Target Birth Intensity Estimation in Dense Clutter

Jiang Yujie\textsuperscript{1a}, Jiang Xiaoxiao\textsuperscript{2b*}

\textsuperscript{1}School of Computer and Information Engineering, Shanghai Polytechnic University, Shanghai, People's Republic of China

\textsuperscript{2}School of electronic and electrical engineering, Shanghai University of Engineering Science, Shanghai, People's Republic of China

\textsuperscript{a}email: yjjiang@sspu.edu.cn, \textsuperscript{b}email: jiangxiaoxiao@sues.edu.cn

Abstract—In order to solve the problem of unknown target birth intensity in multi-target tracking, an improved GM-PHD filtering algorithm based on virtual track is proposed. According to the measurement set in the monitoring area, the virtual tracks of the birth targets are established by using the motion model of the targets. The false tracks modeled by the clutter are eliminated by PHD filter, and the states of the birth targets are extracted. The simulation results show that the algorithm performs well in dense clutter environment.

1. Introduction

Multi-target tracking is the real-time estimation of multi-target motion state by using sensor measurement information, which mainly includes the number of targets and the target state estimation. In recent years, multi-target tracking technology based on RFS (random finite set) has been widely concerned and studied due to its avoidance of complex data association. In this kind of research, the filtering algorithm based on probability hypothesis density (PHD) \cite{1}-\cite{7} is the main method.

The two most representative methods are sequential Monte Carlo probability hypothesis density \cite{2}[3] (SMC-PHD) and Gaussian mixture probability hypothesis density \cite{4} (GM-PHD). Among them, GM-PHD method has been widely used because of its advantages of simple calculation. However, the absence of prior target birth intensity restricts the application of the algorithm in the actual environment.

Some improved approaches have been reported in solving the problem. A PHD/CPHD filter with adaptive estimation of target birth intensity is proposed in reference \cite{8}, and SMC implementation of the two filters is given. The adaptive estimation method of the target birth intensity is based on the latest measurements received by the sensor and the likelihood function of the target measurement at each filtering step. But the filtering performance is seriously affected by clutter. Reference \cite{9} adopts the idea of information feedback, and considers the influence of historical information observation. But it has the limitation of being unable to distinguish the clutter from the target state. Reference \cite{10} used the measurement information driven method to estimate the intensity of the birth targets and the existing targets by setting the signs of the birth targets, so as to avoid the dependence on the prior knowledge. However, it does not give the recursive formula for target birth intensity. An improved multi-target Bayesian filter is proposed in reference \cite{11}. It adopts the method of target trajectory initialization based on sequence probability ratio comparison. Reference \cite{12} proposed a PHD filter based on target component pruning and fusion strategy. In dense clutter environment, the computational burden of the filter is large and the filtering iteration efficiency is low. In reference \cite{13}, an adaptive method of target birth intensity estimation can obtain the measurements originated from the real newborn targets by using
the PHD pre-filtering technology and target velocity characteristic scheme. The proposed algorithm has superior performance in tracking accuracy and estimation error of target number, and has low computational cost. The algorithm of reference [14] is suitable for multi-sensor application of adaptive birth intensity PHD filter. In reference [15], a modified PHD filter with adaptive birth intensity estimation is proposed in low detection probability. The core is to define two state sets as the formal set and the temporary set.

This paper focuses on the problem of birth intensity estimation in dense clutter. The motion model of birth targets is established by using two consecutive measurements. Then based on virtual track derived from the foregoing motion model, the birth intensity is estimated by GM-PHD filter.

2. GM-PHD Filtering Algorithm

The PHD filter based on RFS greatly reduces the computational complexity of multi-target Bayesian filter, but it still needs to solve multi-dimensional integral in the process of filtering iteration. GM-PHD filter provides an approximate method to solve the closed solution of PHD filter. Under the linear Gaussian condition, the GM-PHD filter approximates the target intensity by a series of weighted sums of Gaussian components representing multi-target components. The following assumptions are given as

(1) Both the target state model and the sensor measurement model are linear Gaussian dynamic models.

\[ f_{k|k-1}(x_k|x_{k-1}) = N(x_k; F_{k-1}x_{k-1}, Q_{k-1}) \]  

(2) \[ \varphi_k(x_k) = N(x_k; H_kx_k, R_k) \] 

Where \( N(x; m, P) \) is a random variable, \( x \) satisfies the Gaussian distribution of mean \( m \) and covariance matrix \( P \). Among them, \( F_{k-1} \) and \( Q_{k-1} \) is the target state transition matrix and the target process noise covariance matrix. \( H_k \) and \( R_k \) is the measurement matrix and the measurement noise covariance matrix respectively.

(2) The survival probability and detection probability are independent of the target state.

\[ p_{S,k}(x_{k-1}) = p_{S,k} \]  

\[ p_{D,k}(x_k) = p_{D,k} \] 

(3) The intensity function of the birth targets can be expressed in the form of Gaussian mixture. Assume that there is no derived targets.

\[ \gamma_{k}(x_k) = \sum_{i=1}^{I_{y,k}} \omega_{y,k}^{i} N(x_k; m_{y,k}^{i}, P_{y,k}^{i}) \] 

Where, \( \omega_{y,k}^{i}, m_{y,k}^{i} \) and \( P_{y,k}^{i} \) denotes the weight, mean value and covariance matrix of the i-th birth target component, and the number of birth target components is \( I_{y,k} \).

GM-PHD filtering algorithm is divided into two steps: prediction and update.

Prediction:

Suppose the posterior intensity \( V_{k-1}(x_{k-1}) \) of the target at time \( k-1 \) can be expressed as a form of Gaussian mixture.

\[ V_{k-1}(x_{k-1}) = \sum_{i=1}^{I_{y,k}} \omega_{k-1}^{i} N(x_{k-1}; m_{k-1}^{i}, P_{k-1}^{i}) \] 

Then the target prediction intensity \( V_{k|k-1}(x_k) \) also has the form of Gaussian mixture, which can be expressed as

\[ V_{k|k-1}(x_k) = V_{S,k|k-1}(x_k) + \gamma_{k}(x_k) \] 

\( \gamma_{k}(x_k) \) is the intensity of birth targets, \( V_{S,k|k-1}(x_k) \) is the predicted intensity of survival targets, which can be expressed as

\[ V_{S,k|k-1}(x_k) = p_{S,k} \sum_{j=1}^{I_{f,k}} \omega_{k-1}^{j} N(x_k; m_{S,k|k-1}^{j}, P_{S,k|k-1}^{j}) \] 

\[ m_{S,k|k-1}^{j} = F_{k-1} m_{k-1}^{j} \]  

\[ P_{S,k|k-1}^{j} = F_{k-1} P_{k-1}^{j} (F_{k-1})^{T} + Q_{k-1} \]
Update:
Suppose that the target prediction intensity at time $k$ has a Gaussian mixture form, which can be expressed as

$$V_{k|k-1}(x_k) = \sum_{i=1}^{I_{k|k-1}} \omega_{k|k-1}^{i} N(x_k; m_{k|k-1}^{i}, P_{k|k-1}^{i})$$  \hspace{1cm} (11)$$

Based on Measurement set $Z$ of sensors at time $k$, target posterior intensity $V_k(x_k)$ can be expressed as

$$V_k(x_k) = (1 - p_{D,k})V_{k|k-1}(x_k) + \sum_{z \in Z_k} V_{D,k}(x_k; z)$$  \hspace{1cm} (12)$$

$$V_{D,k}(x_k; z) = \sum_{j=1}^{J_{k|k-1}} \omega_j^{i}(z) N(x_k; m_{k|k-1}^{i}(z), P_{k|k-1}^{i})$$  \hspace{1cm} (13)$$

$$\omega_j^{i}(z) = \frac{p_{D,k} w_{k|k-1}^{i} q_j^{i}(z)}{\lambda_c(z) + p_{D,k} \sum_{i=1}^{I_{k|k-1}} \omega_i^{i} q_j^{i}(z)}$$  \hspace{1cm} (14)$$

$$q_j^{i}(z) = N(z; H_k m_{k|k-1}^{i}, R_k + H_k P_{k|k-1}^{i} (H_k)^{T})$$  \hspace{1cm} (15)$$

$$m_{k|k}^{i}(z) = m_{k|k-1}^{i} + K_k^{i}(z - H_k m_{k|k-1}^{i})$$  \hspace{1cm} (16)$$

$$p_{i|k}^{j} = [I - K_k^{i} H_k] p_{k|k-1}^{i}$$  \hspace{1cm} (17)$$

$$K_k^{i} = p_{k|k-1}^{i} (H_k)^{T} (R_k + H_k p_{k|k-1}^{i} (H_k)^{T})^{-1}$$  \hspace{1cm} (18)$$

Finally, The Gaussian components of the birth targets and the surviving targets are pruned and fused to obtain the target state estimation.

3. Proposed Algorithm
In this section, a novel approach is proposed, where the virtual track prediction technology are utilized to obtain the possible birth target intensity.

3.1 Division of measurement set
The measurement set at any discrete time can be divided into survival target measurement set, newborn target measurement set and clutter measurement set. When the target birth density is unknown, the remaining measurement may be generated by the newborn targets or clutter after extracting the measurement of the surviving target from the measurement set. Therefore, it is necessary to divide the measurement set for the new target states modeling. At the same time, the division of measurement set can reduce the influence of clutter measurement on target estimation.

Suppose that the measurement set of sensors at time $k$ is $Z_k = \{z_k^{i}\}_{i=1}^{M_k}$. The target intensity component set obtained at time $k - 1$ can be expressed as

$$E_{k-1} = \{\omega_{k-1}^{i}, m_{k-1}^{i}, p_{k-1}^{i}, \epsilon_{k-1}^{i}\}_{i=1}^{I_{k-1}}$$  \hspace{1cm} (19)$$

Then the measurement set associated with the surviving target component set is

$$Z_{E,k} = \bigcup_{i=1}^{I_{k-1}} z_k^{i}$$  \hspace{1cm} (20)$$

$$\check{z}_k^{i} = (z_k^{i}; \arg \min \phi^{T}(S_{E,k}^{i})^{-1} \phi), \check{z}_k^{i} \in Z_k, \forall i = 1: M_k$$  \hspace{1cm} (21)$$

$$\phi = z_k^{i} - H_k (F_{k-1} m_{k-1}^{i})$$  \hspace{1cm} (22)$$

$$S_{E,k}^{i} = H_k (Q_{k-1} + F_{k-1} p_{k-1}^{i} F_{k-1}^{T}) (H_k)^{T} + R_k$$  \hspace{1cm} (23)$$

Then the remaining measurement set is

$$Z_{R,k} = Z_k - Z_{E,k}$$  \hspace{1cm} (24)$$
The measurement set of newborn targets is assumed to be $Z_y,k$, then $Z_y,k \in Z_{R,k}$. In order to reduce the influence of clutter, the new target measurement set can be extracted from $Z_{R,k}$ by using ellipsoid threshold method. The new target measurement set can be expressed as

$$Z_y,k = \left( (z - H_k m_{y,k-1})^T (S_{y,k}^{-1}) (z - H_k m_{y,k-1}) \leq \eta, z \in Z_{R,k}, \forall i = 1; J_{y,k-1} \right)$$ (25)

$$S_{y,k} = H_k p_{y,k-1} H_k^T + R_k$$ (26)

$$\eta = -2 \ln(1 - P_0), \ n_z > 2$$ (27)

Where $\eta$ is the threshold of measurement gate, and $P_0$ is the probability of the measurement derived from the target in the ellipsoid measurement gate, and $n_z$ is the measurement dimension.

3.2 Initialization of target birth intensity

A label $\ell$ is added to each new target to establish a new target label set. The labels of different targets are unique, and different Gaussian components of the same target have the same labels. The target intensity component set obtained at $k - 1$ step can be expressed as $E_{k-1} = \{\omega_{k-1}^i, m_{k-1}^i, P_{k-1}^i, \rho_{k-1}^i\}_{i=1}^{k-1}$, when the measurements associated with the survival targets are extracted, each measurement in the remaining measurements may be generated by the new targets. Therefore, assuming that each measurement in the remaining measurement set is related to a target component, the intensity of the newborn targets can be expressed as

$$\gamma_{init,k}(x_k) = \sum_{i=1}^{M_{R,k}} \omega_{y,k}^i N(x_k; m_{y,k}^i, P_{y,k}^i)$$ (28)

$$\omega_{y,k}^i = 0.1$$ (29)

$$m_{y,k}^i = H_k^{-1} x_k$$ (30)

$$P_{y,k}^i = H_k^{-1} R_k (H_k^{-1})^T$$ (31)

$M_{R,k}$ is the measurement number of the remaining measurement set $Z_{R,k}$. The initialization of the newborn target label set can be expressed as follows:

$$L_{\text{init},k} = \bigcup_{i=1}^{M_{R,k}} \rho_{y,k}^i$$ (32)

3.3 Virtual track prediction strategy

Due to the unknown velocity components in the states of the new targets, the prediction step for the states of the newborn targets becomes uncertain, especially in the case of dense clutter, the ellipsoid threshold cannot effectively reduce the clutter measurement in the measurement set, which leads to the larger estimation error. In this section, the delayed track association strategy is used to pre-estimate the predicted states. The velocity state components of the newborn targets are modeled according to the measurements within the threshold. The false tracks are removed by PHD filtering, so as to improve the estimation accuracy of the newborn targets.

3.3.1 Target motion model

Suppose that at time $k$, the state vector of the i-th target is expressed as $[x_k^i, y_k^i, \dot{x}_k^i, \dot{y}_k^i]^T$, where $[x_k^i, y_k^i]^T$ is the target position, and $[\dot{x}_k^i, \dot{y}_k^i]^T$ is the velocity of the target component. The motion equation and measurement equation of the target satisfy the linear Gaussian model.

$$x_k = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} x_{k-1} + \begin{bmatrix} T^2/2 & 0 \\ 0 & T^2/2 \\ T & 0 \\ 0 & T \end{bmatrix} q_k$$ (33)

Where $T$ is the sampling period, and $q_k$ is the process noise.
3.3.2 Maximum velocity threshold strategy

In order to remove the target components modeled by clutter measurement in the initial intensity of newborn targets, the maximum velocity threshold strategy is used to establish the possible tracks of newborn targets. It is assumed that the initial component set of the newborn targets at time \( k \) can be expressed as \( \{ \omega_{\gamma,k}^i, m_{\gamma,k}^i, p_{\gamma,k}^i, t_{\gamma,k}^i \}_{i=1}^{M_k} \). At time \( k + 1 \) the measurement set after removing the correlation measurement of survival target components is \( Z_{R,k+1} = \{ z_{j}^{j} \}_{j=1}^{M_{R,k+1}} \). According to the maximum velocity threshold rule of target motion, there are several possible states for each initialization newborn target component at \( k + 1 \) step:

\[
\gamma_{pro,k+1}(x_{k+1}) = \sum_{i=1}^{M_{R,k+1}} \sum_{j=1}^{M_{R,k+1}} \omega_{\gamma,k}^{ij} N(x_{k+1}; m_{\gamma,k+1}^{ij}, p_{\gamma,k+1}^{ij})
\]

\[
\omega_{\gamma,k}^{ij} = \omega_{\gamma,k}^{i} 
\]

\[
p_{\gamma,k+1}^{ij} = p_{\gamma,k}^{i} 
\]

\[
m_{\gamma,k+1}^{ij} = [x_{k+1}, y_{k+1}, z_{k+1}]^T 
\]

\[
[\dot{x}_{k+1}^{ij}, \dot{y}_{k+1}^{ij}]^T = \begin{bmatrix} 1/T & 0 \\ 0 & 1/T \end{bmatrix} (z_{k+1}^{j} - \hat{z}_{k,k}^{j}), 
\]

\[
\forall i: M_{R,k}, \dot{x}_{k+1}^{ij}, \dot{y}_{k+1}^{ij} \leq v_{x,\text{max}}, \dot{y}_{k+1}^{ij} \leq v_{y,\text{max}} 
\]

Where \( M_{R,k+1}^{i} \) means the virtual target number at time \( k + 1 \) when the state is \( \{ \omega_{\gamma,k}^{i}, m_{\gamma,k}^{i}, p_{\gamma,k}^{i}, t_{\gamma,k}^{i} \} \) at time \( k \).

According to formula (34), the number of virtual newborn target components at time \( k + 1 \) is as follow:

\[
J_{\gamma,k+1} = \sum_{i=1}^{M_{R,k+1}} M_{R,k+1}^{i} 
\]

At time \( k + 1 \), the label set of virtual newborn target components is as follows:

\[
\mathcal{L}_{pro,k+1}^{i} = \bigcup_{i=1}^{M_{R,k+1}^{i}} \mathcal{L}_{pro,k+1}^{i} 
\]

\[
\mathcal{L}_{pro,k+1}^{i} = \bigcup_{j=1}^{M_{R,k+1}^{j}} \mathcal{L}_{pro,k+1}^{j} 
\]

3.3.3 PHD filtering based on virtual tracks

Based on the maximum velocity threshold strategy, the virtual track of each newborn target is established for each initial birth target component with the measurement set at the next moment. At most one of these virtual tracks is the real track. According to the virtual target tracks and the measurements at the next moment, the PHD prediction and update of the target components can be carried out. The track with the largest weight can be found, and the target component label with the largest weight is recorded. The others are false tracks.

Prediction:

\[
\gamma_{k|k-1}(x_{k}) = p_{\delta,k}^{i} \gamma_{pro,k-1}(x_{k-1}) 
\]

\[
\omega_{\gamma,k|k-1}^{ij} = p_{\delta,k} \omega_{\gamma,k-1}^{ij} 
\]

\[
m_{\gamma,k|k-1}^{ij} = F_{k-1} m_{\gamma,k-1}^{ij} 
\]

\[
p_{\gamma,k|k-1}^{ij} = F_{k-1} p_{\gamma,k-1}^{ij} + Q_{k-1} 
\]

Update:

\[
\gamma_{k}(x_{k}) = (1 - p_{D,k}) \gamma_{k|k-1}(x_{k}) 
\]
\[
+ \sum_{z \in \mathcal{Z}_{k}} \sum_{j=1}^{r_{k}-1} \omega_{\gamma,k|k-1}(z) N(x_{k}; m_{\gamma,k|k-1}(z), P_{\gamma,k|k-1}) \tag{47}
\]

\[
\omega_{\gamma,k}(z) = \frac{p_{D,k}a_{D,k}k_{k-1}(z)}{\lambda_{C}(z)+p_{D,k}L_{n}^{r_{k}-1}w_{k|k-1}(z)} \tag{48}
\]

\[
a_{\gamma}^{\mu}(z) = N(z; H_{k}m_{\gamma,k|k-1}^{\mu}, R_{k} + H_{k}p_{\gamma,k|k-1}(H_{k})^{T}) \tag{49}
\]

\[
m_{\gamma,k}^{i}(z) = m_{\gamma,k|k-1}^{i} + K_{\gamma}^{i}(z - H_{k}m_{\gamma,k|k-1}^{i}) \tag{50}
\]

\[
P_{\gamma,k}^{i} = [I - K_{\gamma}^{i}H_{k}]P_{\gamma,k|k-1}^{i} \tag{51}
\]

\[
K_{\gamma}^{i} = p_{\gamma,k|k-1}(H_{k})^{T}(R_{k} + H_{k}p_{\gamma,k|k-1}(H_{k}))^{-1} \tag{52}
\]

After the update step, \( M_{R,k-2} \times M_{R,k-1} \times M_{\gamma,k} \) (\( \forall i = 1: M_{R,k-2} \)) newborn target components are generated. They are used to construct \( M_{R,k-2} \times M_{\gamma,k} \) weight matrices of \( M_{R,k-2} \times M_{\gamma,k} \). Based on the weight of each virtual component in the weight matrix, the false target component modeled by clutter is eliminated and the real target components and their label set is retained.

\[
\mathcal{L}_{\gamma,k} = \bigcup_{i=1}^{M_{\gamma,k}} \mathcal{P}_{\gamma,k} \quad \mathcal{P}_{\gamma,k} \in \mathcal{L}_{\gamma,k}^{pro,k+1} \Omega_{\gamma,k} = \arg \max_{i} (\omega_{\gamma,k}^{i}), \quad \omega_{\gamma,k}^{i} > \omega_{th} \tag{53}
\]

\( M_{\gamma,k} \) is the number of new target components at time \( k \).

4. Simulation

In order to verify the effectiveness of the proposed algorithm, the simulation is compared with MD-PHD algorithm [9]. MD-PHD algorithm similarly uses the velocity strategy, but it only takes advantage of the magnitude of velocity, not the direction of velocity.

Taking multi-target tracking in two-dimensional plane as an example, the monitoring area is assumed to be [-500, 500] (m) \times [-500, 500] (m). The survival probability of the target is 0.99, and the detection probability of the survival target is 0.99, and the measuring gate probability is 0.99. In order to evaluate the tracking performance of the algorithm in dense clutter, the simulation is carried out in different clutter density scenarios. 100 Monte Carlo experiments are carried out in each scenario, and OSPA distance [16] and target number estimation error are used as filter performance evaluation indicators.

In this experiment, three uniform linear moving targets are selected for simulation. The first target appears in the first second and always appears, the second target appears in 15s and disappears in 65s, and the third target appears in 32s and disappears in 80s. Figure 1 illustrates the actual target trajectory and measurement. The number of clutter accords with Poisson distribution with \( \lambda_{C} = 10 \).

Figure 2 shows the estimated trajectory of the targets. The particle plots in Figure 2 represent the estimated positions of the targets. The simulation results show that the tracking trajectory calculated by this algorithm can be better and more effective.

![Figure 1. Actual target trajectory and measurement](image-url)
Figure 2. Estimated target trajectory

The performance comparison results of the two algorithms in OSPA distance and the number of birth targets are shown in Figure 3 and Figure 4. The number of clutter accords with Poisson distribution with $\lambda_c = 20$. It can be seen from Figure 4 that in the OSPA distance, two peaks appear in the two algorithms, which shows that the error is relatively large. This is because both algorithms have a certain delay in the detection of newborn targets. This is also shown in Figure 3. However, due to the use of the directionality of velocity, the algorithm can better eliminate the interference of clutter, which shows the better performance of the algorithm.

Figure 3. Comparison in OSPA distance

Figure 4. Comparison in estimated target number

Figure 5 show the comparison of OSPA distance, target number estimation error of MD-PHD filter and the algorithm in this paper in three newborn target scenarios under the clutter with different mean values. In this group of experiments, the clutter mean values ($\lambda_c$) of three newborn target tracking scenes are set to 5, 10, 15, 20, 25 and 30 respectively.
The estimation error for number of targets by this proposed algorithm does not increase with the increase of clutter number, and it is far lower than MD-PHD filter. The simulation results of newborn target scene under different clutter intensity show that the accuracy of target state estimation and target number estimation of this algorithm are relatively better in dense clutter environment.

![OSPA distance](image1)

(a) OSPA distance

![The number of target estimation errors](image2)

(b) The number of target estimation errors

Figure 5. Results of different algorithms for varied clutter rates

5. Conclusions
The PHD filtering of unknown target birth intensity can not rely on prior knowledge assumption by using measurement driven method. However, the estimation process is greatly affected by clutter interference, especially in dense clutter environment. To solve the above problem, this paper proposes a PHD filtering algorithm based on virtual track prediction, which mainly includes three aspects of improvement: 1) measurement set division, separating the surviving target measurement and clutter measurement set, so as to avoid the interference of clutter on the target intensity estimation; 2) The ellipsoid threshold and the maximum velocity threshold are used to preprocess the measurements of the surviving target and the new target respectively to reduce the influence of clutter in the estimation; 3) using the measurement set between adjacent times, the virtual track of the new target is modeled, and then the real target state is extracted by PHD filter to reduce the false alarm, thus reducing the estimation error of the number of targets and improving the tracking accuracy. Experimental results show that the proposed algorithm outperforms MD-PHD algorithms in dense clutter environment.

Acknowledgment
This work is supported by National Nature Science Foundation of China (No. 61701295) and the Foundation of Shanghai Polytechnic University (No. EGD20XQD04).
REFERENCES

[1] R.P.S. Mahler, “Multi-target Bayes Filtering via First-Order Multi-target Moments,” IEEE Trans. Aerosp. Electron. Syst., vol.39, no. 4, Oct. 2003, pp. 1152–1178.

[2] B.N. Vo, S. Singh, and A. Doucet, “Sequential Monte Carlo Implementation of the PHD Filter for Multi-target Tracking,” Proc. Int. Conf. Inf. Fusion, Queensland, Australia, July 8-11, 2003, pp. 792–799.

[3] VO B N, SINGH S, DOUCET A, “Sequential Monte Carlo methods for multitarget filtering with random finite sets,” IEEE Transactions on Aerospace & Electronic Systems, 2005, 41(4): 1224-1245.

[4] VO B N, MA W K, “The Gaussian mixture probability hypothesis density filter,” IEEE Transactions on Signal Processing, 2006, 54(11): 4091-4104.

[5] S. Reuter et al, “The Labeled Multi-bernoulli Filter,” IEEE Trans. Signal Process, vol. 62, no. 12, May 2014, pp. 3246-3260.

[6] B.N. Vo, B.T. Vo, and D. Phung, “Labeled Random Finite Sets and the Bayes Multi-target Tracking Filter,” IEEE Trans. Signal Process, vol. 62, no. 24, Oct. 2014, pp. 6554–6567.

[7] F. Papi et al., “Generalized Labeled Multi-bernoulli Approximation of Multi-object Densities,” IEEE Trans. Signal Process., vol. 63, no. 20, Oct. 2015, pp. 5487-5497.

[8] Ristic B, Clark D, Vo B N, et al, “Adaptive target birth intensity for PHD and CPHD filters,” IEEE Transactions on Aerospace and Electronic Systems, 2012, 48(2): 1656-1668.

[9] HAN S T, XUE A K, PENG D L, “A historical information feedback multiple-target tracke,” The 33rd Chinese Control Conference (CCC), 2014: 7173-7178.

[10] RISTIC B, CLARK D, VO B N, et al, “Adaptive target birth intensity for PHD and CPHD filters,” IEEE Transactions on Aerospace & Electronic Systems, 2012, 48(2): 1656-1668.

[11] Wang Y, Jing Z, Hu S, et al, “Detection-guided multi-target Bayesian filter,” Signal Processing, 2012, 92(2): 564-574.

[12] Zhang H J, Wang J, Ye B, et al, “A GM-PHD filter for new appearing targets tracking,” In: proceedings of the 6th International Congress on Image and Signal Processing(CISP). IEEE, 2013. 1153-1159.

[13] Zhang H Q, Ge H W, Yang J L, “Target birth intensity estimation using measurement-driven PHD filter,” ETRI Journal, 2016, 38(5): 1019-1029.

[14] Christopher B;Donald J. B;Samuel W S, “Passive Multi-Target Tracking Using the Adaptive Birth Intensity PHD Filter,” the 21st International Conference on Information Fusion (FUSION).IEEE, 2018. 353-360

[15] Zhu Q; Li T; Pan J M, et al, “The Modified Probability Hypothesis Density Filter With Adaptive Birth Intensity Estimation for Multi-Target Tracking in Low Detection Probability,” IEEE Access, 2020, VOL 8:43690-43710

[16] SCHUHMACHERD, VO B T, VO B N, “A consistent metric for performance evaluation of multi-object filters,” IEEE Transactions on Signal Processing, 2008, 56 (8):3447-3457.