS) theory [3], the group target tracking algorithm has a new research idea. American scholar Mahler proposed a probability density hypothesis (PHD) filtering algorithm based on the RFS frame-work. This algorithm eliminates the complicated data association process and can simultaneously estimate the number and state of targets. In order to solve the problem that the PHD filtering algorithm does not have a closed solution, Australian scholar Vo. proposed a sequential Monte Carlo[4](SMC-PHD) implementation and a Gaussian mixture[5](GM-PHD) implementation of the PHD filtering algorithm. Among them, the SMC-PHD algorithm is similar to the particle filter algorithm, and is suitable for nonlinear non-Gaussian environments, but the amount of calculation is large, and there is particle degradation phenomenon. The GM-PHD algorithm is suitable for linear Gaussian environment, and the calculation amount is small and easy to implement. Although many experts and scholars have proposed some group target tracking methods based on PHD filtering algorithm, most of these methods only focus on the overall tracking of group targets, ignoring the movement and track information of the targets within the group. As in [6], the clustering and GM-PHD algorithms are combined to reflect the overall motion trajectory of the group with the center point trajectory. In some specific operational environments, information about the goals within the group is often more concerned. Such as intercepting the group of missiles or missile groups, and eliminating space hazards caused by spacecraft explosions. At present, although there are a few methods[7] that can track the movement of targets within the group, these methods ignore the problems of non-simultaneous group goals. When a new group target occurs during the tracking process, these methods will treat the new group target as clutter due to the difference in distance between the new group target and the known group target, resulting in the omission of the new group target.

Based on the above background, this paper proposes a multi-group target GM-PHD filtering algorithm combined with rapid detection mechanism by using the characteristics of group targets. The effectiveness of the algorithm is verified by simulation experiments.

II. Group Model

A. State Model

It is assumed that the state set of the target in the detection area at time k is $G_k = \{X_k\}_{i=1}^{N_k}$, where $N_k\,(N_k \geq 1)$ is the number of targets in the set. The state of the target i is $X_k^i = \begin{bmatrix} x_k^i & \dot{x}_k^i & y_k^i & \dot{y}_k^i \end{bmatrix}', 1 \leq i \leq N_k$, (x_k^i, y_k^i) and $(\dot{x}_k^i, \dot{y}_k^i)$ are the positions and velocities of the target i in the x and y directions, respectively.

Based on the RFS framework, the state RFS of the k time target is

$$G_k = \left[\bigcup_{X_{k-1}^i \in G_{k-1}} S_{k|k-1}(X_{k-1}^i) \right] \cup \left[\bigcup_{X_{k-1}^i \in G_{k-1}} B_{k|k-1}(X_{k-1}^i) \right] \cup \Gamma_k \quad (1)$$

In the formula (1), Γ_k is the state RFS of the new target, $B_{k|k-1}(X_{k-1}^i)$ is the state RFS of the derivative target, and $S_{k|k-1}(X_{k-1}^i)$ is the state RFS of the survival target.

B. Measurement Model

It is assumed that the measurement set at time k is $Z_k = \left\{ z_k^r \right\}_{r=1}^{N_{Z,k}}$, where $N_{Z,k} (N_{Z,k} \geq 1)$ is the number of measurements in the set. The state of the measurement r is $z_k^r = \left[z_{k,x}^r \quad z_{k,y}^r \right]', 1 \leq \mathrm{r} \leq \mathrm{N}_{Z,k}$, $z_{k,x}^r$ and $z_{k,y}^r$ are the positions of the measurement r in the x and y directions, respectively.

Based on the RFS framework, the measurement RFS of the k time target is

$$Z_k = K_k \cup \left[\bigcup_{X_k^i \in G_k} \Theta_k (X_k^i) \right] \quad (2)$$

In the formula (2), K_k is a k time clutter RFS, and $\Theta_k (X_k^i)$ is a measurement RFS generated by the target X_k^i at time k.

III. Framework and Algorithm

Since the proposed algorithm is based on the GM-PHD filtering algorithm, the assumptions of the algorithm are the same as those of the GM-PHD filtering algorithm. Figure 1 is a block diagram of the algorithm of this paper.

As shown in Figure 1, the algorithm is divided into five steps, namely prediction step, rapid detection mechanism, update step, trimming and fusion of Gaussian components and state extraction. Since the algorithm is proposed for the tracking problem of the new group team in the tracking process, the core of the algorithm is the rapid detection mechanism process. Therefore, only the rapid detection mechanism process is described here. The details of other processes can be found in the literature [5]. The rapid detection mechanism process used in this paper is divided into two stages: clutter rejection and detection of new groups.

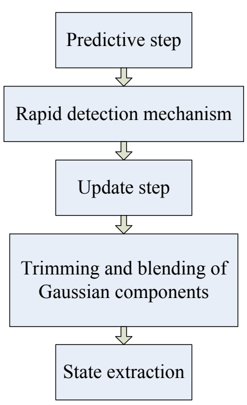

Fig. 1. flow chart

A. ClutterRejection

Since the update process of the GM-PHD filtering algorithm requires each measurement to update each predicted Gaussian component, the clutter in the measurement set can affect the estimated performance. In response to this problem, this paper proposes a clutter rejection method based on the correlation gate.

The correlation-gate-based clutter culling method uses the correlation between the Gaussian component and the measured data at the current time to find all the measurements in each Correlated component of the predicted Gaussian component, and considers these measurements as effective quantities, other measurements as clutter.

The calculation process of the clutter rejection technique based on the relevant gate is as follows:

$$\eta_{z_k^r}^i = z_k^r - H_k m_{k|k-1}^i \quad (3)$$

$$S_k^i = R_k + H_k P_{k|k-1}^i H_k^T \quad (4)$$

$$Dist_{z_k^r}^i = \left[\eta_{z_k^r}^i \right]^T \left[S_k^i \right]^{-1} \eta_{z_k^r}^i \quad (5)$$

$$\Psi_k^i = \bigcup_{r=1}^{N_{Z,k}} \left\{ r \mid \exists z_k^r \in Z_k, Dist_{z_k^r}^i \leq \lambda \right\} \quad (6)$$

$$Y_k = \bigcup_{i=1}^{J_{k|k-1}} \Psi_k^i \quad (7)$$

$$\tilde{Y}_k = Z_k - Y_k \quad (8)$$

In equations (3)~(8), $\eta_{z_k^r}^i$ is the innovation between the Gaussian component and the measurement; H_k is the measurement matrix, R_k is the covariance matrix of the measurement noise; $m_{k|k-1}^i$ and $P_{k|k-1}^i$ are the prediction mean and the prediction covariance matrix respectively for the Gaussian component ; S_k^i is the covariance between the Gaussian component and the measurement; $Dist_{z_k^r}^i$ is the degree of deviation between the measurement and the Gaussian component; λ is the correlation domain parameter, determined by the probability P_G of the correct measurement being tracked, satisfying the probability distribution function $P\left(\chi_n^2 \leq \lambda\right) = P\_G$, and χ_n^2 obey the degree of freedom n The chi-square distribution, n is the dimensions of z_k^r ; Ψ_k^i is the measurement set that satisfies the discriminant condition for the degree of deviation from the Gaussian component; Y_k and $\tilde{Y}_k$ are the filtered measurement set and the clutter set, respectively.

B. New Generation Group Inspection

The detection technology of the new group is to use the characteristics of stable group structure and the same movement state in the team. Combined with the cyclic threshold aggregation method[10] to detect whether there is a new group in the measurement set.

The steps of this technique are as follows:

1) The measurement set is divided based on the distance parameter d , and the set to which each measurement belongs is found to obtain a division result set D_k^q . In the above description, D_k^q is the $q\left(0 \le q \le m\right)$ set at time k ; m is the number of sets after the cyclic threshold aggregation at time k ; d is the distance parameter in the cyclic threshold aggregation method, and the value of d is related to the distance between the targets in the group.

2) Using the characteristics of the group target, the aggregation result is discriminated. If the number of measurements in the D_k^q set is greater than M (the value of M is related to the number of targets in the group), the set is determined to be the measurement set of the new group target; otherwise, the set is considered to be a clutter set. If there is no measurement set of the new group target in D_k , it is considered that there is no new group at time k , and the effective measurement set at this time is $\bar{Z} = Y_k$; otherwise, it is considered that there is a new group at time k, and the effective measurement set at this time is $\bar{Z} = \left[Y_k \quad \tilde{D}_k\right]$ ($\tilde{D}_k$ is a measurement set for all new group targets).

3) If a new group target is present at this time, the center points of all new formation measurement sets need to be found, and these central points are regarded as the new target components of the time added to the predicted Gaussian component set. Since these Gaussian components lack a priori information, it can be assumed that their weights and covariance matrices are the same as the weights and covariance matrices of the a priori new targets, and the mean is

$$\tilde{z}_k^{\mathrm{t}} = \frac{\sum_{i'=1}^{N\_\tilde{\mathrm{D}}_k^t} z_k^{i'}}{N\_\tilde{\mathrm{D}}_k^t} \tag{9}$$

$$m_k^t = \left[\tilde{z}_{k,x}^{\mathrm{t}} \quad 0 \quad \tilde{z}_{k,\mathrm{y}}^{\mathrm{t}} \quad 0\right]' \tag{10}$$

In equation (9), $\tilde{z}_k^{\mathrm{t}}$ is the state of the t center point at time k , $N\_\tilde{\mathrm{D}}_k^t$ is the number measured in the set $\tilde{D}_k^t$ at time k ; in equation (10), m_k^t is the mean of the t Gaussian component at time k .

IV. Simulation Results

A. Simulation Scene Settings

Assume that there are 3 groups in the detection area that are doing uniform linear motion. There are 3 targets in the first group. The initial position of each target is (600 m, -600 m), (550 m, -600 m), (650 m, -600 m), and the initial velocity is (-12 m/s, 6 m/s), the exercise time is 1-50 s; there are 3 targets in the 2nd group, and the initial position of each target is (-800 m, -200 m), (-830 m, -230 m), (-770 m, -230 m), initial speed (26 m/s, 6 m/s), exercise time is 10-60 s; in the third group 4 targets, the initial position of each target is (-200 m, 800 m), (-230 m, 830 m), (-260 m, 860 m), (-290 m, 890 m), initial velocity Both are (5 m/s, -25 m/s) and the exercise time is 20-80 s.

Assume that the target detection probability P_D is 0.98, the survival probability P_S is 0.99, and the clutter follows the Poisson distribution of the mean $\lambda = 10$. The covariance matrix of the process noise $Q_{k-1} = diag\left(\left[5^2, 5^2\right]\right)$, the sampling interval of the measurement data is 1 s, the covariance matrix $R_k =$ $diag\left(\left[10^2, 10^2\right]\right)$ of the measurement noise, and the probability P_G of the correct measurement being tracked is 0.999. The loop parameter aggregation method has a distance parameter d of 60 and a quantity parameter M of 2. The target's pruning threshold is 4, the fusion threshold is 4, the maximum Gaussian component is 100, and the state extraction threshold is 0.5. The number of Monte Carlo simulations is 100 and the simulation time is 80 s.

Suppose that three new Gaussian components are generated at each moment, and their weights are 0.03. The mean values are (600 m, 0 m/s, -600 m, 0 m/s), (550 m, 0 m/s). , -600 m, 0 m/s), (650 m, 0 m/s, -600 m, 0 m/s), and the covariance matrix is $diag\left(\left[10^2, 10^2, 10^2, 10^2\right]\right)$. One derivative Gaussian component is generated at each moment, its weight is 0.05, the state transition matrix is $diag\left(\left[1,1,1,1\right]\right)$, the process noise is 0, and the covariance matrix is $diag\left(\left[10^2, 10^2, 10^2, 10^2\right]\right)$.

Figure 2 depicts the actual motion trajectory and measurement data for the group target. In the figure, "x" is the measurement data generated by the target and the clutter, "○" is the position at which the target starts moving, and "△" is the position at which the target stops moving.

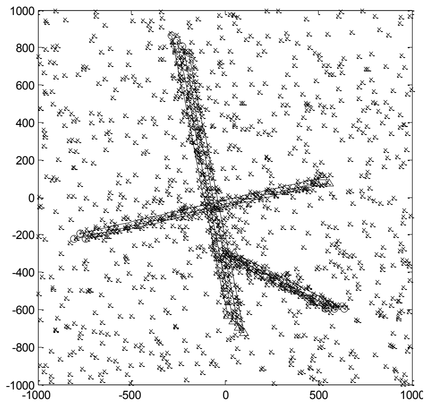

Fig. 2. Real motion trajectory and measurement data

B. Simulation Result Analysis

The algorithm in this paper is mainly compared with the GM-PHD algorithm. Figure 3 and Figure 4 are state estimation diagrams for a single simulation of the two algorithms, respectively. Comparing Fig. 3 and Fig. 4, it is obvious that the estimation of the target state is more accurate than the GM-PHD algorithm. Especially when there is a new group goal, the GM-PHD algorithm can't track the target, but the algorithm can track the target in about 3 s, and the effect gap is obvious.

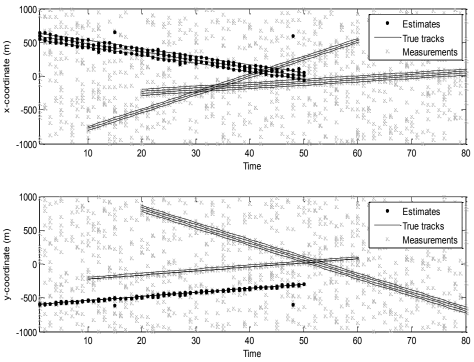

Fig. 3. State estimation of single simulation of GM-PHD algorithm

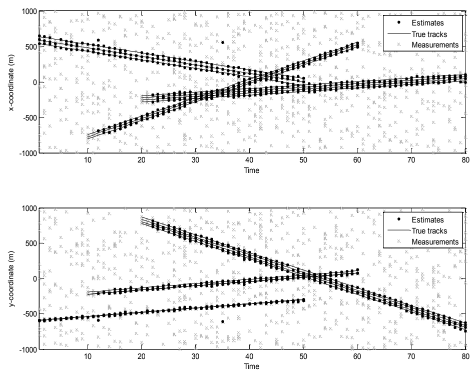

Fig. 4. State estimation of single simulation of the algorithm in this paper

Figures 5 and 6 are estimates of the number of targets for the two algorithms, respectively. Comparing Fig. 5 and Fig. 6, it can be clearly seen that compared with the GM-PHD algorithm, the proposed algorithm can better estimate the number of targets. Especially in the sudden emergence of new group goals, the tracking effect of this algorithm is significantly better.

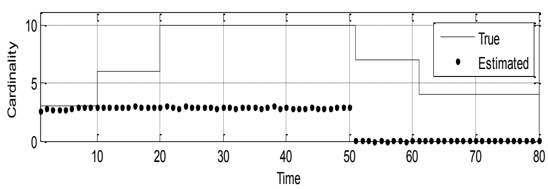

Fig. 5. Estimation of the number of targets of the GM-PHD algorithm

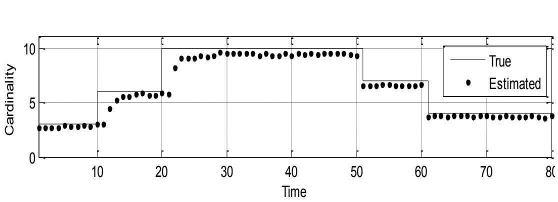

Fig. 6. Estimation of the number of targets of the algorithm in this paper

Figure 7 is a comparison of the optimal sub-pattern allocation (OSPA) distance[11] for the two methods. The OSPA distance is a commonly used performance evaluation index for the current research PHD algorithm. The larger the OSPA distance value, the larger the error between the estimated target state set and the real target state set, and the worse the performance of the algorithm. As shown in Figure 7, after the 10th s new group, the GM-PHD algorithm's OSPA distance is much larger than the OSPA distance of the proposed algorithm. Therefore, compared with the GM-PHD algorithm, the error between the estimated target state set and the real target state set of the proposed algorithm is smaller, and the performance of the algorithm is better.

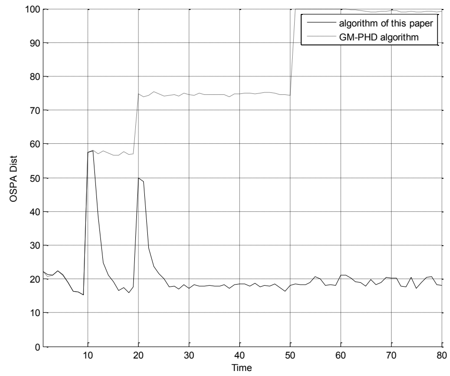

Fig. 7. OSPA distance comparison

V. CONCLUSION

In this paper, a multi-team group target GM-PHD filtering algorithm combined with rapid detection mechanism is proposed for multi-team target tracking problem. After the prediction phase is completed, the algorithm adds rapid detection mechanism, uses the relevant gates of the predicted Gaussian component to eliminate clutter, and reduces the computational complexity of the algorithm. It uses the characteristics of stable group structure and the same movement state in the team, combined with cyclic threshold aggregation. The method detects the new group goals at each moment and improves the sensitivity to the new group goals. The simulation results show that compared with the GM-PHD algorithm, the proposed algorithm has higher tracking accuracy, better estimation effect, stronger ability to deal with emergencies, and wider application range.

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