Particle labeling PHD filter
for multi-target track-valued estimates

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Abstract—Multi-target tracking is a difficult problem due to the measurement origin uncertainty. Recently, the probability hypothesis density (PHD) filter provides a promising tool for joint estimation of target number and multi-target states, without using data association technique. In particle implementations of the PHD filter, clustering is used to extract the target state from the particle population. This technique yields poor performance when the estimated number of targets differs from the number of clusters in the particle population. A particle labeling PHD filter for multi-target track-valued estimates is developed in this paper. By implementing the efficient sampling and particle labeling technique, the proposed method can yield not only better state estimate, but also track-valued estimate. The multi-scan measurement information is also employed to reduce the uncertainty of the estimates. Simulation results demonstrate the efficiency of the proposed method.

Keywords: Probability hypothesis density, random finite set, track-valued estimate.

1 Introduction

For the multi-target tracking (MTT) problem in the presence of measurement origin uncertainty, data association [1-8] can be done to determine the assignments between measurements and targets. The performance of state estimate will be seriously affected by the accuracy of data association.

The random finite sets (RFSs) theory [9]-[12] provides a promising tool to the MTT problem. The probability hypothesis density (PHD) filter [13] is a suboptimal but computationally tractable alternative to the RFSs Bayesian multi-target filtering. It is a recursive mechanism which propagates the first-order statistical moment—the posterior expectation, instead of the posterior distribution. Multi-target state estimates can be obtained by applying the peak extraction technique over the PHD function. The PHD filter can be especially used in the cases with unknown target number, and gives the estimation of target number and multi-target states simultaneously. Reference [14] relaxed the Poisson assumption on the target number and derived a generalization of the PHD recursion known as the Cardinalized (CPHD) recursion, by jointly propagating the posterior intensity function and the posterior cardinality distribution.

Since the PHD filter equations still include some high-dimension integrals, there is no closed-form solution in general. In [15], the Gaussian mixture PHD (GM-PHD) filter is developed, which is a closed-form solution to the PHD filter under linear Gaussian assumptions. In non-linear non-Gaussian cases, the Sequential Monte Carlo (SMC) techniques [16]-[19] are regarded as an efficient means to approximate the density function, by recursively propagating a group of weighted particles. An SMC implementation of the PHD filter is proposed in [20]-[21], and the analogous idea can also be seen in [22]-[24].

Unfortunately, since the original PHD filter [21] keeps no record of track identities, the estimation of individual target can’t be obtained directly. Some approaches [25]-[28] have been developed in order to acquire the track-valued estimate. In [25]-[26], multi-target state estimates are firstly obtained by standard clustering...
techniques, and then track-valued estimates were
acquired by performing track-to-estimate association
based on the MHT mechanism. Reference [27] keeps a
separate tracker for each target, and constructs a
two-dimensional assignment problem to perform
'peak-to-track' association across the adjacent two scans.
Reference [28] also introduced extra indices to each one
in the whole particle set to store the track identity. But
when the estimated number of target differs from the
number of clusters in the particle population, the original
particle PHD filter fails to give good state estimates.

In the above methods, the clustering is done among the
whole particle set to obtain multi-target state estimates.
But when the targets are close, the particle cloud from
different targets can overlap each other. The particles
generated from one target can be partitioned wrongly into
another cluster from other target, which will yield poor
performance.

In this paper, a particle labeling PHD filter for
multi-target track-valued estimates is proposed. Each one
in the whole particle set has its own label which indicates
the target identity. The particles are evolved with its label,
and the weights are predicted and updated according to
the measurement information. The estimation for
individual targets will be obtained by the weighted sum
of particles with the same label, in order to avoid being
influenced by those particles from other targets. When
the targets are close, high weights of some particles are
possibly due to the measurement generated by the other
target. So, the directly weighted combination of all the
particles with the same label may be wrong. For this
reason, we need to develop an efficient method to extract
some particles from the particle set with the same label,
which can represent the target state with a high quality.

Here we do clustering in those particles with the same
label firstly, and then establish a temporary node for each
cluster. Next, we should make the decision to tell which
node will be used to update the target state. Hence, we
define a decision window with a given width by using of
the multi-scan measurement information. When the time
index is within the decision window, each temporary
node will be extended into several new nodes according
to the clustering result. Each node records all its particles,
the weights, and the node history indicating how it is
generated from the beginning. If the time index just lies
on the decision time, then the decision is made based on
the maximal weight criteria, and the whole track-valued
estimate can be obtained by going back the node history.
In addition, we draw the samples based on a mixture
proposal based on the measurement set, instead of using
the transition density. In this way, the sampling efficiency
can be improved greatly.

2 Problem formulation

2.1 Multi-target state model and
measurement model

Let $\mathcal{X}$ and $\mathcal{Z}$ denote the multi-target state space and
measurement space, $N_k$ and $M_k$ be the number of
targets and measurements at time $k$, respectively. Then
the multi-target states are $x_{k,1}, x_{k,2}, \ldots, x_{k,N_k} \in \mathcal{X}$, and
the measurements are $z_{k,1}, z_{k,2}, \ldots, z_{k,M_k} \in \mathcal{Z}$.

The multi-target state set and measurement set at time
$k$ can be described as the finite set variables:

$$ X_k = \{x_{k,1}, x_{k,2}, \ldots, x_{k,N_k}\}, X_k \in \mathcal{F}(\mathcal{X}) $$
$$ Z_k = \{z_{k,1}, z_{k,2}, \ldots, z_{k,M_k}\}, Z_k \in \mathcal{F}(\mathcal{Z}) $$

where $\mathcal{F}(\mathcal{X})$ and $\mathcal{F}(\mathcal{Z})$ represent the respective
collections of all finite subsets generated
from $\mathcal{X}$ and $\mathcal{Z}$. Let $Z^k$ be the cumulative
measurement set until time $k$, and $f_{k|k-1}(X_k | X_{k-1})$
and $g_k(Z_k | X_k)$ be the multi-target transition
probability and the likelihood function. The optimal
multi-target Bayesian recursive formula are given by

$$ p_{k|k-1}(X_k | Z^{k-1}) = \int f_{k|k-1}(X_k | X)p_{k-1|k-1}(X | Z^{k-1})dX $$

(1)

$$ p_{k|k}(X_k | Z^k) = \frac{g_k(Z_k | X_k)p_{k|k-1}(X_k | Z^{k-1})}{\int g_k(Z_k | X)p_{k|k-1}(X | Z^{k-1})dX} $$

(2)

2.2 Probability hypothesis density filter

The optimal multi-target Bayesian recursive formula
is computationally intractable. The Finite set statistics
(FISST) theory [13] provides a powerful tool that allows
the extension of the Bayesian inference to multi-target
tracking cases directly. The PHD filter is a suboptimal
alternative to the multi-target Bayesian recursive formula in the FISST framework.

The probability hypothesis density \( D_{k|k} (x | Z^k) \) is the first order statistical moment of the multi-target posterior density \( f_{k|k} (X_k | Z^k) \), which is a non-negative function with the following property
\[
\tilde{N}_k (S) = \int_S \int X \cap S f_{k|k} (X | Z^k) dx = \int S D_{k|k} (x | Z^k) dx \tag{3}
\]

where \( \tilde{N}_k (S) \) is the expected number of targets in region \( S \).

The PHD filter involves a prediction step and an update step as follows.

**Prediction step:**
\[
D_{k|k-1} (x_k | Z^{k-1}) = \gamma_k (x_k) + \int \varphi (x_k | x_{k-1}) D_{k-1|k-1} (x_{k-1}) dx_{k-1} \tag{4}
\]

where
\[
\varphi (x_k | x_{k-1}) = P_s (x_k | x_{k-1}) f_{k|k-1} (x_k | x_{k-1}) + b_{k|k-1} (x_k | x_{k-1}) \tag{5}
\]

The target survives with a probability \( P_s (x_k | x_{k-1}) \), and \( f_{k|k-1} (x_k | x_{k-1}) \) denotes the transition probability density for individual targets. Let \( b_{k|k-1} (x_k | x_{k-1}) \) be the intensity of the target RFS spawned from previous state \( x_{k-1} \), and \( \gamma_k (x_k) \) be the intensity function of the spontaneous birth RFS.

**Update step:**
\[
D_{k|k} (x_k | Z^k) = \left[ 1 - P_D (x_k) + \sum_{z \in Z_k} \frac{P_D (x_k) g_k (z | x_k)}{\kappa_k (z) + C_k (z)} \right] D_{k|k-1} (x_k) \tag{6}
\]

where
\[
C_k (z) = \int P_D (x_k) g_k (z | x_k) D_{k|k-1} (x_k | Z^{k-1}) dx_k \tag{7}
\]

where \( P_D (x_k) \) and \( g_k (z | x_k) \) are the detection probability and the likelihood function for individual targets, respectively. \( \kappa_k (z) \) denotes the intensity of the clutter RFS. It can be also written to be \( r_k c_k (\cdot) \), and \( r_k \) is the average clutter number per scan assuming a Poisson distribution. \( c_k (\cdot) \) is the probability distribution for each clutter measurement.

### 2.3 Particle PHD filter

Since the PHD filter still involves high dimensional integrals, the SMC technique is combined with the PHD filter to deal with the computational intractability [21].

For simplicity, assuming \( P_s (x) = 0 \). Let \( L_{k-1} \) be the total number of particles at time \( k-1 \) and set \( L_0 = 0 \). Given a particle representation of \( D_{k-1|k-1} \) by the particle set \( \{ x^{(i)}_{k-1}, w^{(i)}_{k-1} \}_{i=1}^{L_{k-1}} \) at time \( k-1 \),
\[
D_{k-1|k-1} (x_{k-1}) = \sum_{i=1}^{L_{k-1}} w^{(i)}_{k-1} \delta (x_{k-1} - x^{(i)}_{k-1}) \tag{8}
\]

**Prediction step:**
For \( i = 1,...,L_{k-1} \), sample \( \tilde{x}^{(i)}_k \) \( \sim q (\cdot | x^{(i)}_{k-1}, Z_k) \), where \( q (\tilde{x}^{(i)}_k | x^{(i)}_{k-1}, Z_k) \) is the proposal distribution. And then the predicted weights can be given by
\[
\tilde{w}^{(i)}_{k|k-1} = \frac{q (\tilde{x}^{(i)}_k | x^{(i)}_{k-1}, Z_k)}{q (x_k | x^{(i)}_{k-1}, Z_k)} w^{(i)}_{k-1} \tag{9}
\]

To explore newborn targets, \( J_k \) new particles are generated. For \( i = L_{k-1} + 1,...,L_{k-1} + J_k \), sample \( \tilde{x}^{(i)}_k \) \( \sim p_k (\cdot | Z_k) \), and compute the weights
\[
\tilde{w}^{(i)}_{k|k-1} = \frac{1}{J_k} \frac{\gamma_k (\tilde{x}^{(i)}_k)}{p_k (\tilde{x}^{(i)}_k | Z_k)} \tag{10}
\]

Where \( p_k (\cdot | Z_k) \) is the probability density for newborn targets.

**Update step:**
For each measurement \( z \in Z_k \), compute
\[
C_k (z) = \sum_{i=1}^{L_{k-1} + J_k} \psi_{k,z} (\tilde{x}^{(i)}_k) \tilde{w}^{(i)}_{k|k-1} \tag{11}
\]

where \( \psi_{k,z} (x) = P_D (x) g_k (z | x) \), and then update the weights
\[
\tilde{w}^{(i)}_k = \left[ 1 - P_D (\tilde{x}^{(i)}_k) + \sum_{z \in Z_k} \psi_{k,z} (\tilde{x}^{(i)}_k) \right] \tilde{w}^{(i)}_{k|k-1} \tag{12}
\]

**Resampling step:**
Firstly, the sum of weights are given by
\[
\tilde{N}_{k|k} = \sum_{i=1}^{L_{k-1} + J_k} \tilde{w}^{(i)}_k \tag{13}
\]

and then resample \( \{ x^{(i)}_k, w^{(i)}_k / \tilde{N}_{k|k} \}_{i=1}^{L_{k-1} + J_k} \) to get
\[
\{ x^{(i)}_k, w^{(i)}_k \}_{i=1}^{L_k} \text{, where } L_k = L_{k-1} + J_k \text{. Finally,}
\]
rescale the weights by $\hat{N}_{k|i}$ to get the updated particle set $\{\hat{x}_{k|i}^{(i)}, \hat{w}_{k|i}^{(i)}\}_{i=1}^{L_k}$ at time $k$.

State estimate:

Multi-target state estimates can be obtained by the peak extraction over the PHD function represented by a set of weighted particles, and standard clustering techniques [33] can be used to acquire these peaks.

3 Particle labeling PHD filter

3.1 Basic idea

In the original particle PHD filter described in Section 2, multi-target state estimates are obtained by standard clustering technique. But if the estimated number of targets is incorrect, multi-target state estimates given by standard clustering technique are unreliable.

Actually, each one in the whole particle set is produced from different origin, either from some existing target or newborn target. This information is ignored in the original particle PHD filter. If we add a label to each particle which records the target identity and can be inherited along with the particle evolution procedure, then the state estimate for individual target can be obtained by using of the particles with the same label. If the targets are well-separated, the weighted sum of particles with the same label can give good state estimate. But the result is unsatisfactory when the targets are close together, because the high weight of some particles may be produced by measurements from other targets.

At time $k \geq 1$,

1) Sample for existing targets.

For $i = 1, \ldots, L_{k-1}$, sample $\hat{x}_{k|i}^{(i)} \sim q(. \mid \hat{x}_{k-1|i}, Z_k)$, where $q(. \mid \hat{x}_{k-1|i}, Z_k)$ denotes the proposal distribution. Here, a mixture proposal is given by

$$p(. \mid \hat{x}_{k-1|i}, Z_k) = \sum_{j=0}^{M} b_j p(. \mid \hat{x}_{k-1|i}, z_{k,j})$$

where $b_j \triangleq p(\theta_j \mid Z_k)$ ($j = 0, 1, \ldots, M_k$), and $\theta_j$ ($j > 0$) is the association hypothesis which means that the measurement $z_{k,j}$ originates from the target.

The hypothesis $\theta_0$ means no measurement comes from the target. The probability can be computed similar to the association probability in probabilistic data association [1].

The sample procedure is drawn from the mixture proposal as follows.
Sample from the proposal \( q_1(\cdot / .) \) for the measurement index
\[
m \sim q_1(\cdot | x^{(0)}_{k-1}, Z_k)
\]
where the proposal \( q_1(\cdot / .) \) is chosen to be discrete distribution \( \{(0, b_0),(1, b_1), \ldots, (M_k, b_{M_k})\} \).

Sample from the proposal \( q_2(\cdot / .) \) for the target state
\[
\bar{x}^{(i)}_k \sim q_2(\cdot / x^{(i)}_{k-1}, z_{k,m}),
\]
where the proposal \( q_2(\cdot / .) \) is set to be the posterior distribution, which can be approximated easily by applying the local-linearization technique or the unscented transformation. If \( m = 0 \), then the sample can be drawn from the transition probability. The predicted weights can be computed by the following formula
\[
\bar{w}^{(i)}_{k\mid k-1} = \frac{\theta(\bar{x}^{(i)}_k, x^{(i)}_{k-1})}{p(\bar{x}^{(i)}_k / x^{(i)}_{k-1}, Z_k)} w^{(i)}_{k-1} \tag{15}
\]

2) Sampling for newborn targets.
For \( i = L_{k-1} + 1, \ldots, L_k + J_k \), sampling \( \tilde{x}^{(i)}_k \sim p_k(\cdot | Z_k) \), and compute the weights for newborn targets
\[
\tilde{w}^{(i)}_{k\mid k-1} = \frac{1}{J_k} \gamma_k(\tilde{x}^{(i)}_k) p_k(\tilde{x}^{(i)}_k / Z_k) \tag{16}
\]

3) The whole particle set \( \{x^{(i)}_k, \tilde{x}^{(i)}_{k\mid k-1}, z^{(i)}_{k+l_{i}^{(i)}}, j_{i}^{(i)}\}_{j=1}^{L_k+J_k} \) can be obtained by combining all the particles generated from the above two steps. For \( i = 1, \ldots, L_{k-1} \), the label \( l_k^{(i)} \) can be inherited from \( l_{k-1}^{(i)} \) directly, that is \( l_k^{(i)} = l_{k-1}^{(i)} \).
For \( i = L_{k-1} + 1, \ldots, L_k + J_k \), a temporary label ‘0’ is assigned, until it is finally confirmed in Step 5). Then the weights can be updated as the following formula
\[
\hat{w}^{(i)}_k = \left[1 - P_D(\tilde{x}^{(i)}_k) + \sum_{z \in \mathcal{Z}_k} \psi_{k,z}(\tilde{x}^{(i)}_k) \kappa_k(z) + C_k(z)\right] \bar{w}^{(i)}_{k\mid k-1} \tag{17}
\]
\[
C_k(z) = \sum_{j=1}^{L_k+J_k} \psi_{k,z}(\tilde{x}^{(i)}_k) \tilde{w}^{(i)}_{k\mid k-1} \tag{18}
\]

Then the resampling procedure is done as the original particle PHD filter does, and then the whole particle set \( \{x^{(i)}_k, w^{(i)}_k, \tilde{x}^{(i)}_{k\mid k-1}, z^{(i)}_{k+l_{i}^{(i)}}, j_{i}^{(i)}\}_{j=1}^{L_k+J_k} \) can be obtained. The estimated number for newborn targets is given by
\[
\hat{N}_n = \text{round} \left( \sum_{i=L_k+1}^{L_k+J_k} w^{(i)}_k \right) \tag{19}
\]

4) Clustering
In this step, clustering is done among those particles with the same label. We denote \( P_j \) as the particle set with label \( j \) \((j \in \{0, \Gamma_{k-1}\}) \). For \( j \in \Gamma_{k-1} \), the particle set \( P_j \) is classified into \( \hat{N}_j \) clusters. Where \( \hat{N}_j = \min \{m_j, \hat{N}_a\} \), and \( m_j \) is the measurement number in the validation gate of target \( j \).
\[
\hat{N}_a = 1 + \hat{N}_j, \text{ where } \hat{N}_j \text{ means the target number which are close to target } j. \text{ It can be computed as the number of targets whose validation gate intersects with the one of target } j. \text{ For } j = 0, \text{ the particle set } P_0 \text{ is partitioned into } \hat{N}_n \text{ clusters.}
\]

5) Track Extension and decision
We set a time window using the multi-scan measurement information. When the time index is within the time window, we establish a node for each cluster \( I(1 \leq l \leq \hat{N}_j) \) from \( P_j \) which carries all the information about the particles, the weight, and its generation history. When the time index is just on the decision time, the final decision will be made as follows.

a) we denotes \( \omega_j \) as the sum of weights for each cluster \( I(1 \leq l \leq \hat{N}_j) \) from \( P_j \) \((j \in \Gamma_{k-1}) \), and let
\[
I^* = \arg \max_{1 \leq l \leq \hat{N}_j} \{\omega_j\}, w^* = \omega_j^* \tag{19}
\]
If \( w^* \) is larger than some given threshold \( G_T \), then the \( I^\text{th} \) cluster is kept. The multi-scan target states within the time window can be obtained by going back in the node history of cluster \( I^\text{th} \). The other clusters with label \( j \) will be deleted along with its ancestor nodes. If \( w^* \) is less than the threshold \( G_T \), the track will be terminated. As a result, the particle set \( \{x^{(i)}_k, w^{(i)}_k, l^{(i)}_{i=1}^{L_k+J_k}\} \) at time \( k \) will be updated by all the left particles.

b) For each cluster from \( P_0 \), if the sum of weights is greater than some given threshold \( G_T \), then a new target can be initiated and a new track identity is assigned to all the particles in this cluster. The maximal target identity is also modified by \( \hat{N}_\text{max} = \hat{N}_\text{max} + 1 \). Otherwise, the
cluster will be deleted.

4 Simulation results

For simplicity, we only consider linear Gaussian model in 2-D plane. The target moves in the surveillance region $[-1000,1000] \times [-1000,1000] m$. The target state takes the form $x(k)=[x(k), \dot{x}(k), y(k), \dot{y}(k)]^T$, where $x(k)$ and $y(k)$ are the position components, $\dot{x}(k)$ and $\dot{y}(k)$ denote the velocity components of the target state at time $k$. The target dynamics is given by

$$x(k+1) = \begin{bmatrix} 1 & T^2/2 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & T \end{bmatrix} x(k) + \begin{bmatrix} 0 \\ T^2/2 \\ 0 \\ 0 \end{bmatrix} v(k)$$ \hspace{1cm} (20)

where the process noise $v(k) \sim \mathcal{N}(0, Q_k)$ with $Q_k = \text{diag}([\sigma_{xw}^2, \sigma_{wy}^2, \sigma_{xv}^2, \sigma_{vy}^2])$. The measurement equation is

$$z(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} x(k) + w(k)$$ \hspace{1cm} (21)

where the measurement noise $w(k) \sim \mathcal{N}(0, R_k)$ with $R_k = \text{diag}([\sigma_{xw}^2, \sigma_{wy}^2])$, $\sigma_{xw} = 2 m$ and $\sigma_{wy} = 1.5 m$. The process noise is assumed independent of the measurement noise.

We set the sample interval $T = 1 s$. The clutter measurements are uniformly distributed over the surveillance region with an average rate $r$ points per scan. New-born targets can appear according to a Poisson point process with the intensity function

$$\gamma_k = 0.5 \mathcal{N}(\cdot; \bar{x}, Q_n) + 0.5 \mathcal{N}(\cdot; \bar{x}_2, Q_n)$$

with $\bar{x} = [-200 \ 10 \ 200 \ -2]^T$, $\bar{x}_2 = [80 \ -2 \ 70 \ 5]^T$, and $Q_n = \text{diag}([1, 0.01, 1, 0.04])^T$. The particle number for each existing target is set to be 500, and 1000 for newborn targets. For simplicity, we only consider the unity detection probability and survival probability.

The Optimal Sub-pattern Assignment (OSPA) metric presented in [29] is employed to evaluate the performance. It is a mathematically and intuitively consistent metric, which tries to capture the estimate quality both the cardinality and multi-target states.

Let $X = \{x_1, \ldots, x_m\}$ and $Y = \{y_1, \ldots, y_n\}$ represent the real multi-target state set and the estimated one with the cardinality $m$ and $n$ ( $m, n \in \mathbb{N}_0 = \{1, 2, \ldots\}$ ), and $\prod_k$ be the permutations on the set $\{1,2,\ldots,k\}$ for any $k \in \mathbb{N} = \{1,2,\ldots\}$ . For $1 \leq p < \infty$, $c > 0$, The OSPA metric of order $p$ with cut-off $c$ is defined as:

$$\bar{d}_p^c(X,Y) = \left( \frac{1}{n} \left( \sum_{i=1}^{m} d_p^{(c)}(x_i, y_{\pi(i)})^p + c^p (n-m) \right) \right)^{\frac{1}{p}}$$ \hspace{1cm} (22)

if $m \leq n$ ,

$$\bar{d}_p^c(X,Y)=\bar{d}_p^c(Y,X)$$ \hspace{1cm} (23)

where $d_p^{(c)}(x,y) = \min(c, d(x,y))$ denotes the distance between $x,y$ with cut off $c > 0$. We define $d(x,y)$ as the Euclidean distance, and set $c = 100$ and $p = 2$ . The thresholds for track initiation and track termination are set $G_t = 0.8$ and $G_r = 0.5$ , respectively. The measurements are supported by 50 MC runs performed on the same target trajectory but with independently generated measurements for each trial.

Example 1

In this scenario, the average number of clutter measurement per scan is set $r = 10$, and the standard derivation of process noise is $\sigma_{xv} = \sigma_{vy} = 2$. The width of decision window is set to be 1. The multi-target trajectories and state estimates against time are plotted in Fig.2. In Fig.3, the OSPA error is shown.
Example 2

In this example, the expected number of clutter measurement per scan is set $r = 60$, and the standard derivation of process noise is $\sigma_{\text{vx}} = \sigma_{\text{vy}} = 10$. The width of decision window is set to be 1 and 3, respectively. The multi-target trajectories and state estimates against time are illustrated by the Fig.4-6.

Fig.4. State Estimates by the Original Particle PHD Filter

Fig.5. State Estimates by the Presented Method with Single-Scan

Fig.6. State Estimates by the Presented Method with Multi-Scan

The OSPA error is shown Fig. 7.

In this scenario, when we apply the original particle PHD filter and the presented method with single-scan measurements, track loss phenomena happened. But if we set the width of decision window to be 3, good tracking performance can be achieved. It shows that multi-scan measurement information is needed to improve the performance, in cases with large process noise and high clutter density.

5 Discussions and conclusions

A Particle labeling PHD filter for multi-target track-valued estimates is developed in this paper. There are some possible future research directions. To reduce the uncertainty of the problem, the multi-scan measurement is employed in the presented method. As a result, the decision delay and high computational burden is inevitable. So a variable width of the decision window may be more economic and can keep the balance between computational burden and algorithm performance, according to the current measurement distribution and the target maneuvering level.

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