A Labeled SMC-Cbmember Filter with Adaptive Track Initiation

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Abstract. The initial Sequential Monte Carlo cardinality balanced multi-target multi-Bernoulli (SMC-CBMeMBer) filter assumes that the target birth intensity is known as a priori, but in fact the new target may appear anywhere in the detected area. And SMC-CBMeMBer does not extract track label information and cannot distinguish the target. Therefore, this paper proposes a labeled SMC-CBMeMBer filter with adaptive track initiation (SMC-CBMeMBer-D-L-ATI). Firstly, the filter introduces the track label information in the prediction process, and selects the measurement that may correspond to the newborn target, obtaining the initial state of the newborn target according to the converted measurement. Then, the label information in the prediction process is inherited during the update process, and the target states are updated sequentially through the converted position measurement and Doppler measurement. The simulation proves that the proposed filter can effectively perform adaptive track initiation, with good tracking performance, and can provide the target track information.

1. Introduction

The multi-target multi-Bernoulli (MeMBer) filter is the probability density approximation of the optimal multi-target Bayesian filter [1], which is different from the potential distribution and moment of the recursive transmission posterior density of CPHD [2] and PHD [3]. MeMBer recursively propagate the multi-Bernoulli parameter of multi-target posterior density. In order to solve the problem that the number of targets in MeMBer is overestimated, Ba-Tuong Vo et al. derived the CBMeMBer filter based on MeMBer filter and proposed two execution algorithms, namely GM-CBMeMBer and SMC-CBMeMBer [4]. Compared with GM-CBMeMBer, SMC-CBMeMBer is more suitable for nonlinear non-Gaussian models. Under nonlinear non-Gaussian conditions, the implementation of SMC-PHD [5] and SMC-CPHD [6] filters must use clustering algorithm to extract multi-target state estimated from particle swarm. This process requires huge cost and the results obtained are less reliable [7-8]. SMC-CBMeMBer can not only directly extract the multi-target state estimated, but also provide the target existence probability information.

The track initiation is the first step of multi-target tracking, and the quality of the initial track directly affects the subsequent of the tracks. However, several of the above filters all base on the initial target state are known a priori and do not provide valid track information. During the actual target tracking process, the new target may appear anywhere. At this point, the method of starting the track initiation at a fixed position will no longer apply. Therefore, many scholars use the measurement...
information to drive the new target to adaptive track initiation. Reference [9] uses azimuth measurements and slant range measurements to drive the target birth strength starting adaptive track initiation. Literature [10] further introduces Doppler velocity information to start adaptive track initiation of GM-PHD filters. In order to comprehensively utilize the slant range, azimuth and Doppler measurement information, the author has proposed a GM-CBMeMBer filter with adaptive track initiation [11]. The standard tracking algorithm is not limited to a fixed position for track initiation, and does not provide effective track information. Based on SMC-CBMeMBer, this paper introduces Doppler velocity measurement and particle label information, using the selected measurement to drive the new target starting adaptive track initiation. The simulation proves that the proposed filter can not only successfully initiate track, but also provide effective track information.

2. Coordinate Conversion and Measurement Selection

Coordinate system and coordinate conversion are the basic theory of target tracking. When performing coordinate conversion in different coordinate systems, corresponding error compensation is needed. The SMC-CBMeMBer filter proposed in [4] converts the measurement from the polar coordinate system to the Cartesian coordinate system, only converts simply the formula without considering error compensation. In the polar coordinate system, the measurement consists of slant range and azimuth, i.e., $z_k = [r_{n,k}, \theta_{n,k}]^T$. Assuming that the state of sensor at time $k$ is $x_k' = [x_k', y_k', \dot{x}_k', \dot{y}_k']^T$, after introducing the Doppler velocity information, the measurement can be expressed as

$$z_k = [r_{n,k}, \theta_{n,k}, d_{n,k}]^T = \begin{bmatrix} \sqrt{(x_k - x_k')^2 + (y_k - y_k')^2} \\ \arctan\left(\frac{y_k - y_k'}{x_k - x_k'}\right) \\ (\dot{x}_k - \dot{x}_k') \cos(\dot{\theta}_k) + (\dot{y}_k - \dot{y}_k') \sin(\dot{\theta}_k) \end{bmatrix} + n_k$$

(1)

Assuming that the measurement noises are independent of each other, the measurement noise is Gaussian white noise with zero mean and the covariance $\mathbf{R}_k = \text{diag}[\sigma_r^2, \sigma_\theta^2, \sigma_d^2]$, where, $\sigma_r$, $\sigma_\theta$ and $\sigma_d$ are the measurement noise standard deviations of the slant range, the azimuth, and the Doppler, respectively. According to the literature [8], the position measurement is converted to the XOY Cartesian coordinate system $\mathbf{y}_{C,k} = [x_{n,k}, y_{n,k}]^T$ as follow:

$$\begin{align*}
x_{n,k} &= \lambda_\theta r_{n,k} \cos(\theta_{n,k}) + x_k'
n_{n,k} &= \lambda_\theta r_{n,k} \sin(\theta_{n,k}) + y_k'
\end{align*}$$

(2)

Where, $\lambda_\theta = e^{-\gamma_1/\theta}$ is the azimuth compensation factor, and the corresponding position component covariance is $\mathbf{R}_{C,k} = \begin{bmatrix} \sigma_x^2 & \sigma_{xy}^2 \\ \sigma_{xy}^2 & \sigma_y^2 \end{bmatrix}$

$$\begin{align*}
\sigma_x^2 &= -(\lambda_\theta r_{n,k} \cos(\theta_{n,k}))^2 + 0.5[r_{n,k}^2 + \sigma_r^2][1 + \lambda_\theta^2 \cos 2\theta_{n,k}]
\sigma_y^2 &= -(\lambda_\theta r_{n,k} \sin(\theta_{n,k}))^2 + 0.5[r_{n,k}^2 + \sigma_r^2][1 - \lambda_\theta^2 \cos 2\theta_{n,k}]
\sigma_{xy}^2 &= -(\lambda_\theta r_{n,k})^2 \sin(\theta_{n,k}) \cos(\theta_{n,k}) + 0.5[r_{n,k}^2 + \sigma_r^2] \lambda_\theta^2 \sin 2\theta_{n,k}
\end{align*}$$

(3)

Then, the converted measurement set is $\mathbf{Z}_{C,k} = [\mathbf{Y}_{C,k}; \mathbf{D}_{C,k}] = \{z_{C,k}^{(i)}\}$ ($i = 1, 2, \ldots, J_k$), where $z_{C,k}^{(i)} = [x_{C,k}^{(i)}, y_{C,k}^{(i)}, \dot{x}_{C,k}^{(i)}, \dot{y}_{C,k}^{(i)}]^T = [x_{n,k}^{(i)}, y_{n,k}^{(i)}, \dot{x}_{n,k}^{(i)}, \dot{y}_{n,k}^{(i)}]^T$, $\mathbf{D}_{C,k} = \{d_{C,k}^{(i)}\}$ and $\mathbf{Y}_{C,k} = \{y_{C,k}^{(i)}\}$ are Doppler measurement
set and converted position measurement set, respectively. If the multi-target state at time $k - 1$ is $\hat{X}_{k-1} = \{\hat{e}_{k-1}^{(1)}, \hat{e}_{k-1}^{(2)}, \ldots, \hat{e}_{k-1}^{(N)}\}$ and the converted measurement set is $\hat{Z}_{c,k-1} = [\hat{y}_{c,k-1}^{(1)}; D_{c,k-1}]$, then the Euclidean distance between the measurement and states estimated is $\Delta d_{k-1}^{(ij)} = \|H \cdot \hat{e}_{k-1}^{(i)} - \hat{y}_{c,k-1}^{(j)}\|$

($i = 1, 2, \ldots, I_{k-1}; j = 1, 2, \ldots, J_{k-1}$). Because the measurements near $\hat{e}_{k-1}^{(i)}$ is less likely to match the new target at the next moment, this part of the measurement is excluded:

\[
\begin{align*}
\hat{Z}_{c,k-1} & := \emptyset, \quad \hat{Y}_{c,k-1} := \emptyset \\
\text{For } i = 1, 2, \ldots, I_{k-1} & \text{; for } j = 1, 2, \ldots, J_{k-1} \text{ if } \Delta d_{k-1}^{(ij)} \leq \tau & \text{ then } \hat{Y}_{c,k-1} := \hat{Y}_{c,k-1} \cup y_{c,k-1}^{(j)}, \hat{Z}_{c,k-1} := \hat{Z}_{c,k-1} \cup \hat{e}_{k-1}^{(i)} \tag{4} 
end; \text{ end}
\end{align*}
\]

Where, set the distance threshold $\tau$ to $\sigma$, can make the excluded measurements $\hat{Z}_{c,k-1}$ and $\hat{Y}_{c,k-1}$ come from the target at time $k - 1$ with the greatest probability. Therefore, the measurement set $Z_{b,k-1} = Z_{k-1} - \hat{Z}_{k-1}$, and its corresponding position measurement set $Y_{b,k-1} = Y_{c,k-1} - \hat{Y}_{c,k-1}$ can be used to calculate the new target multi-Bernoulli RFS at time $k$.

### 3. The implementation of the SMC-CBMeMBer-D-L-ATI

This section gives the specific steps for the SMC-CBMeMBer-D-L-ATI filter to achieve adaptive track initiation: first perform coordinate conversion, then set the distance threshold for selecting measurement (the first two steps have been given in the first section), further give the specific form of the label, and finally calculate the newborn target multi-Bernoulli RFS $\{\{(l_{k,i}^{(0)}, r_{k,i}^{(0)}, p_{k,i}^{(0)})\}_{i=1}^{M}\}$ by the selected measurement.

The multi-Bernoulli RFS is a union of multiple independent Bernoulli RFSs and can be expressed as $\pi = \{(l^{(i)}, r^{(i)}, p^{(i)})\}_{i=1}^{M}$ ($i = 1, 2, \ldots, M$). Where, $l^{(i)}$, $r^{(i)}$ and $p^{(i)}$ represent the label, existence probability, and probability density of the $i$th Bernoulli RFS, respectively. As with the implementation of SMC-CBMeMBer, the implementation of the SMC-CBMeMBer-D-L-ATI filter is also completed by two stages of prediction and update.

#### 3.1. Prediction step

In order to distinguish the track corresponding to each target, label information is introduced in the prediction step. If the Multi-Bernoulli RFS is expressed $\pi_{k-1} = \{(l_{k-1}^{(0)}, r_{k-1}^{(0)}, p_{k-1}^{(0)})\}_{i=1}^{M_{k-1}}$ at time $k - 1$, the Multi-Bernoulli RFS predicted at time $k$ consists of the surviving target Multi-Bernoulli RFS and the newborn target Multi-Bernoulli RFS, i.e.,

\[
\begin{align*}
\pi_{k} & := \{(l_{k}^{(0)}, r_{k}^{(0)}, p_{k}^{(0)})\}_{i=1}^{M_{k}} \cup \{(l_{k}^{(i)}, r_{k}^{(i)}, p_{k}^{(i)})\}_{i=1}^{M_{k}} \\
\pi_{k} & := \{(l_{k}^{(i)}, r_{k}^{(i)}, p_{k}^{(i)})\}_{i=1}^{M_{k}} \cup \{(l_{k}^{(i)}, r_{k}^{(i)}, p_{k}^{(i)})\}_{i=1}^{M_{k}} \tag{5} 
\end{align*}
\]

\[
\begin{align*}
l_{k}^{(i)} & = l_{k-1}^{(i)} \tag{6} 
\end{align*}
\]

Where, the label of the $i$th newborn target at time $k$ can be uniquely indicated by the label index number $(k, i)$

\[
l_{k}^{(i)} = (k, i) \tag{7}
\]
Since the initial position of the newborn target is unknown, according to the formula (19) of the literature [10], the probability density \( p(x_i, y_i) \) of the newborn target at time \( k \) can be calculated by the measurement selected \( Z_{k,i} = \{x_{k,i}\} \) and \( Y_{k,i} = \{y_{k,i}\} \), \( i = 1, 2, \ldots, J_{g,k-1} \).

Where,

\[
m^{(i)}_{r,k-1} = [x^{(i)}_{r,k-1}, y^{(i)}_{r,k-1}, x^{(i)}_{r,k-1}, y^{(i)}_{r,k-1}]^T
\]

\[
P^{(i)}_{r,k-1} = \begin{bmatrix}
\sigma^2_x & 0 & \sigma^2_{xy} & 0 \\
0 & \sigma^2_x & 0 & \sigma^2_{xy} \\
\sigma^2_{xy} & 0 & \sigma^2_y & 0 \\
0 & \sigma^2_{xy} & 0 & \sigma^2_y
\end{bmatrix}
\]

The mean of the position components is \([x^{(i)}_{r,k-1}, y^{(i)}_{r,k-1}]\), the covariance \( R^{(i)}_{k-1} \) is given by equation (3), the mean of the velocity components is \([x^{(i)}_{r,k-1}, y^{(i)}_{r,k-1}]\), and the covariance is \( P_{k-1} \).

\[
[x^{(i)}_{r,k-1}, y^{(i)}_{r,k-1}] = \beta[\cos(\theta^{(i)}_{r,k-1}), \sin(\theta^{(i)}_{r,k-1})] d_{r,k-1}^{(i)} + [\dot{x}_{r,k-1}, \dot{y}_{r,k-1}]^T
\]

\[
\begin{align*}
\sigma^2_x &= \sigma^2_{\dot{x}} \left( 1 - \beta \cos^2(\theta^{(i)}_{r,k-1}) \right) \\
\sigma^2_y &= \sigma^2_{\dot{y}} \left( 1 - \beta \sin^2(\theta^{(i)}_{r,k-1}) \right) \\
\sigma^2_{xy} &= -\sigma^2_{\dot{x}} \beta \cos(\theta^{(i)}_{r,k-1}) \sin(\theta^{(i)}_{r,k-1}) \\
\beta &= \frac{\sigma^2_{\dot{y}}}{\sigma^2_{\dot{x}} + \sigma^2_{\dot{y}}}
\end{align*}
\]

Finally, the obtained newborn target probability density is substituted into the prediction step of the SMC-CBMeMBer filter to generate particle components. The specific formula of the prediction step refers to Eq. 39-42 of the literature [4].

3.2. Update steps

Assume that the multi-Bernoulli RFS predicted at time \( k \) is \( \pi_{k-1} = \{p_{k-1}^{(i)}\}_{i=1}^{M_{k-1}} \), where, \( p_{k-1}^{(i)}(x) = \sum_{j=1}^{N_{k-1}} w^{(i)}_{k-1} \delta_{x}^{(i)}(x) \), then the updated multi-Bernoulli RFS is \( \pi_k = \{p_{k}^{(i)}\}_{i=1}^{M_{k}} \). The first and second items are the legacy track and measurement updated multi-Bernoulli RFS, and the label \( L_{l,k}^{(i)} \) of legacy track multi-Bernoulli RFS inherits the label \( L_{l,k}^{(i)} \) of the predicted multi-Bernoulli RFS.

\[
L_{l,k}^{(i)} = L_{l,k}^{(i-1)}
\]
Using the converted position measurement and Doppler velocity sequentially updates the multi-Bernoulli RFS, and the multi-Bernoulli RFS formula of the measurement updated as follow:

\[
\begin{aligned}
L_{k|x} (z_{c,k}) &= L_{k|x}^{(1)} \\
&= \left[ \frac{r_{\vartheta,k}^{(1)} (1 - r_{\vartheta,k}^{(1)}) \left( \sum_{j=1}^{M_{k|x}} u_{\vartheta,k}^{(j)} P_{D,k} \left( x_{\vartheta,k}^{(j)} \right) \right)}{\left( 1 - r_{\vartheta,k}^{(1)} \sum_{j=1}^{M_{k|x}} u_{\vartheta,k}^{(j)} P_{D,k} \left( x_{\vartheta,k}^{(j)} \right) \right)^2} \right] \\
n &= \arg \max \left[ \sum_{i=1}^{M_{k|x}} \frac{r_{\vartheta,k}^{(1)} (1 - r_{\vartheta,k}^{(1)}) \rho_{\vartheta,k}^{(i)} (z)}{\left( 1 - r_{\vartheta,k}^{(1)} \sum_{j=1}^{M_{k|x}} \rho_{\vartheta,k}^{(j)} \right)^2} \right] \\
p_{U,k} (x; z) &= \sum_{i=1}^{M_{k|x}} \sum_{j=1}^{M_{k|x}} \rho_{\vartheta,k}^{(i)} (z) \delta_{x^{(i)},x^{(j)}} (x)
\end{aligned}
\]

Where

\[
\begin{aligned}
w_{\vartheta,k}^{(i)} &= w_{\vartheta,k}^{(i)} (1 - P_{D,k} x_{\vartheta,k}^{(i)}) \\
w_{\vartheta,k}^{(i)} &= w_{\vartheta,k}^{(i)} (1 - P_{D,k} x_{\vartheta,k}^{(i)}) \\
\rho_{\vartheta,k}^{(i)} (z) &= \sum_{j=1}^{M_{k|x}} \frac{r_{\vartheta,k}^{(1)} (1 - r_{\vartheta,k}^{(1)}) \rho_{\vartheta,k}^{(i)} (z)}{\left( 1 - r_{\vartheta,k}^{(1)} \sum_{j=1}^{M_{k|x}} \rho_{\vartheta,k}^{(j)} \right)^2} \\
p_{U,k} (x; z) &= \sum_{i=1}^{M_{k|x}} \sum_{j=1}^{M_{k|x}} \rho_{\vartheta,k}^{(i)} (z) \delta_{x^{(i)},x^{(j)}} (x)
\end{aligned}
\]

Due to the introduction of Doppler velocity information, the likelihood function \(g_k \left( z_{k | x_{\vartheta,k}^{(i)}} \right)\) in Eq. (20) is re-derived as

\[
\begin{aligned}
g_k \left( z_{k | x_{\vartheta,k}^{(i)}} \right) &= N \left( y_{\vartheta,k}^{(i)} ; H_{\vartheta,k} x_{\vartheta,k}^{(i)} , R_{\vartheta,k} \right) N \left( \left( d_{\vartheta,k}^{(i)} + h_{\vartheta,k} \left( x_{\vartheta,k}^{(i)} \right) \right) , \sigma_{\vartheta,k}^2 \right) \\
h_{\vartheta,k} \left( x_{\vartheta,k} \right) &= \frac{x_{\vartheta,k} \hat{x}_{\vartheta,k} + y_{\vartheta,k} \hat{y}_{\vartheta,k}}{\sqrt{x_{\vartheta,k}^2 + y_{\vartheta,k}^2}}
\end{aligned}
\]
Eq. (13), (14) shows that if the \( n \)th predicted track has the largest contribution to the existence probability \( r_k(z_{c,k}) \) of the measurement updated, the corresponding track label inherits the label \( I_{k-1}^{(i)} \) of the \( n \)th predicted multi-Bernoulli RFS. \( \kappa_k(l) \) and \( \kappa_k(d) \) are position clutter and Doppler velocity clutter, respectively. \( H_{c,k} = [I_2, \theta] \) is position measurement matrix, \( I_2 \) and \( \theta \) are \( n \times n \) dimensional unit matrix and all-zero matrix, respectively. In addition, since the number of multi-Bernoulli RFS and particle components increases with time, after the end of the update step, the multi-Bernoulli RFS and particle components need to be “pruned and merged”. The specific steps refer to [4].

4. Simulation and Analysis

Assume that the range of the slant range and azimuth detected by the sensor are \((0m,1000m)\) and \((-\pi, \pi)\), respectively, the sampling interval is \( \Delta = 1s \). Table 1 shows the initial state of each target and its initial time and terminal time, the survival probability \( P_{sk} = 0.99 \), the detection probability \( P_{dk} = 0.98 \), the existence probability of the newborn target \( r_{y,k}^{(i)} = 0.03 \), and the standard deviation of the prior speed \( 17 m/s \). State transition matrix \( \Phi_{k-1} = \begin{bmatrix} I_2 & \Delta T_2 \\ 0_2 & I_2 \end{bmatrix} \); process noise covariance \( Q_{k-1} = \sigma_n^2 \begin{bmatrix} \Delta^2 T_2/4 & \Delta T_2/2 \\ \Delta T_2/2 & \Delta^2 T_2 \end{bmatrix} \), where process noise standard deviation \( \sigma_n = 5 m/s^2 \). The standard deviations of the slant range, azimuth, and Doppler measurement noise are \( \sigma_r = 20m \), \( \sigma_\theta = 2^\circ \) and \( \sigma_d = 0.5m/s \). The clutter follows Poisson distribution with mean of 20 in the detection zone, and its Doppler is uniformly distributed at \([-35 m/s, 35 m/s]\). In the "pruning and merging" step, the existence probability threshold of multi-Bernoulli RFS is \( P = 10^{-3} \), the maximum number \( T_{\text{max}} = 100 \);

| Target number | Initial time | Terminal time | Initial state \( (x_0^{(i)}, y_0^{(i)}, x_0^{(i)}, y_0^{(i)}) \) |
|---------------|--------------|---------------|--------------------------------------------------|
| 1             | 3s           | 64s           | \((500 m, 400 m, -11 m/s, -5 m/s)\)               |
| 2             | 6s           | 69s           | \((450 m, 8 m, -15 m/s, 5 m/s)\)                 |
| 3             | 9s           | 72s           | \((0 m, 150 m, -2 m/s, -10 m/s)\)               |
| 4             | 11s          | 80s           | \((600 m, 200 m, -5 m/s, 10 m/s)\)              |
| 5             | 15s          | 80s           | \((-100 m, -150 m, 12 m/s, 2 m/s)\)            |

Table 1: Initial target state

Figure 1 shows the results of the target single tracking simulation. The different colors in the figure represent different target tracks. The simulation proves that the SMC-CBMeMBar-DL-ATI filter proposed can successfully initiate track, effectively track the target and can provide track information to distinguish different target tracks.
The whole process of tracking is divided into three processes: the track initiation process (3s-15s), the track maintenance process (16s-65s), and the track termination process (66s-80s). Fig. 2 is OSPA comparison diagram of Monte Carlo simulation between SMC-CBMeMBer-D-L-ATI and SMC-CBMeMBer-D. It can be seen from Fig. 2(a) that the SMC-CBMeMBer-D-L-ATI cannot initiate the track immediately for the newborn target during the track initiation process, so the total error of the SMC-CBMeMBer-D-L-ATI in the first process is always higher than SMC-CBMeMBer-D. However, both filters enter the track maintenance process at 16s. The OSPA of SMC-CBMeMBer-D-L-ATI is always better than SMC-CBMeMBer-D in the second process. In the third process, because the targets 1, 2 and 3 disappeared one after another, the total errors are slightly increased. In general, compared with the SMC-CBMeMBer-D limited to the fixed position, SMC-CBMeMBer-D-L-ATI can adaptively initiate track of the newborn target by measurement.

The author has proposed the GM-CBMeMBer-D-L-ATI filter in the literature [11]. Now, the Monte Carlo simulation of the two filters is performed under the above simulation conditions. In the multi-target tracking process, if the track is terminated, re-initiation will generate new track label. Therefore, the unique track label for each track is the most ideal result. The optimal sub-Pattern Assignment with Label (OSPA-L) [6] can effectively compare tracking performance between SMC-CBMeMBer-D-L-ATI and GM-CBMeMBer-D-L-ATI. In addition to the distance truncation parameter $c$ and the order parameter $p$, OSA-L introduces the label truncation parameter $\alpha$. Let $c=100\text{m}$, $p=1$, $\alpha=50\text{m}$, Fig. 3(a) shows the performance statistics of the two filters under 200 Monte Carlo simulations. It can be seen from the figure that the total OSPA-L error curve of the two
filters is basically the same at track initiation process. In the track maintenance and termination phase, the performance of SMC-CBMeMBer-D-L-ATI is always slightly better than that of GM-CBMeMBer-D-L-ATI. Compared with the OSPA curve in Fig. 2, there is no large charge, which proves that the SMC-CBMeMBer-D-L-ATI filter not only can effectively track the target in the multi-target tracking process, but also is more accurately and stably provide track information.

![OSPAs comparison between SMC-CBMeMBer-D-L-ATI and GM-CBMeMBer-D-L-ATI](image)

Fig. 3 OSPA comparison between SMC-CBMeMBer-D-L-ATI and GM-CBMeMBer-D-L-ATI

The literature [4] mentions that the SMC implementation of CBMeMBer is more suitable for processing nonlinear non-Gaussian models than the GM implementation, so that the measurement noise parameters are $\sigma_1 = 50m$, $\sigma_2 = 2^2$, $\sigma_3 = 1m/s$, respectively. It can be seen from Fig. 3(b) that although the OSPA error values of both filters are improved overall, the OSPA-L value of SMC-CBMeMBer-D-L-ATI is consistently maintained at about 35 m during the track maintenance and termination phases, and the performance is significantly better than GM-CBMeMBer-D-L-ATI.

5. Conclusion
A labeled SMC-CBMeMBer filter adaptive track initiation proposed in this paper solves the problem that the SMC-CBMeMBer filter is limited to initiate the track at a fixed position and can effectively provide track information. The algorithm can effectively drive the adaptive track initiation through selected measurement, and the tracking performance is good. Compared with the GM-CBMeMBer-D-L-ATI filter, it is more suitable for processing nonlinear non-Gaussian models. On this basis, the next step will introduce the Minimum Detectable Velocity (MDV) to study the multi-target tracking problem under Doppler blind zone conditions.

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