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Extended Target Tracking Algorithm Based on Random Hypersurface Model with Glint Noise

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Due to the fact that the unmatching of extended targets' measurements noise is also assumed as Gaussian distribution and conventional algorithm cannot estimate target's extent under the circumstance of unknown measurement noise covariance, a new multiple extended target tracking algorithm based on variational bayesian random hypersurface model (VB-RHM) is proposed, which is embedded into CPHD filter frame. Measurement noise is modeled by glint noise with t-distribution, its parameters are assumed to have a Gamma prior distribution so that the predicted and updated PHDs can have mixture of Gaussians representations. A variational bayesian procedure is applied to iteratively estimate parameters of the mixture distributions through random hypersurface model CPHD prediction and update steps. The simulation results show that the proposed algorithm VB-RHM-CPHD can track multiple extended targets' kinematic state and object extension under the condition of unknown numbers and measurement noise covariance adaptively. In addition, it has an improved precision compared with conventional RHM-GGM-CPHD algorithm.

1. Introduction

Conventional extended target algorithms are mainly based on that measurement noise model is known, and the noise is also assumed as Gaussian distribution (Gilholm and Salmond, 2005; Gilholm et al., 2005). But in many conditions, the parameters of noise, such as inverse covariance of measurement noise, are always unknown, particularly for radar tracking systems, changes in the target aspect toward the radar may cause irregular electromagnetic wave reflections and this gives rise to outliers or glint noise (Li et al., 2014). It was found that glint noise has a heavy-tailed probability density function and conventional filtering algorithms are known to show unsatisfactory performance in the presence of glint noise. So it is eagerly to introduce another measurement noise model. It is proved that when measurement noise model is matched with true noise, effect tracking result can be reached, while the accuracy of target tracking will drop dramatically or obtained a poor result once model unmatched.

In order to solve the estimation problem of unknown measurement noise, a number of approximation algorithms are proposed to deal with errors. In Oussalah et al. 2000), weight least square method is used to identify noise. In Zhu (Zhu, 1999), recursive least square filtering method with forgetting factor is used to make up for the lack of statistical noise problem. Recently, variationally Bayesian (VB) method is applied to estimate joint probability density of the target state and unknown measurement noise covariance (Zhu et al., 2013). Because the performance of the conventional extended objects tracking degrades significantly under the condition of unknown measurement noise covariance, a new multiple extended object-tracking algorithm based on variationally Bayesian cardinality-balanced multi-object multi-Bernoulli was proposed in Li et al. (Li et al., 2015) without taking target extension into consideration. In that case, an extended object tracking algorithm based on Variationally Bayesian Random Hypersurface Model (VB-RHM) is proposed, which is in the situation of glint noise, and it can also estimate target extension (Li, 2016).

Random Hypersurface Model (RHM) is a new object modeling method proposed by Baum in 2009 (Baum and Hanebeck, 2009), in the model, object's measurements are produced by measurement sources and the noise from sensor device, while the modeling of measurement source stands for target extent, but when using this method to tracking object, Baum doesn't take clutter and missing decection into consideration, which against application in practical engineering. In 2013, Zhang Hui and Han Yu Lan etc (Zhang et al., 2013; Han et al.,

2013) propose a novel filter called RHM-PHD which combined RHM with ET-PHD. On this basis, we present an algorithm called VB-RHM-CPHD that embedded RHM into CPHD filter, it's worth noting that the algorithm can also estimate object extension besides kinematic state, also, it is under the assumption of a glint measurement noise model with unknown inverse covariance.

2. Extended object tracking modeling

2.1 Extended target tracking model

We denote the dynamics (motion equation) of the kth time step as:

$$\boldsymbol{x}_k = \boldsymbol{F}_{k-1}\boldsymbol{x}_{k-1} + \boldsymbol{w}_{k-1} \tag{1}$$

where $x_k = [m_{x,k}, m_{y,k}, v_{x,k}, v_{y,k}]^T$ is the kinematic state of an extended object, (mx, k, my, k) is the position of the centroid of the object, (vx, k, vy, k) is the velocity of the object, and W_{k-1} is a zero-mean Gaussian process noise with the covariance matrix Q_{k-1}. The state transition matrix F_{k-1} is assumed known.
An elliptic random hypersurface model (RHM) (Zhang et al., 2013) is used to model the spread of the extended objects in 2-D space. With the RHM model, the measurement vector z must lie within an ellipse defined as follows:

$$\left\{\boldsymbol{z} \mid \boldsymbol{z} \in \mathbb{R}^2,\ \left(\boldsymbol{z}-\boldsymbol{m}_k\right)^T \boldsymbol{A}_k^{-1}\left(\boldsymbol{z}-\boldsymbol{m}_k\right) \le 1\right\} \tag{2}$$

where $m_{x,k}, m_{y,k}{}^T$. The positive-definite inverse covariance matrix A_K^{-1} may be factorized as: $A_K^{-1} = L_K L_K^T$ where$l_k = \begin{bmatrix} l_k^{(1)} & 0 \\ l_k^{(3)} & l_k^{(2)} \end{bmatrix}$ is a lower triangular matrix with positive diagonal elements. The kinematic state vector of an extended object thus should be extended to a 1 × 7 vector:

$$\boldsymbol{x}_k = \left[m_{x,k}, m_{y,k}, v_{x,k}, v_{y,k}, l_k^{(1)}, l_k^{(2)}, l_k^{(3)}\right]^T \tag{3}$$

We assume this extended target is associated with a set of n_T measurements:
$\boldsymbol{z}_k = \left\{\boldsymbol{z}_k^j\right\},\ j = 1,\ldots,n_T$.

The measurement source model and relevant measurement model of the jth measurement can be expressed as:

$$\boldsymbol{y}_k^{(j)} = \boldsymbol{m}_k + s_k^{(j)} \cdot R\left(\theta_k^{(j)}; a_k, b_k, \phi_k\right) \cdot \left(\boldsymbol{e}_k^{(j)}\right)^T \tag{4}$$

$$\boldsymbol{z}_k^{(j)} = \boldsymbol{y}_k^{(j)} + \boldsymbol{c}_k^{(j)} \qquad j = 1,\ldots,n_T \tag{5}$$

where $c_k^{(j)}$ denotes the measurement noise with unknown covariance, it is modelled by a Student's-distribution with unknown parameters. The scaling factor $s_k^{(j)}$ is a random variable uniformly distributed over (0, 1] with mean μs = 0.5 and variance σs2 = 1/12. $\theta_k^{(j)}$is unknown, but it can be substituted by a proper estimation given by the angel between the positive x-axis and the vector from the current center to the measurement $z_k^{(j)}$. a_k, b_k are the semi-major and semi-minor axis of the ellipse, respectively. $\emptyset_k \in [0,2\pi]$ is the angle between the positive x-axis and semi-major axis which is positive in the clock-wise direction. Where

$$R\left(\theta_k^{(j)}; a_k, b_k, \phi_k\right) = \left\|\boldsymbol{y}_k^{(j)} - \boldsymbol{m}_k\right\| \big/ s_k^{(j)} \quad s_k^{(j)} \neq 0 \text{ and } \qquad \boldsymbol{e}_k^{(j)} = \left(\boldsymbol{y}_k^{(j)} - \boldsymbol{m}_k\right) \big/ \left\|\boldsymbol{y}_k^{(j)} - \boldsymbol{m}_k\right\|$$

is a uniceptor along the direction of $\boldsymbol{y}_k^{(j)}$-$\boldsymbol{m}_k$.

$$\begin{aligned} 0 = h\left(x_k, s_k^{(j)}, \boldsymbol{z}_k^{(j)}, \boldsymbol{c}_k^{(j)}\right) &= \left(s_k^{(j)} R(\theta_k^{(j)}; a_k, b_k, \phi_k)\right)^2 \\ &+ 2 s_k^{(j)} R(\theta_k^{(j)}; a_k, b_k, \phi_k) \boldsymbol{e}_k \cdot \boldsymbol{c}_k^{(j)} + \| \boldsymbol{c}_k^{(j)} \|^2 - \| \boldsymbol{z}_k^{(j)} - \boldsymbol{m}_k \|^2 \end{aligned} \tag{6}$$

$\mathrm{h}(X_k,\ s_k^{(j)}, z_k^{(j)}, c_k^{(j)})$ maps the state vector X_k, the measurement noise vector $c_k^{(j)}$, the scaling factor $s_k^{(j)}$ and the physical measurement vector $z_k^{(j)}$ into a pseudo-measurement 0. Because the measurement model is nonlinear, an Unscented Transform (Julier andUhlmann, 2004) is applied to deal with this tracking situation.

With the Unscented Transform, we augment X_k as $x_k^a = [x_k^T \; s_k \; c_k^T]^T$. The corresponding mean and covariance can be expressed as

$$\boldsymbol{\mu}_k^a = \begin{bmatrix} \boldsymbol{\mu}_k^T \\ \mu_s \\ \boldsymbol{0}_2 \end{bmatrix}, \text{ and } \boldsymbol{C}_k^a = \begin{bmatrix} \boldsymbol{P}_x & 0 & 0 \\ 0 & \sigma_s^2 & 0 \\ 0 & 0 & \boldsymbol{R}_k \end{bmatrix}. \tag{7}$$

Where, μ_k is the mean of X_k. s_k is a Gaussian distribution with mean μ_s and covariance σ_s^2. R_k denotes the unknown covariance of measurement noise.

2.2 Variational bayesian method

The goal of the Bayesian filtering is to estimate the posterior density given the measurement set at time k:

$$p(\boldsymbol{x}_k, \boldsymbol{R}_k, v_k \mid \boldsymbol{Z}_k) = \frac{p(\boldsymbol{z}_k \mid \boldsymbol{x}_k, \boldsymbol{R}_k, v_k) p(\boldsymbol{x}_k, \boldsymbol{R}_k, v_k \mid \boldsymbol{Z}_{k-1})}{\int p(\boldsymbol{z}_k \mid \boldsymbol{x}_k, \boldsymbol{R}_k, v_k) p(\boldsymbol{x}_k, \boldsymbol{R}_k, v_k \mid \boldsymbol{Z}_{k-1}) d\boldsymbol{x}_k d\boldsymbol{R}_k dv_k} \tag{8}$$

This posterior density is in general rather complicated. We employ the Variational Bayesian approach to approximate the posterior distribution with a simpler distribution (Zhu et al., 2013)

$$p(\boldsymbol{x}_k, \boldsymbol{R}_k, v_k \mid \boldsymbol{Z}_k) \approx Q_x(\boldsymbol{x}_k) Q_R(\boldsymbol{R}_k) Q_v(v_k) \tag{9}$$

This approach promises significant reduction of computational complexity. Qx(xk), QR(Rk), and Qv(vk) are found by minimizing the KL divergence between $Q_x(X_k)Q_r(R_k)Q_v(V_k)$ and $p(X_k, R_k, V_k|Z_k)$:

$$\begin{aligned} & KL\left[Q_x(\boldsymbol{x}_k)Q_R(\boldsymbol{R}_k)Q_v(v_k) \,\|\, p(\boldsymbol{x}_k, \boldsymbol{R}_k, v_k \mid \boldsymbol{Z}_k)\right] \\ & = \int Q_x(\boldsymbol{x}_k)Q_R(\boldsymbol{R}_k)Q_v(v_k) \ln\left[\frac{Q_x(\boldsymbol{x}_k)Q_R(\boldsymbol{R}_k)Q_v(v_k)}{p(\boldsymbol{x}_k, \boldsymbol{R}_k, v_k \mid \boldsymbol{Z}_k)}\right] d\boldsymbol{x}_k d\boldsymbol{R}_k dv_k \end{aligned} \tag{10}$$

Minimizing eq. (10), one has:

$$Q_x(\boldsymbol{x}_k) = N(\boldsymbol{x}_k; \bar{\boldsymbol{x}}_{k|k}, \boldsymbol{P}_{k|k}) \tag{11}$$

$$Q_R(\boldsymbol{R}_k) = \prod_{l=1}^{M} G(r_{k,l}; \alpha_{k|k,l}, \beta_{k|k,l}), \tag{12}$$

$$Q_v(v_k) = G(v_k; \gamma_{k|k}, \eta_{k|k}). \tag{13}$$

where M is the dimensions of the measurement noise inverse covarianceRk, $\alpha_{k|k,l}$, $\beta_{k|k,l}, \gamma_{k|k}$ and $\eta_{k|k}$ are parameters with the Gamma distribution.

3. Extended object tracking algorithm based on VB

Based on eq.(11) to eq.(13), the complex task of joint estimation of the object state, measurement noise inverse covariance and degrees of freedom is simplified into parameter estimations of the product of three density functions, and these parameters can be predicted and updated in the framework of an extended object CPHD filter. The detailed process is as follows:

Step 1 prediction

The prediction step of the extended object CPHD filter propagates the joint PHD of object state, measurement noise inverse covariance, and degrees of freedom (hereafter called the joint PHD), this joint PHD can be expressed as (Li et al., 2014).

$$D_{k|k-1}(\boldsymbol{x}, \boldsymbol{R}, v) = D_{S,k|k-1}(\boldsymbol{x}, \boldsymbol{R}, v) + D_{B,k}(\boldsymbol{x}, \boldsymbol{R}, v) \tag{14}$$

Where $D_{k|k-1}(x, r, v)$ and $D_{b,k}(x, r, v)$ denote respectively the predicted joint PHD intensity of survival object and birth object. The expression is below:

$$\begin{aligned} D_{S,k|k-1}(\boldsymbol{x}, \boldsymbol{R}, \boldsymbol{v}) = P_{S,k} \sum_{i=1}^{J_{k-1}} \prod_{l=1}^{M} w_{k-1}^{(i)} N\left(\boldsymbol{x}_k; \boldsymbol{m}_{S,k|k-1}^{(i)}, \boldsymbol{P}_{S,k|k-1}^{(i)}\right) \\ \times G\left(r_{k,l}; \alpha_{S,k|k-1,l}^{(i)}, \beta_{S,k|k-1,l}^{(i)}\right) G\left(v_k; \gamma_{S,k|k-1}^{(i)}, \eta_{S,k|k-1}^{(i)}\right) \end{aligned} \tag{15}$$

Here, $P_{S,k}$ stands for the survival probability. $W_{k-1}^{(i)}, m_{s,k|k-1}^{(i)}, P_{s,k|k-1}^{(i)}$ $and\, J_{k-1}$ are the ith Gaussian component parameters of survival object, $\alpha_{s,k|k-1,l}^{(i)}$ and $\beta_{s,k|k-1,l}^{(i)}$ are the inverse covariance parameters of the ith Gamma component, $\gamma_{s,k|k-1}^{(i)}$ and $\eta_{s,k|k-1}^{(i)}$ are the degrees of freedom of the ith Gamma component.

$$D_{B,k}\left(\boldsymbol{x},\boldsymbol{R},\boldsymbol{v}\right)=\sum_{i=1}^{J_{b,k}}\sum_{l=1}^{M} w_{b,k}^{(i)} N\left(\boldsymbol{x}_k;\boldsymbol{m}_{b,k}^{(i)},\boldsymbol{P}_{b,k}^{(i)}\right) \times G\left(r_{k,l};\alpha_{b,k,l}^{(i)},\beta_{b,k,l}^{(i)}\right) G\left(v_k;\gamma_{b,k}^{(i)},\eta_{b,k}^{(i)}\right) \tag{16}$$

Here, $W_{b,k}^{(i)}, m_{b,k}^{(i)}, P_{b,k}^{(i)}$ $and\, J_{b,k}$ are the ith Gaussian component parameters of birth object, $\alpha_{b,k,l}^{(i)}$ and $\beta_{b,k,l}^{(i)}$ are the inverse covariance parameters of the ith Gamma component, $\gamma_{b,k}^{(i)}$ and $\eta_{b,k}^{(i)}$ the degrees of freedom of the ith Gamma component. Detailed prediction process can be found in [14].

Step 2 update

Set the Gamma distribution parameters at first, $\alpha_{k,l}^{(i)}=\alpha_{k|k-1,l}^{(i)}+0.5$, $\beta_{|k,l}^{(i)(0)}=\beta_{k|k-1,l}^{(i)}$, $\gamma_{k|k}^{(i)}=\gamma_{k|k-1}^{(i)}+0.5$, $\eta_{k|k}^{(i)(0)}=\eta_{k|k-1}^{(i)}$, $\hat{s}_k^{(i)(0)}=1$, for l =1, …, M, i = 1, …, K. K is the number of predicted object Gaussian components in current time, M is the dimension of the measurement noise inverse covariance. The main update equations are below:

$$\boldsymbol{R}_k^{(i)(n)}=diag\left[\frac{\alpha_{k,1}^{(i)}}{\beta_{k,1}^{(i)(n)}},\ldots,\frac{\alpha_{k,M}^{(i)}}{\beta_{k,M}^{(i)(n)}}\right],\ \beta_{k,1}^{(i)(n)}=\beta_{k,1}^{(i)(n-1)}+\frac{1}{2|W|}\cdot\sum_{j=1}^{|W|}tr\left\{\hat{s}_k^{(i)(n)}[\boldsymbol{z}_k^j-\boldsymbol{\mu}_{k|k}^{(j),W}][\boldsymbol{z}_k^j-\boldsymbol{\mu}_{k|k}^{(j),W}]^T+B\boldsymbol{P}_{k|k}^{(j),W}B^T\right\} \tag{17}$$

$$z_p=h(\chi_p),\ \hat{z}_{nz}=\sum_{p=1}^{\text{nsigma}}W_m^{(p)}\cdot z_p,\ \mathrm{S}_{nz}=\sum_{p=1}^{\text{nsigma}}W_c^{(p)}\left(z_p-\hat{z}_{nz}\right)\left(z_p-\hat{z}_{nz}\right)^T,\ \boldsymbol{P}_{xz}=\sum_{p=1}^{\text{nsigma}}W_c^{(p)}\left(\chi_p-\boldsymbol{\mu}_k^a\right)\left(z_p-\hat{z}_{nz}\right)^T \tag{18}$$

$$K=\boldsymbol{P}_{xz}\left(\mathrm{S}_{nz}\right)^{-1},\ \boldsymbol{\mu}_k^a=\boldsymbol{\mu}_k^a+K\left(0-\hat{z}_{nz}\right),\ \boldsymbol{C}_k^a=\boldsymbol{C}_k^a-K\cdot\mathrm{S}_{nz}\cdot K^T,\ \boldsymbol{\mu}_{k|k}^{(j),W}=\boldsymbol{\mu}_x^a(1:2) \tag{19}$$

$$\boldsymbol{P}_{k|k}^{(j),W}=\boldsymbol{C}_k^a(1:4,1:4),\ \hat{\boldsymbol{R}}_k^{(i)(n)}=(\hat{s}_k^{(i)(n)}\boldsymbol{R}_k^{(i)(n)})^{-1},\ \hat{s}_k^{(i)(n)}=\frac{a_k^{(i)(n)}}{b_k^{(i)(n)}},\ a_k^{(i)(n)}=\frac{\gamma_{k|k}^{(i)}}{2\eta_{k|k}^{(i)(n)}}+0.5 \tag{20}$$

$$b_k^{(i)(n)}=\frac{\gamma_{k|k}^{(i)}}{2\eta_{k|k}^{(i)(n)}}+\frac{1}{2|W|}\cdot\sum_{j=1}^{|W|}tr\left\{\boldsymbol{R}_k^{(i)(n)}[\boldsymbol{z}_k^j-\boldsymbol{\mu}_{k|k}^{(j),W}][\boldsymbol{z}_k^j-\boldsymbol{\mu}_{k|k}^{(j),W}]^T+B\boldsymbol{P}_{k|k}^{(j),W}B^T\right\} \tag{21}$$

$$\eta_{k|k}^{(i)(n)}=\eta_{k|k-1}^{(i)(n-1)}-0.5[1+\log(\hat{s}_k^{(i)(n-1)})-\hat{s}_k^{(i)(n-1)}] \tag{22}$$

W refers to a measurement cell obtained currently after the distance partition (Granstrom et al., 2010), and |W| is the cardinal number of the set W. Equations are used to perform the Unscented Transform, while the parameter B in eq. The notation X_P represents the pth Sigma point after the Unscented Transform, and the total number of Sigma points equals to n sigma. $W_m^{(p)}$ and $W_c^{(p)}$ denote the relevant weight.

4. Simulation results

We consider a two-dimensional simulation scenario where the ground truth is described as follows: Two objects moves inside a surveillance region for a duration of 40 seconds. The surveillance region is a rectangle area with lower left coordinate (500, 1000) meters and upper right coordinate (500, 200) meters. The initial positions of these targets are at (930, 210) meters and (930, 210) meters. During the first 10 seconds, both targets move toward east at a constant velocity (a CV model) V=28 m/sec. These yield two parallel trajectories. Then for the next 10 seconds, these objects turn toward each other at a constant turn rate (a CT model) of 4.5 degrees/sec ($\omega=\pi/40$ *rad/sec*), while maintaining the constant speed V. During the last 20 seconds, these objects move straight along their headings at the 20th second, namely south east (upper one) and north east (lower one) while maintaining the constant speed V. Their trajectories cross-over at the 25th second, and then separate apart. Their trajectories terminate at (400, 80) and (400, 80) respectively at the end of the 40th second. The sampling period is set to $\tilde{T}$=1 sec. Detail parameters are shown in the following Table.

Table 1: The parameters in simulation

Survival probability $p_{S,k} = 0.99$	Detection probability $p_{D,k} = 0.98$	True measurement noise standard deviation $\sigma = \sigma_x = \sigma_y = 1.118$
Clutter mean $\lambda = 10$	Pruning threshold $T = 10^{-5}$	Gaussian components number $J_{\max} = 100$
Empirical threshold convcrit = 0.01	Merge threshold $U = 10$	Spread factors $\rho_\alpha = \rho_\beta = \rho_\gamma = \rho_\eta = 0.75$
Measurement noise covariance $\hat{\boldsymbol{R}}_k = diag\left\{\sigma_x^2, \sigma_y^2\right\}$	Initial state means of birth objects $\boldsymbol{x}_\gamma^{(1)} = [-930, 210, 0, 0, 20, 20, 0]^T$ $\boldsymbol{x}_\gamma^{(2)} = [-930, -210, 0, 0, 20, 20, 0]^T$	Initial state covariance of birth objects $\boldsymbol{P}_{b,k}^{(i)} = diag\left\{5,5,15,15,5,5,5\right\}$

So as to verify the availability of the proposed algorithm, traditional extended object tracking with RHMS (RHM-GGM-CPHD) under the measurement noise covariance being $\sigma = 0.25, 1.11, 6.8$ were done. The following part is the presentation of the performance of extended object's tracking, such as the angle (deg), semi-major axis's length, semi-minor axis's length etc. 100 Monte Carlo (MC) simulations are performed.

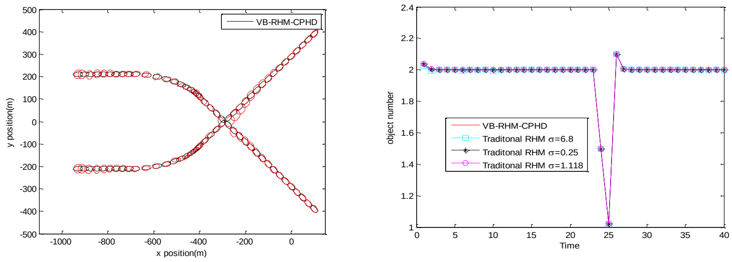

Figure 1: Estimation of object trajectory and Estimation of object number

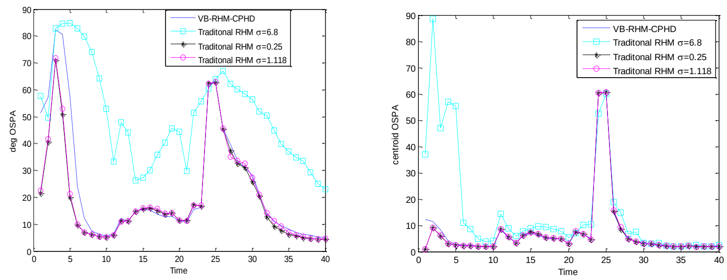

Figure 2: Centroid OSPA and Degree OSPA

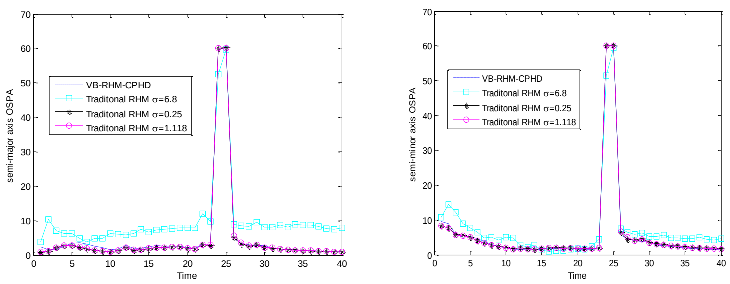

Figure 3: Semi-major axis OSPA and Semi-minor axis OSPA

From Figure 1- Figure 3, it can be found that the proposed VB method can have a good estimation for object's centroid and shape by combining with the Elliptic RHM. In traditional method of extended object tracking with

Elliptic RHM, improper measurement noise covariance leads to poor estimation performance of object’s centroid and shape especially using a bigger covariance. When the measurement noise covariance is little, the impact on object’s shape is little caused by measurement noise. Meanwhile, an undetected phenomenon occurs because of the objects’ coming across at time 25. But when two objects come close to each other, the estimation performance of extended object’s shape is also good.

5. Conclusion

Based on the parameters of the Student’s t-distribution being Gamma distribution, and enlightened by ideas of the GM-CPHD filtering, a new implementation form of CPHD filtering is proposed in this paper, i.e., the predicted and updated PHD intensities are all substituted with a mixture of Gaussian-Gamma distribution. Meanwhile, in order to overcome the complex computing problem with the unknown measurement noise inverse covariance and the joint estimation of object state and measurement noise inverse covariance, the VB step is used to derive an approximating distribution, and the RHM-CPHD step is used to estimate the parameters of the approximating distribution. Simulation results show that the proposed approach costs a longer time, but improves the accuracy of extended objects tracking. It is expected that the proposed algorithm can be utilized to the extended objects tracking under the condition of unknown clutter or unknown detection probability.

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