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Improved CPHD Filtering With Unknown Clutter Rate

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Abstract - To accommodate the model mismatch in clutter rate, a cardinality probability hypothesis density (CPHD) filter with unknown clutter rate has been proposed by Mahler. It has proved to be a promising algorithm for multi-target tracking in complex environment. However, in Mahler's algorithm, the calculation of the number of clutters without observations is determined by the hybrid cardinality distribution and hybrid probability of misses, it will cause the confusion between undetected targets and clutters. To solve this problem, an improved CPHD filter is proposed which increases an estimation of the number of targets based on the measurement likelihood in the process of update and then modifies the hybrid cardinality distribution by treating the confused targets as detected ones more reasonably. Simulation results show that the improved CPHD filter is superior to the traditional method in both the estimates of clutter number and target state.

Index Terms - cardinalized probability hypothesis density filter; unknown clutter rate; hybrid cardinality distribution; multi-target tracking; random finite set

I. INTRODUCTION

Uncertainties, including the number of targets, the association of measurements with targets and clutter rate, make multi-target tracking (MTT) become an urgent problem to be solved. Recently, some researchers have presented the theory of random finite sets (RFSs) [1] which treat the finite target sets as random finite sets and in which the number of random variables is a discrete random variable. On the basis of RFSs, probability hypothesis density (PHD) filter [2] has been proposed to solve the multi-target tracking problem. This filter convert the complex arithmetic on the multi-target state space to a simplified solution on the single-target state space, and effectively solve the combinatorial problem in data association [3]. However, it has a disadvantage that the Poisson assumption for target number distribution may lead to an exaggerating effect of missed detection problem [4]. This problem has been solved by the cardinalized probability hypothesis density (CPHD) filter [5, 6] through the increased estimation of cardinality. To obtain the closed form solutions of PHD and CPHD, sequential Monte Carlo (SMC) [7] and Gaussian mixtures [8] have been used. Recent works have shown that the PHD/CPHD filters are promising approaches for multi-target tracking.

In MTT environment, there is a significant source of uncertainty, clutter, in addition to the process and measurement noise associated with each target. Usually, the comprehensive information of clutter like state, number and probability of detection can't be obtained directly. However, these information of clutter are extremely important in Bayesian multi-target filtering. Without it, PHD/CPHD filters result in large errors. Therefore, in order to adapt PHD/CPHD filters to the more complex and real tracking environment, Mahler has presented a CPHD filter with unknown clutter rate [9] which carry on the estimation to the posterior hybrid cardinality distribution and the number of clutters. It exhibits similar performance to the same error value as that for the standard PHD filter and has lower computational complexity than the standard CPHD filter. Unfortunately, that the calculation of the number of clutters without observations is determined by the hybrid cardinality distribution and hybrid probability of missing detection which are composed of information of target and clutter, it will cause the confusion between undetected targets and clutters.

To solve this problem, an improved CPHD filter with unknown clutter rate is proposed in this paper. We increase an estimation of the number of target based on the measurement likelihood in the process of update. By defining the difference between the estimations in continuous two scans as the number of confusion, we treat the confused targets as detected ones and modify the hybrid cardinality distribution. Simulation results show that the proposed algorithm is superior to the traditional method in both the aspects of clutter number estimate and target state estimate.

The remainder of the paper is organized as follows. First of all, we present the PHD algorithm as Background knowledge in Section 2. Then, a brief introduction to the CPHD filter with unknown clutter rate is presented in Section 3. Section 4 discusses the major problem in the CPHD tracker with unknown clutter rate and presents the improved CPHD filter with unknown clutter rate. Simulation results are presented in Section 5. Finally, some conclusions are provided in Section 6.

II. PHD ALGORITHM

The PHD filter was proposed in [2] as a first-order multi-target moments approximation to the Bayes recursion (1) and (2).

$$p\left(\mathbf{x}_k \mid \mathbf{Z}_{k-1}\right) = \int_{\mathbb{R}^{n_x}} p\left(\mathbf{x}_k \mid \mathbf{x}_{k-1}\right) p\left(\mathbf{x}_{k-1} \mid \mathbf{Z}_{k-1}\right) d\mathbf{x}_{k-1} \quad (1)$$

$$p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right) = \frac{p\left(\mathbf{z}_k \mid \mathbf{x}_k\right) p\left(\mathbf{x}_k \mid \mathbf{Z}_{k-1}\right)}{\int_{\mathbb{R}^{n_x}} p\left(\mathbf{z}_k \mid \mathbf{x}_k\right) p\left(\mathbf{x}_k \mid \mathbf{Z}_{k-1}\right) d\mathbf{x}_k} \quad (2)$$

Let $v_{k|k-1}$ and v_k denote the intensities associated with the predicted and posterior multi-target state, then the PHD recursion is

$$v_{k|k-1}(x) = \int p_{S,k}(\xi) f_{k|k-1}(x|\xi) v_{k-1}(\xi) d\xi + \gamma_k(x) \quad (3)$$

$$v_k(x) = [1 - p_{D,k}(x)] v_{k|k-1}(x) + \sum_{z \in Z_k} \frac{p_{D,k}(x) g_k(z|x) v_{k|k-1}(x)}{\kappa_k(z) + \int p_{D,k}(\xi) g_k(z|\xi) v_{k|k-1}(\xi) d\xi} \quad (4)$$

Where $p_{S,k}(\cdot)$ is the probability of target existence, $f_{k|k-1}(\cdot|\cdot)$ is the single-target transition density, $\gamma_k(\cdot)$ is the intensity of target births, $g_k(\cdot|\cdot)$ is the measurement likelihood, $p_{D,k}(x)$ is the probability of target detection and $\kappa_k(z)$ is the intensity of clutter. As (3) and (4), the PHD algorithm propagates the posterior intensity of the RFS of targets in time and does not require any data association computations.

III. CPHD FILTER WITH UNKNOWN CLUTTER RATE

A. Hybrid Random Finite Sets

Let $\chi^{(1)}$ denote the state space of targets, $\chi^{(0)}$ denote the state space of clutters. Define the hybrid state space

$$\ddot{\chi} = \chi^{(1)} \oplus \chi^{(0)} \quad (5)$$

where $\oplus$ denotes a disjoint union. It's noteworthy that a superscript $^{(1)}$ is used to denote functions or variables pertaining to actual targets, while a superscript $^{(0)}$ is used to denote functions or variables on the space of clutters. And for any space χ, let $\mathbb{F}(\chi)$ denote the set of all finite subsets of χ. At time *k*, the multi-target state evolves to $\ddot{X}_k \in \mathbb{F}(\ddot{\chi})$ and is given by

$$\ddot{X}_k = X_k^{(1)} \oplus X_k^{(0)} \quad (6)$$

where $X_k^{(1)} \in \mathbb{F}(\chi^{(1)})$ and $X_k^{(0)} \in \mathbb{F}(\chi^{(0)})$. The actual multi-target state and clutter multi-target state at time *k* are stated as follows.

$$X_k^{(1)} = \bigcup_{x_{k-1} \in X_{k-1}^{(1)}} S_{k|k-1}^{(1)}(x_{k-1}) \bigcup \Gamma_{\mathrm{k}}^{(1)} \quad (7)$$

$$X_k^{(0)} = \bigcup_{c_{k-1} \in X_{k-1}^{(0)}} S_{k|k-1}^{(0)}(c_{k-1}) \bigcup \Gamma_{\mathrm{k}}^{(0)} \quad (8)$$

where $S_{k|k-1}^{(1)}(x_{k-1})$ is the RFS of targets that have survived at scan *k* from multi-target state $X_{k-1}^{(1)}$, $\Gamma_{\mathrm{k}}^{(1)}$ is the RFS of targets that appear spontaneously at scan k, $S_{k|k-1}^{(0)}(c_{k-1})$ is the RFS of clutters that have survived at scan *k* from multi-target state $X_{k-1}^{(0)}$, $\Gamma_{\mathrm{k}}^{(0)}$ is the RFS of targets that appear spontaneously at scan *k*.

The multi-target measurement Z_k is modeled by RFS,

$$Z_k = D_k^{(1)}(X_k^{(1)}) \bigcup D_k^{(0)}(X_k^{(0)}) \quad (9)$$

where $D_k^{(1)}(X_k^{(1)})$ denotes measures produced by actual targets, $D_k^{(0)}(X_k^{(0)})$ denotes measures produced by clutters.

B. The Gaussian Mixture CPHD Recursion

The CPHD filter with unknown clutter rate propagates three parameters: the posterior intensity $\ddot{v}_k(\cdot)$, posterior hybrid cardinality distribution $\ddot{\rho}_k(\cdot)$ and the number of clutter $N_k^{(0)}$. The steps of prediction and update are described as follows.

Prediction: At time *k*-1, suppose the posterior intensity for targets $v_{k-1}^{(1)}$ is a Gaussian mixture of the form

$$v_{k-1}^{(1)}(x) = \sum_{i=1}^{J_{k-1}} w_{k-1}^{(i)} N(x; m_{k-1}^{(i)}, P_{k-1}^{(i)})$$

given the posterior mean number of clutters $N_{k-1}^{(0)}$, and the posterior hybrid cardinality distribution $\ddot{\rho}_{k-1}$. Then at time *k*, the prediction of them is presented as follow.

$$v_{k|k-1}^{(1)}(x) = \gamma_k^{(1)}(x) + \int p_{S,k}^{(1)}(\varsigma) f_{k|k-1}^{(1)}(x|\varsigma) v_{k-1}^{(1)}(\varsigma) d\varsigma \quad (10)$$

$$N_{k|k-1}^{(0)} = N_{\Gamma,k}^{(0)} + p_{S,k}^{(0)} \cdot N_{k-1}^{(0)} \quad (11)$$

$$\ddot{\rho}_{k|k-1}(\ddot{n}) = \sum_{j=0}^{\ddot{n}} \ddot{\rho}_{\Gamma,k}(\ddot{n} - j) \sum_{l=j}^{\infty} C_j^l \ddot{\rho}_{k-1}(l)(1-\phi)^{l-j} \phi^j \quad (12)$$

where

$$\phi = \left(\frac{< v_{k-1}^{(1)}, p_{S,k}^{(1)} > + N_{k-1}^{(0)} p_{S,k}^{(0)}}{< 1, v_{k-1}^{(1)} > + N_{k-1}^{(0)}}\right) \quad (13)$$

and $\gamma_k^{(1)}$ denotes the posterior intensity for birth targets, $p_{S,k}^{(1)}$ and $p_{S,k}^{(0)}$ denote the survival probability of target and clutter, respectively. $f_{k|k-1}^{(1)}(\cdot|\cdot)$ denotes the transition density of targets; $N_{\Gamma,k}^{(0)}$ denotes the number of birth clutter; $\ddot{\rho}_{\Gamma,k}$ denotes the posterior cardinality distribution of birth hybrid; ϕ denotes the hybrid probability of survival; $< \cdot, \cdot >$ denotes the inner product.

Update: Suppose the predicted intensity for targets $v_{k|k-1}^{(1)}(x)$ is a Gaussian mixture of the form

$$v_{k|k-1}^{(1)}(x) = \sum_{i=1}^{J_{k|k-1}} w_{k|k-1}^{(i)} N(x; m_{k|k-1}^{(i)}, P_{k|k-1}^{(i)})$$

For a given measurement set Z_k, $g_k(\cdot|\cdot)$ denotes the single target measurement likelihood. $p_{D,k}^{(1)}$ and $p_{D,k}^{(0)}$ denote the detection probability of target and clutter, respectively. $\tilde{\chi}_k(\cdot)$ denotes the spatial likelihood. Updates of $v_{k|k-1}^{(1)}(\cdot)$, $N_{k|k-1}^{(0)}$ and $\ddot{\rho}_{k|k-1}(\cdot)$ are stated as follows:

$$v_k^{(1)}(x) = v_{k|k-1}^{(1)}(x)[\frac{q_{D,k}^{(1)}(x)\frac{<\ddot{\gamma}_k^1[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}{<\ddot{\gamma}_k^0[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}}{<1, v_{k|k-1}^{(1)}> + N_{k|k-1}^{(0)}} + \sum_{z\in Z_k}\frac{p_{D,k}^{(1)}(x)g_k(z|x)}{p_{D,k}^{(0)}N_{k|k-1}^{(0)}\tilde{\chi}_k(z) + <v_{k|k-1}^{(1)}, p_{D,k}^{(1)}g_k(z|\cdot)>}] \quad (14)$$

$$N_k^{(0)}(x) = N_{k|k-1}^{(0)}(x)[\frac{q_{D,k}^{(0)}(x)\frac{<\ddot{\gamma}_k^1[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}{<\ddot{\gamma}_k^0[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}}{<1, v_{k|k-1}^{(1)}> + N_{k|k-1}^{(0)}} + \sum_{z\in Z_k}\frac{p_{D,k}^{(0)}(x)\tilde{\chi}_k(z)}{p_{D,k}^{(0)}N_{k|k-1}^{(0)}\tilde{\chi}_k(z) + <v_{k|k-1}^{(1)}, p_{D,k}^{(1)}g_k(z|\cdot)>}] \quad (15)$$

$$\ddot{\rho}_k(\ddot{n}) = \begin{cases} 0 & \ddot{n} < |Z_k| + u \\ \frac{\ddot{\rho}_{k|k-1}(\ddot{n})\ddot{\gamma}_k^0[v_{k|k-1}, Z_k](\ddot{n})}{<\ddot{\rho}_{k|k-1}, \gamma_k^0>} & \ddot{n} \ge |Z_k| + u \end{cases} \quad (16)$$

where

$$\ddot{\gamma}_k^u[\ddot{v}_{k|k-1}, Z_k](\ddot{n}) = \begin{cases} 0 & \ddot{n} < |Z_k| + u \\ P_{|Z_k|+u}^{\ddot{n}}\Phi^{\ddot{n}-(|Z_k|+u)} & \ddot{n} \ge |Z_k| + u \end{cases} \quad (17)$$

$$\Phi = 1 - \frac{<v_{k|k-1}^{(1)}, p_{D,k}^{(1)}> + N_{k|k-1}^{(0)}p_{D,k}^{(0)}}{<1, v_{k|k-1}^{(1)}> + N_{k|k-1}^{(0)}} \quad (18)$$

$$q_{D,k}^{(1)}(x) = 1 - p_{D,k}^{(1)} \quad (19)$$

$$q_{D,k}^{(0)}(x) = 1 - p_{D,k}^{(0)} \quad (20)$$

where Φ denotes the hybrid probability of miss. In the CPHD filter with unknown clutter rate, compared with the standard CPHD, the estimation of number of clutter is added in the process of recursion, which is composed of the part of detection and that of missing detection, and the estimation of cardinality of target is changed into the estimation of cardinality of entirety. Also the estimation of number of target is added, which is obtained by the hybrid cardinality distribution and the number of clutter. As these estimations are introduced, the algorithm can solve the problem of unknown clutter rate.

IV. IMPROVED CPHD FILTER WITH UNKNOWN CLUTTER RATE

A. *The problem of confusion*

Because the number of undetected clutter in the CPHD filter with unknown clutter rate is decided by both the hybrid probability of misses and the hybrid cardinality distribution, instead of the probability of undetected clutter, the hybrid probability of misses will influence the accuracy of the estimation to the number of target.

In the actual circumstances, target and clutter have different detection probabilities for their different characteristics. Generally, the detection probability of target is larger than that of clutter. Therefore, besides the considerable gap between the number of target and clutter, the hybrid probability of missing detection (Eq. 18) is almost equal to the miss probability of clutter (Eq. 20). It results in that the entirety which is composed of targets and clutters is treated as clutters only in the recursion calculation based on the hybrid probability of misses. In other words, the missing target is regarded unreasonably as the missing clutter. On the contrary, if the hybrid probability of misses is almost equal to probability of misses of target, the missing clutter will be regarded falsely as the missing target. Of cause, it will seldom take place actually.

To solve the problem of confusion between missing detected target and clutter, we present an improved CPHD filter with unknown clutter rate here.

B. *Improved method*

The step of prediction is same with the original algorithm and no longer repeated here. The step of update is revised as follows.

Update: Besides for updates of $v_{k|k-1}^{(1)}(\cdot)$, $N_{k|k-1}^{(0)}$ and $\ddot{\rho}_{k|k-1}(\cdot)$, we increase an estimation to the number of target based on the measurement likelihood. Compared with that in the previous scan, the difference is defined as $N_{c,k}$ in (26). We call it number of confusion. On the bases of the number of confusion, we modify the hybrid cardinality distribution in the process of recursion.

$$v_k^{(1)}(x) = v_{k|k-1}^{(1)}(x)[\frac{q_{D,k}^{(1)}(x)\frac{<\ddot{\gamma}_k^1[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}{<\ddot{\gamma}_k^0[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}}{<1, v_{k|k-1}^{(1)}> + N_{k|k-1}^{(0)}} + \sum_{z\in Z_k}\frac{p_{D,k}^{(1)}(x)g_k(z|x)}{p_{D,k}^{(0)}N_{k|k-1}^{(0)}\tilde{\chi}_k(z) + <v_{k|k-1}^{(1)}, p_{D,k}^{(1)}g_k(z|\cdot)>}] \quad (21)$$

$$N_k^{(0)}(x) = N_{k|k-1}^{(0)}(x)[\frac{q_{D,k}^{(0)}(x)\frac{<\ddot{\gamma}_k^1[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}{<\ddot{\gamma}_k^0[\ddot{v}_{k|k-1}, Z_k], \ddot{\rho}_{k|k-1}>}}{<1, v_{k|k-1}^{(1)}> + N_{k|k-1}^{(0)}} + \sum_{z\in Z_k}\frac{p_{D,k}^{(0)}(x)\tilde{\chi}_k(z)}{p_{D,k}^{(0)}N_{k|k-1}^{(0)}\tilde{\chi}_k(z) + <v_{k|k-1}^{(1)}, p_{D,k}^{(1)}g_k(z|\cdot)>}] \quad (22)$$

$$\ddot{\rho}_k(\ddot{n}) = \begin{cases} 0 & \ddot{n} < |Z_k| \\ \frac{\ddot{\rho}_{k|k-1}(\ddot{n})\ddot{\gamma}_k^0[v_{k|k-1}, Z_k](\ddot{n})}{<\ddot{\rho}_{k|k-1}, \gamma_k^0>} & \ddot{n} \ge |Z_k| \end{cases} \quad (23)$$

$$N_{E,k}=\sum_{z\in Z_k}\frac{<v_{k|k-1}^{(1)},p_{D,k}^{(1)}g_k(z|\cdot)>}{p_{D,k}^{(0)}N_{k|k-1}^{(0)}\tilde{\chi}_k(z)+<v_{k|k-1}^{(1)},p_{D,k}^{(1)}g_k(z|\cdot)>} \quad (24)$$

where

$$\ddot{\gamma}_k^u[\ddot{v}_{k|k-1},Z_k](\ddot{n})$$

$$=\begin{cases}0 & \ddot{n}<|Z_k|+u+N_{c,k}\\ P_{|Z_k|+u+N_{c,k}}^{\ddot{n}}\Phi^{\ddot{n}-(|Z_k|+u+N_{c,k})} & \ddot{n}\geq|Z_k|+u+N_{c,k}\end{cases} \quad (25)$$

$$N_{c,k}=\begin{cases}0 & N_{E,k-1}-N_{E,k}\leq 0\\ N_{E,k-1}-N_{E,k} & N_{E,k-1}-N_{E,k}>0\end{cases} \quad (26)$$

$$\Phi=1-\frac{<v_{k|k-1}^{(1)},p_{D,k}^{(1)}>+N_{k|k-1}^{(0)}p_{D,k}^{(0)}}{<1,v_{k|k-1}^{(1)}>+N_{k|k-1}^{(0)}} \quad (27)$$

The equation (24) is the estimation to the number of target, which is approximately equal to the number of detected target.

As seen in the equation (26), if the estimation to the number of target in previous scan is larger than that in current scan, as $N_{E,k-1}-N_{E,k}>0$, the missing detected targets will be unreasonably regarded as the missing detected clutters in the CPHD filter with unknown clutter rate. It is necessary to amend this mistake. By defining the difference between the estimations in continuous two scans as the number of confusion, we can treat the confused targets as detected ones and modify the hybrid cardinality distribution in equation (25). On the other hand, the undetected clutters will be regarded as the undetected targets for $N_{E,k-1}-N_{E,k}\leq 0$. While the same result will appear when new target birth or inaccurate measurements are got, we do not make any change.

It is noteworthy that we hardly change the estimated number of entirety, although we modify the equation (17). This is because we only solve the confusion problem of undetected part.

V. Simulation Results

Consider a three target scenario on the region [0,2000]m $\times$[0,2000]m. Targets move with constant velocity as shown in Fig.1. The sampling period is T=1*s*, and the target dynamic equation is described as

$$x_k=Fx_{k-1}+w_k$$

where state $x_k=\left[\xi_{x,k},\xi_{y,k},\dot{\xi}_{x,k},\dot{\xi}_{y,k}\right]^{\mathrm{T}}$ consists of the position and the velocity of a moving target at scan *k*, and

$$F=\begin{bmatrix}1 & T & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & T\\ 0 & 0 & 0 & 1\end{bmatrix},\ Q=\sigma_v^2\begin{bmatrix}T^4 I_2 & \frac{T^3}{2}I_2\\ \frac{T^3}{2}I_2 & \frac{T^2}{4}I_2\end{bmatrix},$$

where I_n denotes the $n\times n$ identity matrices, $\sigma_v=1ms^{-2}$ is the standard deviation of the process noise.

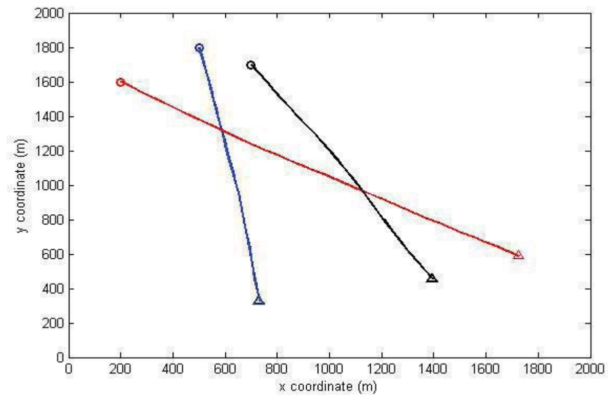

Fig.1 Tracks in x-y plane. Start/Stop position for each track are shown with circular/triangle.

For simplicity, we assume that the target position can be observed, and that the measurement equation is described as

$$z_k=Hx_k+v_k$$

where $H=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 0 & 1 & 0\end{bmatrix}$, $R=\sigma_\varepsilon^2 I_2$ and $\sigma_\varepsilon=4$ is the standard deviation of the measurement noise.

The following parameters are used. The birth RFS is the Poisson distribution with intensity

$$\Gamma_k(x)=\sum_{i=1}^{3}0.9\mathcal{N}(x;m_\gamma^i,\mathbf{P}_\gamma)$$

Where

$$m_\gamma^1=\left[500,1800,10,\text{-}60\right]'$$

$$m_\gamma^2=\left[200,1600,40,\text{-}30\right]'$$

$$m_\gamma^3=\left[700,1700,30,\text{-}50\right]'$$

and $\mathbf{P}_\gamma=diag([100,100,100,100])$. The survival probability for actual targets is $p_{S,k}^{(1)}=0.99$. The detection probability for measurements is $p_{D,k}^{(1)}=0.99$. For the clutter model, the number of clutter is $N_k^{(0)}=10$, the detection probability for measurements is $p_{D,k}^{(0)}=0.5$ and the births is $N_{\Gamma,k}^{(0)}=1$ while deaths are given by the survival probability of $p_{S,k}^{(0)}=0.9$. Pruning and merging is used at each scan with the weight threshold $T=10^{-6}$ and the merging threshold $U=4m$. The maximum number of targets is $N_{\max}=20$. The parameters of the OSPA distance are set to be $p=2$ and $c=70m$. To evaluate the average performance, 100 Monte Carlo (MC) trials are performed.

The average number of clutter is shown in Fig. 2. As seen in the figure, the proposed method is more accurate than the traditional one in estimating to the clutter number. The confusion that undetected targets were regarded as undetected clutters is modified, therefore, the number of clutter of the proposed method is less than or equal to that of the traditional method.

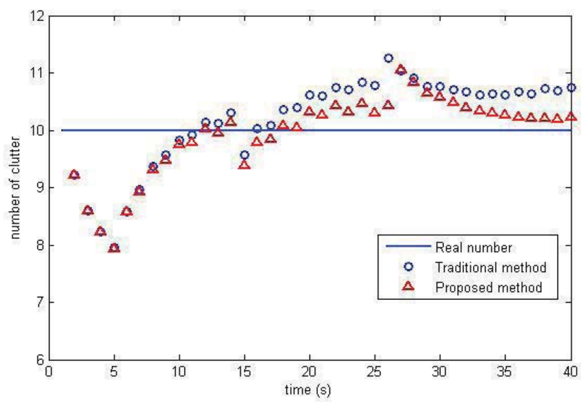

Fig.2 The average number of clutter.

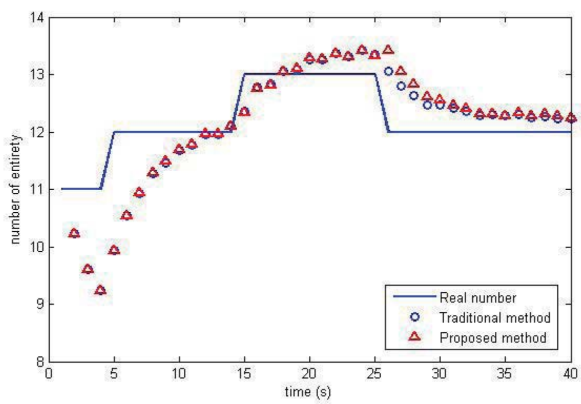

Fig. 3 The average number of entirety.

The number of target is obtained by the number of entirety minus the number of clutter. The average number of entirety and target are shown in Fig. 3 and Fig. 4, respectively.

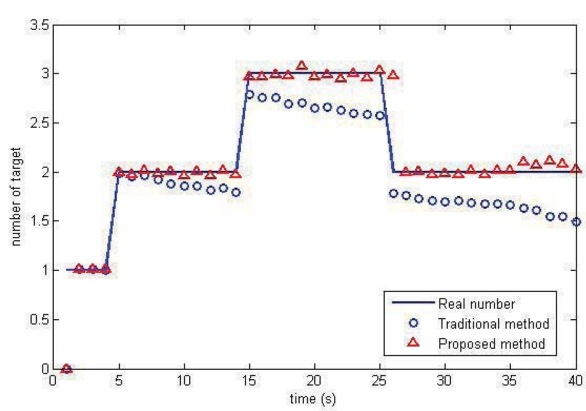

Fig. 4 The average number of target

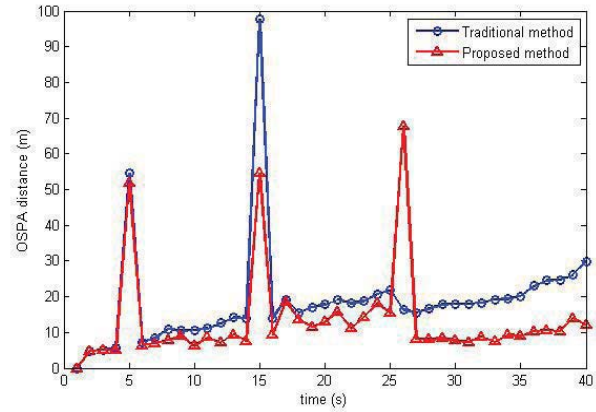

Fig. 5 The average OSPA distance.

As seen in Fig. 3, we solve the confusion problem of undetected part but not change the estimated number of entirety. Consequently, the number of entirety of the proposed method is almost same with that of traditional method. A slight error is occurred only when target disappears, since it is impossible to distinguish whether target has disappeared or been missing detected. Therefore, the tracking performance will become worse when targets appearance and dis-appearance very frequently, we should avoid it as far as possible.

Because the estimation of clutter number is more accurate and the estimation of entirety number is unchanged, the number of target of proposed method is more accurate than that of traditional method as seen in Fig. 4. The average OSPA distance is shown in Fig. 5. The error of proposed method is smaller than that of traditional method.

VI. Conclusions

To solve the confusion problem in Mahler's CPHD filter with unknown clutter rate, an improved algorithm is proposed in this paper, which increases an estimation of the number of targets based on the measurement likelihood and then compares with the estimation in previous scan to modify the hybrid cardinality distribution by treating the confused targets as detected ones more reasonably. Simulation results show that the proposed method is superior to the traditional method in both the estimates of clutter number and target state. In the future, more uncertainties, such as the unknown probability of detection, should be taken into account to make the CPHD algorithm more adapted to the reality application.

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