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IMPROVED CBMEMBER FILTER FOR MULTI-TARGET TRACKING

Bo Li*, Shuo Wang, Jianli Zhao and Xu Jia

School of Electronics and Information Engineering
Liaoning University of Technology
No. 169, Shiying Street, Guta District, Jinzhou 121001, P. R. China
*Corresponding author: leeboo@yeah.net

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Abstract. *Multi-target tracking (MTT) is widely applied in many surveillance systems. To efficiently select existence probability and adaptively correct under-estimated number of targets, an improved cardinality balanced multi-target multi-Bernoulli (CBMeMBer) filter is presented in this paper. Employing the adaptive target birth intensity method, we design the novel CBMeMBer filter and optimize its particle implementation. Numerical study results confirm validity and efficiency of the proposed filter.*
Keywords: Multi-target tracking, CBMeMBer filter, Particle implementation, Cardinality

1. **Introduction.** The goal of multi-target tracking (MTT) is to jointly estimate the number of moving targets and their states from noise-corrupted measurements. By modelling target states and measurements as the random finite set (RFS), Vo et al. proposed the cardinality balanced multi-target multi-Bernoulli (CBMeMBer) filter as a tractable approximation to the Bayes recursion for the MTT [1]. This kind of filter can complete reliable and inexpensive extraction of state estimates without data association.

So far, some scholars have researched the CBMeMBer filter and many articles have been published in important journals [2-7]. In [2], the particle implementation of the CBMeMBer filter more efficient than the traditional RFS filters, was proposed in detail. Subsequently, a novel CBMeMBer filter in [3] was presented to offer statistical frame in update step. [4] represented a proposed filter for the Poisson extended-target measurement models. However, the effectiveness of them needs to be improved. In [5], a particle implementation was discussed to improve the accuracy of distributions. Further, [6] corrected the posterior cardinality by modifying the legacy rather than the measurement-updated parameters. Recently, a CBMeMBer filter combined degenerate unmixing estimating technique has been applied in moving speaker tracking [7]. Nevertheless, it is not obvious to choose the existence probability of newborn targets in the above filters that have inherited the defect of under-estimated number of targets.

In this paper, an improved CBMeMBer filter and its particle implementation are explored. We mainly propose adaptive target birth intensity method to obtain the existence probability of newborn targets and then correct target number estimates. The rest of this note is organized as follows. In Section 2, the standard CBMeMBer filter is analyzed. Section 3 presents the filtering principle and particle implementation of the proposed filter in detail. In Section 4, the numerical study validates tracking performance of the proposed filter. Section 5 draws the conclusion by providing the future work.

2. **Problem Formulation.** Assume the single Bernoulli RFS $X^{(i)}$ in the space $\mathcal{X} \subseteq \mathbb{R}^{n_k}$ has the existence probability r of being a singleton whose component is distributed based

on the probability density p, then the probability density of the Bernoulli RFS is defined by:

$$\pi(X^{(i)}) = \begin{cases} 1-r, & X^{(i)} = \emptyset \\ rp(x_i), & X^{(i)} = \{x_i\} \end{cases} \tag{1}$$

Due to the multi-Bernoulli RFS $\boldsymbol{X}$ in $\mathcal{X}$ combined with a fixed number of the independent $X^{(i)}$, i.e., $\boldsymbol{X} = \cup_{i=1}^{M} X^{(i)}$, the related probability density can be written as:

$$\pi(\boldsymbol{X}) = \begin{cases} \prod_{i=1}^{M} \left(1 - r^{(i)}\right), & \boldsymbol{X} = \emptyset \\ \prod_{i=1}^{M} \left(1 - r^{(i)}\right) \sum_{1 \le j_1 \ne \cdots \ne j_n \le M} \prod_{i=1}^{n} r^{(j_i)} p^{(j_i)}(x_i) / \left(1 - r^{(j_i)}\right), & \boldsymbol{X} = \{x_1, \ldots, x_n\} \end{cases} \tag{2}$$

To simplify, we use $\pi = \left\{\left(r^{(i)}, p^{(i)}\right)\right\}_{i=1}^{M}$ to represent (2) with the cardinality $\sum_{i=1}^{M} r^{(i)}$. Assume the posterior multi-target density is $\pi_{k-1} = \left\{\left(r_{k-1}^{(i)}, p_{k-1}^{(i)}\right)\right\}_{i=1}^{M_{k-1}}$, then the predicted density can be written as $\pi_{k|k-1} = \left\{\left(r_{P,k|k-1}^{(i)}, p_{P,k|k-1}^{(i)}\right)\right\}_{i=1}^{M_{k-1}} \cup \left\{\left(r_{\Gamma,k}^{(i)}, p_{\Gamma,k}^{(i)}\right)\right\}_{i=1}^{M_{\Gamma,k}}$, where M_{k-1} is the number of survival hypothesized tracks at time $k-1$ and $M_{\Gamma,k}$ is the number of newborn hypothesized tracks at time k. Given the existence probability $p_{S,k}$ and transition density $f_{k|k-1}(x|\cdot)$, we have the predicted parameters based on the inner product $\langle \cdot, \cdot \rangle$:

$$r_{P,k|k-1}^{(i)} = r_{k|k-1}^{(i)} \left\langle p_{k-1}^{(i)}, p_{S,k} \right\rangle \tag{3}$$

$$p_{P,k|k-1}^{(i)} = \left\langle f_{k|k-1}(x|\cdot), p_{k-1}^{(i)} p_{S,k} \right\rangle \Big/ \left\langle p_{k-1}^{(i)}, p_{S,k} \right\rangle \tag{4}$$

Suppose that the total number of predicted hypothesized tracks is $M_{k|k-1} = M_{k-1} + M_{\Gamma,k}$, then the posterior density is $\pi_k = \left\{\left(r_{L,k}^{(i)}, p_{L,k}^{(i)}\right)\right\}_{i=1}^{M_{k|k-1}} \cup \{(r_{U,k}(z), p_{U,k}(\cdot; z))\}_{z \in Z_k}$. Based on the detection probability $p_{D,k}$, we have the updated parameters as follows:

$$r_{L,k}^{(i)} = r_{k|k-1}^{(i)} \left(1 - \left\langle p_{k|k-1}^{(i)}, p_{D,k} \right\rangle\right) \Big/ \left(1 - r_{k|k-1}^{(i)} \left\langle p_{k|k-1}^{(i)}, p_{D,k} \right\rangle\right) \tag{5}$$

$$p_{L,k}^{(i)} = p_{k|k-1}^{(i)} \left(1 - p_{D,k}\right) \Big/ \left(1 - \left\langle p_{k|k-1}^{(i)}, p_{D,k} \right\rangle\right) \tag{6}$$

$$\begin{aligned} r_{U,k}(z) = \sum_{i=1}^{M_{k|k-1}} \frac{r_{k|k-1}^{(i)} \left(1 - r_{k|k-1}^{(i)}\right) \left\langle p_{k|k-1}^{(i)}, \psi_{k,z} \right\rangle}{\left(1 - r_{k|k-1}^{(i)} \left\langle p_{k|k-1}^{(i)}, p_{D,k} \right\rangle\right)^2} \Bigg/ \Bigg(\lambda_k c_k(z) \\ + \sum_{i=1}^{M_{k|k-1}} \frac{r_{k|k-1}^{(i)} \left\langle p_{k|k-1}^{(i)}, \psi_{k,z} \right\rangle}{1 - r_{k|k-1}^{(i)} \left\langle p_{k|k-1}^{(i)}, p_{D,k} \right\rangle} \Bigg) \end{aligned} \tag{7}$$

$$p_{U,k}(x; z) = \sum_{i=1}^{M_{k|k-1}} \frac{r_{k|k-1}^{(i)} p_{k|k-1}^{(i)} \psi_{k,z}}{1 - r_{k|k-1}^{(i)}} \Bigg/ \sum_{i=1}^{M_{k|k-1}} \frac{r_{k|k-1}^{(i)} \left\langle p_{k|k-1}^{(i)}, \psi_{k,z} \right\rangle}{1 - r_{k|k-1}^{(i)}} \tag{8}$$

where λ_k and $c_k(z)$ are the mean number and prior probability of clutters, and $\psi_{k,z} = g_k(z|x) p_{D,k}(x)$ is modeled by the single target likelihood function $g_k(z|x)$.

According to $r_{L,k|k-1}^{(i)}$ and $r_{U,k}(z)$, the estimated number of targets is given by:

$$\hat{n}_k = \sum_{i=1}^{M_{k|k-1}} r_{L,k|k-1}^{(i)} + \sum_{z \in Z_k} r_{U,k}(z) \tag{9}$$

Finally, we extract the related dynamics of $\hat{n}_k$ targets as the states estimates.

Remark 2.1. *Note that the existence probability of newborn target* $r_{\Gamma,k}^{(i)}$ *is not obviously to be selected owing to little prior knowledge. Moreover, the updated existence probability* $r_{U,k}(z)$ *is proportional to* $\left(1-r_{k|k-1}^{(i)}\right) \Big/ \left(1-r_{k|k-1}^{(i)}\left\langle p_{k|k-1}^{(i)}, p_{D,k}\right\rangle\right) = 1-r_{L,k}^{(i)}$ *when the occurrence probability of clutters* $\lambda_k c_k(z)$ *approaches 0. On this case,* $r_{U,k}(z)$ *has very small value when* $r_{L,k}^{(i)}$ *approximates 1. Thus, the under-estimated* $\hat{n}_k$ *may lead to undetected targets.*

3. The Proposed CBMeMBer Filter.

3.1. Filtering principle. We rewrite (7) as $r_{U,k}(z) = \sum_{i=1}^{M_{k|k-1}} r_{U,k}^{(i)}(z) + \sum_{i=1}^{M_{\Gamma,k}} r_{U,k}^{(i)}(z)$, where the ith Bernoulli distribution $r_{U,k}^{(i)}(z)$ is defined as:

$$r_{U,k}^{(i)}(z) = \frac{r_{k|k-1}^{(i)}\left(1-r_{k|k-1}^{(i)}\right)\left\langle p_{k|k-1}^{(i)}, \psi_{k,z}\right\rangle}{\left(1-r_{k|k-1}^{(i)}\left\langle p_{k|k-1}^{(i)}, p_{D,k}\right\rangle\right)^2} \Bigg/ \left(\lambda_k c_k(z) + \sum_{i=1}^{M_{k|k-1}} \frac{r_{k|k-1}^{(i)}\left\langle p_{k|k-1}^{(i)}, \psi_{k,z}\right\rangle}{1-r_{k|k-1}^{(i)}\left\langle p_{k|k-1}^{(i)}, p_{D,k}\right\rangle}\right) \tag{10}$$

To boost the existence probability of newborn targets $\hat{r}_{\Gamma,k}^{(i)}(z)$ $(i = 1, \ldots, M_{\Gamma,k})$, we define $\hat{r}_{\Gamma,k}^{(i)}$ by the product of $r_{U,k}^{(i)}(z)$ and its information content $-\log_2 r_{U,k}^{(i)}(z)$, i.e.,

$$\hat{r}_{\Gamma,k}^{(i)}(z) = -r_{U,k}^{(i)}(z)\log_2 r_{U,k}^{(i)}(z) \tag{11}$$

In (11), there is $\log_2\left(r_{U,k}^{(i)}(z)\right)^{-1} \le \left(r_{U,k}^{(i)}(z)\right)^{-1}$ owing to $r_{U,k}^{(i)}(z) \le 1$. Therefore, we have $\hat{r}_{\Gamma,k}^{(i)}(z) \le 1$ that satisfies the condition of existence probability. We can also achieve $\hat{r}_{\Gamma,k}^{(i)}(z) \ge r_{U,k}^{(i)}(z)$ under the condition of $r_{U,k}^{(i)}(z) \le 1/2$, that is, $\hat{r}_{\Gamma,k}^{(i)}(z)$ can reach a comparative high existence when $r_{U,k}^{(i)}(z)$ is relative low. Besides, to avoid overshoot for newborn target model, the upper bound $r_{\Gamma,k,\max}^{(i)}(z) = \max\left(r_{\Gamma,k}^{(i)}(z)\right)$ should be set in advance. Then we have the adaptive birth distribution $r_{\Gamma,k}^{(i)}$:

$$r_{\Gamma,k}^{(i)}(z) = \min\left(\hat{r}_{U,k}^{(i)}(z), r_{\Gamma,k,\max}^{(i)}(z)\right) \tag{12}$$

According to $r_{\Gamma,k}^{(i)}$ and the particle number χ of each target, the number of newborn particles is $L_{\Gamma,k}^{(i)} = \chi r_{\Gamma,k}^{(i)}$. In view of under-estimated number of targets, we define the threshold of the Bernoulli distribution ε to balance undetected targets after merging and pruning. When $r_k^{(i)} \ge \varepsilon$, $\hat{n}_k$ is increased by 1.

3.2. Particle implementation. The particle implementation is derived in this subsection.

Prediction: Suppose that the multi-Bernoulli posterior multi-target density is $\pi_{k-1} = \left\{\left(r_{k-1}^{(i)}, p_{k-1}^{(i)}\right)\right\}_{i=1}^{M_{k-1}}$, and $p_{k-1}^{(i)}$ comprises a set of weighted particles $\left\{\left(x_{k-1}^{(i,j)}, w_{k-1}^{(i,j)}\right)\right\}_{j=1}^{L_{k-1}^{(i)}}$ at time $k-1$:

$$p_{k-1}^{(i)}(x_{k-1}) = \sum_{j=1}^{L_{k-1}^{(i)}} w_{k-1}^{(i)}\delta\left(x_{k-1} - x_{k-1}^{(i,j)}\right) \tag{13}$$

where $L_{k-1}^{(i)}$ is the required number of particles.

Assume the particle set $\left\{\left(x_{P,k|k-1}^{(i,j)}, w_{P,k|k-1}^{(i,j)}\right)\right\}_{j=1}^{L_{k-1}^{(i)}}$ for survival targets is given by:

$$x_{P,k|k-1}^{(i,j)} \sim q_k^{(i)}\left(\cdot\middle|x_{k-1}^{(i,j)}, Z_k\right), \quad j = 1, \ldots, L_{k-1}^{(i)} \tag{14}$$

$$w_{P,k|k-1}^{(i,j)} = f_{k|k-1}\left(x_{P,k|k-1}^{(i,j)}\middle|x_{k-1}^{(i,j)}\right) p_{S,k}\left(x_{k-1}^{(i,j)}\right) w_{k-1}^{(i,j)} \Big/ q_k^{(i)}\left(x_{P,k|k-1}^{(i,j)}\middle|x_{k-1}^{(i,j)}, Z_k\right) \tag{15}$$

Then the predicted existence probability and posterior density are:

$$r_{P,k|k-1}^{(i)} = r_{k-1}^{(i)} \sum_{j=1}^{L_{k-1}^{(i)}} p_{S,k}\left(x_{k-1}^{(i,j)}\right) w_{k-1}^{(i,j)} \tag{16}$$

$$p_{P,k|k-1}^{(i)}(x_k) = \sum_{j=1}^{L_{k-1}^{(i)}} \tilde{w}_{P,k|k-1}^{(i,j)} \delta\left(x_k - x_{P,k|k-1}^{(i,j)}\right) \tag{17}$$

where $\tilde{w}_{P,k|k-1}^{(i,j)} = w_{P,k|k-1}^{(i,j)} \Big/ \sum_{j=1}^{L_{k-1}^{(i)}} w_{P,k|k-1}^{(i,j)}$. Given that the ith target birth model is $b_k^{(i)}\left(x_{\Gamma,k}^{(i,j)}|Z_k\right)$, $L_{\Gamma,k}^{(i)}$ newborn particles $\left\{\left(x_{\Gamma,k}^{(i,j)}, w_{\Gamma,k}^{(i,j)}\right)\right\}_{j=1}^{L_{\Gamma,k}^{(i)}}$ can be written as:

$$x_{\Gamma,k}^{(i,j)} \sim b_k^{(i)}\left(\cdot|Z_k\right), \quad i = 1, \ldots, L_{\Gamma,k}^{(i)} \tag{18}$$

$$w_{\Gamma,k}^{(i,j)} = p_{\Gamma,k}\left(x_{\Gamma,k}^{(i,j)}\right) / b_k^{(i)}\left(x_{\Gamma,k}^{(i,j)}\middle|Z_k\right) \tag{19}$$

To represent $M_{\Gamma,k}$ newborn tracks using the multi-target density $\left\{\left(r_{\Gamma,k}^{(i)}, p_{\Gamma,k}^{(i)}\right)\right\}_{i=1}^{M_{\Gamma,k}}$, we define $p_{\Gamma,k}^{(i)}$ with the weight $\tilde{w}_{\Gamma,k}^{(i,j)} = w_{\Gamma,k}^{(i,j)} \Big/ \sum_{j=1}^{L_{\Gamma,k}^{(i)}} w_{\Gamma,k}^{(i,j)}$, i.e.,

$$p_{\Gamma,k}^{(i)}(x_k) = \sum_{j=1}^{L_{\Gamma,k}^{(i)}} \tilde{w}_{\Gamma,k}^{(i,j)} \delta\left(x_k - x_{\Gamma,k}^{(i,j)}\right) \tag{20}$$

Remark 3.1. *At time 0, we have in hand* $r_{\Gamma,0}^{(i)}$ *and* $L_{\Gamma,0}^{(i)}$. *Otherwise,* $r_{\Gamma,k}^{(i)}$ *and* $L_{\Gamma,k}^{(i)} = \chi r_{\Gamma,k}^{(i)}$ *are utilized in the last filtering cycle.*

Update: At time k, suppose the predicted multi-target density is $\pi_{k|k-1} = \left\{\left(r_{k|k-1}^{(i)}, p_{k|k-1}^{(i)}\right)\right\}_{i=1}^{M_{k|k-1}}$ ($M_{k|k-1} = M_{k-1} + M_{\Gamma,k}$), then $p_{k|k-1}^{(i)}$ can be approximated by $\left\{\left(x_{k|k-1}^{(i,j)}, w_{k|k-1}^{(i,j)}\right)\right\}_{j=1}^{L_{k|k-1}^{(i)}}$:

$$p_{k|k-1}^{(i)}(x_k) = \sum_{j=1}^{L_{k|k-1}^{(i)}} \tilde{w}_{k|k-1}^{(i,j)} \delta\left(x_k - x_{k|k-1}^{(i,j)}\right) \tag{21}$$

where $L_{k|k-1} = L_{k-1} + L_{\Gamma,k}$ is the predicted number of particles. Further, (21) can be rewritten as:

$$p_{k|k-1}^{(i)}(x_k) = \sum_{j=1}^{L_{k-1}^{(i)}} \tilde{w}_{P,k|k-1}^{(i,j)} \delta\left(x_k - x_{P,k|k-1}^{(i,j)}\right) + \sum_{j=1}^{L_{\Gamma,k|k-1}^{(i)}} \tilde{w}_{\Gamma,k|k-1}^{(i,j)} \delta\left(x_k - x_{\Gamma,k|k-1}^{(i,j)}\right) \tag{22}$$

Then the updated multi-target density $\pi_k = \left\{\left(r_{L,k}^{(i)}, p_{L,k}^{(i)}\right)\right\}_{i=1}^{M_{k|k-1}} \cup \{(r_{U,k}(z), p_{U,k}(z))\}_{z\in Z_k}$ can be computed by the following equations:

$$r_{L,k}^{(i)} = r_{k|k-1}^{(i)} \left(1 - \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{k|k-1}^{(i,j)} p_{D,k}\left(x_{k|k-1}^{(i,j)}\right)\right) \Bigg/ \left(1 - r_{k|k-1}^{(i)} \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{k|k-1}^{(i,j)} p_{D,k}\left(x_{k|k-1}^{(i,j)}\right)\right) \tag{23}$$

$$p_{L,k}^{(i)}(x_k) = \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{L,k}^{(i,j)} \delta\left(x_k - x_{k|k-1}^{(i,j)}\right) \tag{24}$$

We compute $r_{\Gamma,k}^{(i)}$ $(i = 1, \ldots, M_{\Gamma,k})$ using (12), and then get the sum $\sum_{i=1}^{M_{\Gamma,k}} r_{\Gamma,k}^{(i)}(z)$. As for other Bernoulli components, we use the following equations:

$$r_{U,k}(z) = \sum_{i=1}^{M_{k|k-1}} \frac{r_{k|k-1}^{(i)}\left(1 - r_{k|k-1}^{(i)}\right) \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{k|k-1}^{(i,j)} \psi_{k,z}\left(x_{k|k-1}^{(i,j)}\right)}{\left(1 - r_{k|k-1}^{(i)} \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{k|k-1}^{(i,j)} p_{D,k}\left(x_{k|k-1}^{(i,j)}\right)\right)^2} \Bigg/ \left(\lambda_k c_k(z) + \sum_{i=1}^{M_{k|k-1}} \frac{r_{k|k-1}^{(i)} \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{k|k-1}^{(i,j)} \psi_{k,z}\left(x_{k|k-1}^{(i,j)}\right)}{1 - \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{k|k-1}^{(i,j)} p_{D,k}\left(x_{k|k-1}^{(i,j)}\right)}\right) \tag{25}$$

$$p_{U,k}^{(i)}(x_k; z_k) = \sum_{i=1}^{M_{k|k-1}} \sum_{j=1}^{L_{k|k-1}^{(i)}} \tilde{w}_{U,k}^{(i,j)}(z) \delta\left(x_k - x_{k|k-1}^{(i,j)}\right) \tag{26}$$

$$\tilde{w}_{L,k}^{(i,j)}(z) = w_{L,k}^{(i,j)} \Bigg/ \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{L,k}^{(i,j)} \tag{27}$$

$$w_{L,k}^{(i,j)} = \left(1 - p_{D,k}\left(x_{k|k-1}^{(i,j)}\right)\right) \tilde{w}_{k|k-1}^{(i,j)} \tag{28}$$

$$\tilde{w}_{U,k}^{(i,j)}(z) = w_{U,k}^{(i,j)}(z) \Bigg/ \sum_{i=1}^{M_{k|k-1}} \sum_{j=1}^{L_{k|k-1}^{(i)}} w_{U,k}^{(i,j)}(z) \tag{29}$$

$$w_{U,k}^{(i,j)}(z) = r_{k|k-1}^{(i)} \psi_{k,z}\left(x_{k|k-1}^{(i,j)}\right) w_{k|k-1}^{(i,j)} \Big/ \left(1 - r_{k|k-1}^{(i)}\right) \tag{30}$$

$$\psi_{k,z}\left(x_{k|k-1}^{(i,j)}\right) = p_{D,k}\left(x_{k|k-1}^{(i,j)}\right) g_k\left(z_k \middle| x_{k|k-1}^{(i,j)}\right) \tag{31}$$

The updated multi-target density is $\pi_k = \left\{\left(r_k^{(i)}, p_k^{(i)}\right)\right\}_{i=1}^{M_k}$, where $M_k = M_{k|k-1} + |Z_k|$ is the updated number of tracks, and $p_k^{(i)}$ is defined as:

$$p_k^{(i)}(x_k) = \sum_{j=1}^{L_k^{(i)}} w_k^{(i,j)} \delta\left(x_k - x_k^{(i,j)}\right) \tag{32}$$

Subsequently the operations of merging and pruning are necessary when $r_k^{(i_1)} + r_k^{(i_2)} < 1$. If $r_k^{(i_1)} > r_k^{(i_2)}$, we have the following equations:

$$r_k^{(i)} = r_k^{(i_1)} + r_k^{(i_2)} \tag{33}$$

$$p_k^{(i)}(x_k) = p_k^{(i_1)}(x_k) p_k^{(i_2)}(x_k) \Bigg/ \int p_k^{(i_1)}(x_k) p_k^{(i_2)}(x_k) \mathrm{d}x_k \tag{34}$$

State estimation: Due to the merged number of tracks $\hat{M}_k$ and the condition $r_k^{(i)} \geq \varepsilon$, the estimated number of targets is updated as $\hat{n}_k \leftarrow \hat{n}_k + 1$. Finally the states estimates are given by $\hat{X}_k = \left\{ \sum_{j=1}^{L_{k|k-1}^{(i)}} w_k^{(i,j)} \hat{x}_k^{(i,j)} \right\}_{i=1}^{\hat{M}_k}$.

4. **Numerical Study and Discussions.** In this section, a typical numerical study is presented to compare the proposed CBMeMBer filter with standard filter under 100 Monte Carlo trails, where the surveillance period is 60s and the sampling period is 1s. Three targets move with the constant turn (CT) motion and one target has the constant velocity (CV) motion.

Figure 1 shows the true tracks and measurements. As seen, four targets (T1∼T4) travel in cluttered area, where T1 moves with velocity of $(-20, 0)$m/s and turn of $-0.5°$/s from position $(1000, 1500)$m during $1^{\text{st}}\sim 4^{\text{th}}$s. T2 travels from position $(250, 750)$m with velocity of $(-20, 10)$m/s and turn of $0.5°$/s during $5^{\text{th}}\sim 50^{\text{th}}$s. T3 moves with velocity of $(-20, -10)$m/s and turn of $1°$/s from position $(-250, 1000)$m during $10^{\text{th}}\sim 55^{\text{th}}$s. T4 keeps CV motion with velocity of $(40, 0)$m/s from position $(-1500, 250)$m during $10^{\text{th}}\sim 60^{\text{th}}$s. Figure 2 plots the x and y coordinates of true tracks, measurements and two filter estimates versus time. It indicates that the position estimates from the standard filter become poor when targets move close to dense clutter areas, whereas the proposed filter boosts estimation accuracy. Figure 3 demonstrates the estimated number of targets. Note that the standard filter cannot exactly evaluate the cardinality, which underestimates one target on the 19^{th}s and 30^{th}s. On the contrary, the estimated number of targets using the proposed filter during the whole surveillance period coincides with the ground truth owing to the adaptive target birth intensity method for obtaining reliable existence probability of newborn targets. Finally, Figure 4 shows the optimal sub pattern assignment (OSPA) distance. Note that the tracking performance of the standard filter is worse because it exaggerates distance error, which has two intensity peaks as a result of underestimated number of targets. It can be verified that the proposed filter again achieves lower error as a direct result of always correcting true number and approaching true position.

5. **Conclusions.** This paper discusses an improved CBMeMBer filter for the MTT. It applies adaptive target birth intensity method to achieve the existence probability of newborn targets for correcting target-number estimates. The numerical study suggests that the proposed CBMeMBer filter has remarkable improvement in tracking performance with promising results. As future developments of this work, we will shorten running time under the current tracking accuracy of this filter.

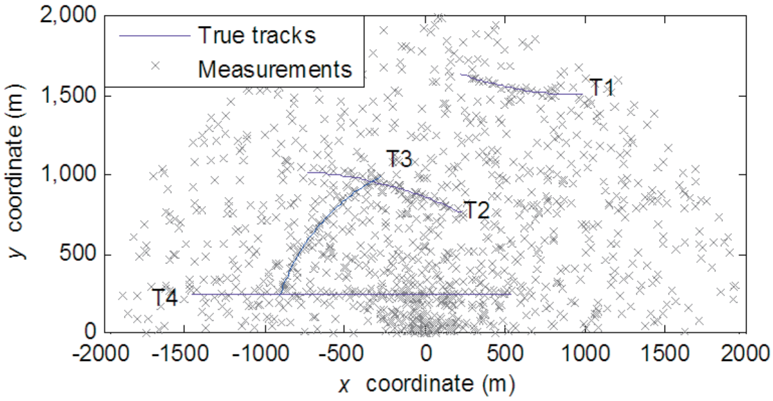

Figure 1. Target tracks and measurements

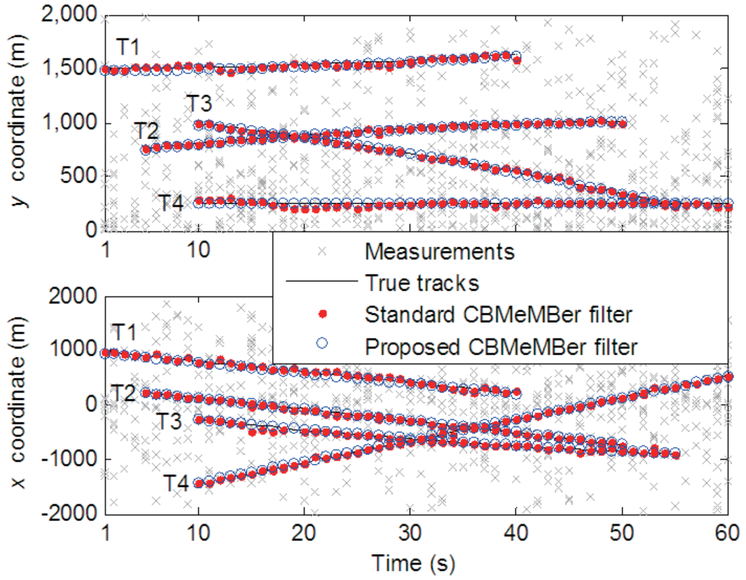

FIGURE 2. Target tracks and position estimates in x-y coordinates

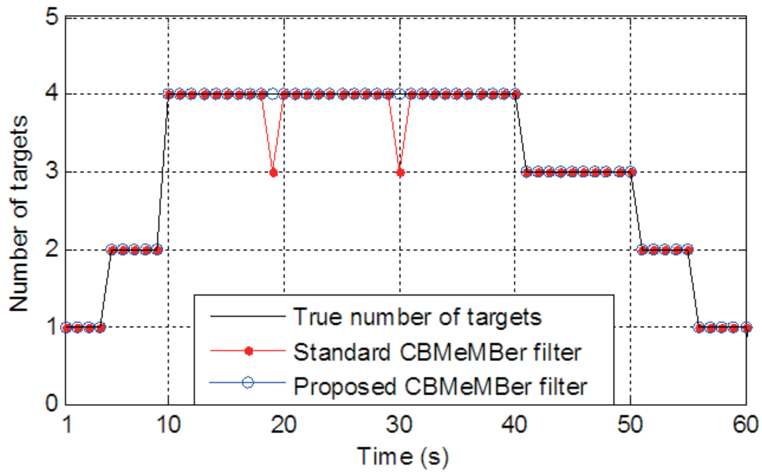

FIGURE 3. Target number and estimates

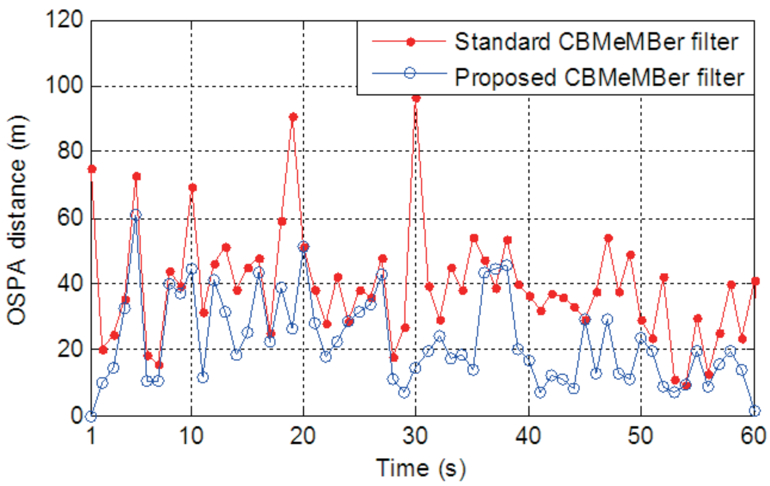

FIGURE 4. OSPA distance

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