Multiple Extended Targets Tracking Algorithm Based on Generalized Labeled Multi-Bernoulli Filter

Zhuo CAO, Xin-xi FENG and Luo-jia CHI

Information and Navigation Institute, Air Force Engineering University, China

*Corresponding author

Keywords: Target tracking, Extended target, Extension information

Abstract. An extended target filter based on random finite sets (RFS) is proposed with modeling for Star-Convex. The proposed algorithms combine multiple hypotheses tracking (MHT) and labeled RFS to smooth the multiframe measurements. Experimental results show that the proposed algorithm is able to form the track and estimate the target state effectively, the tracking performance is better than that of the traditional extended target filter in the low signal-to-noise ratio (SNR) scenario.

Introduction

In the traditional multi-target tracking theory, it is assumed that each target has only one measurement at most [1]. With the wide application of modern high resolution sensor, which can provide many measurements when tracking a large or a close target, which is called the extended target [2]. If the traditional data association is used to solve the extended target tracking problem, the curse of dimensionality will occur and the computational cost will increase remarkably. Random finite set theories [3] (RFS) set state and observation as units, thus operation process is simplified by a large margin.

The extended target is characterized by kinematic state and extended information. Gilholm [4] proposed to model with ellipse. Later Koch [5] introduced random positive definite matrix to model the extended form, however, these model can only describe an ellipsoidal target, it is difficult to characterize the abundant shape, so reference [6] presented a method of modeling with Star-Convex extended form based on Random Hyper surface Model (RHM). This paper proposes an Extended Target generalized labeled multi-Bernoulli filter (ET-GLMB) tracking algorithm with shape modeling for Star-Convex, which is a kind of nonlinear filter and it can estimate kinematic state and extension information with irregular shape accurately.

Standard GLMB Filtering Algorithm

GLMB RFS consist of target state space and discrete label space, the statistical probability distribution is described as

\[
\pi(X) = \Delta(X) \sum_{s \in S} \omega_k(\xi(x)) \cdot [p_s(x,l)]^Y
\]

\[
\Delta(X) \text{ is the discrete label indicating function, } s \text{ is the indication index, } S \text{ is the indication space and } \omega_k \text{ is the weight corresponding to } p_s(x,l).
\]

The survival target probability distribution is described as

\[
\pi(G|X) = \Delta(G)\Delta(X)\gamma_{\xi(x)}(\xi(X))\cdot[\phi(G;x,l)]
\]

317
The newborn target probability distribution is described as

\[
\pi_x(B) = \Delta(B)\omega_B(\xi(B))[p_y(\cdot)]^B
\]  
(3)

The GLMB prediction equation is

\[
\pi(X^r|X) = \pi_c(X^r \cap X|X) \cdot \pi_\delta(X^r - X)
\]  
(4)

The target measurement \( D \) can be expressed as Multi-Bernoulli RFS

\[
\pi_D(D|X) = \{(p_{D}(x,l), g(z|x)); (x,l) \in X\}
\]  
(5)

\( K \) represents the clutter measurements, \( c(\cdot) \) represents the spatial distribution and the probability distribution is described as

\[
\pi(K) = e^{-\lambda}[\lambda c(\cdot)]^K
\]  
(6)

In summary, the measurement likelihood function is described as

\[
g(Z|X) = e^{-\lambda}[\lambda c(x,l)]^T \sum_{\theta \in \Theta} [\phi_z(x,l;\theta)]^X
\]  
(7)

**Star-Convex Outline Modeling**

As shown in figure 1, we assume the modeling of Star-Convex extended target.

![Figure 1. The diagram of Star-Convex.](image)

Fourier series function of \( r_k(\varphi) \) can be expressed as:

\[
r_k(\varphi) = \frac{a_k^0}{2} + \sum_{n=1}^{N} a_k^n \cos(n\varphi) + b_k^n \sin(n\varphi)
\]  
(8)

The nonlinear measurement is

\[
z_k = m_k + s_k \cdot r_k(\varphi) \cdot [\cos(\varphi), \sin(\varphi)]^T + v_k = h(x_k, s) + v_k
\]  
(9)

The single measurement likelihood function can be expressed as:

\[
g(z_k|x_k) = \int \delta[z_k - (h(x_k, s) + v_k)] \cdot N(v_k;0,R_k) \cdot f^+(s)dv_k ds
\]

\[
= \int N(z_k - h(x_k, s);0,R_k) \cdot f^+(s) ds
\]  
(10)

The multiple measurements likelihood function can be expressed as

\[
g(W_k|x_k) = \prod_{i=1}^{N_k} g(W_k^i|x_k)
\]  
(11)
Extended Target GLMB Filtering Algorithm

The distribution of measurement $D$ set is expressed as

$$
\pi(D|X) = \sum_{W_{1},\ldots,W_{n}} \pi(W_{1}|\xi_{1})\ldots\pi(W_{n}|\xi_{n})
$$

(12)

It is assumed that the number of clutter measurement is in the form of Poisson distribution, the measurement likelihood function is

$$
\pi(Z|X) = \sum_{D \subseteq Z} \pi_{D}(D|X)\pi_{K}(Z-D) = e^{-\lambda}[\lambda c()]^{Z} \sum_{W \subseteq P} \phi_{W}(\theta) \chi^{X}
$$

(13)

In the formula, $p \perp Z$ represents all the possible division of the measurement set. $\tilde{g}(W_{\theta,l}|[(\xi_{l}, l)]$ represents the single target likelihood function.

Assuming that the probability distribution satisfy the formula (4), the target prediction equation can be expressed as

$$
\pi_{k+1}(X_{k+1}) = \Delta(X_{k+1}) \sum_{s \in S} \omega_{k+1}^{s} (\xi(X_{k+1})) \cdot \left[ p_{k+1}^{s}(x_{k+1}, l) \right]^{X_{k+1}}
$$

(14)

$$
\omega_{k+1}^{s}(\xi_{k+1}) = \omega_{k}^{s}(\xi_{k+1} \cap \xi) \cdot \omega_{k}^{s}(\xi_{k+1} - \xi)
$$

(15)

$$
\omega_{k}^{s}(J) = [p_{G}^{s}(x,l)]^{T} \sum_{\omega = \xi} \gamma_{o}^{s}(J) [q_{G}^{s}(x,l)]^{T} \omega_{G}^{s}(o)
$$

(16)

$$
\omega_{k}^{s}(\xi_{k+1} - \xi) = \prod_{B}(1-r_{B}^{l}) \prod_{l \in (\xi_{k+1} - \xi)} \gamma_{B}^{s}(l) 1/r_{B}^{l}
$$

(17)

$$
p_{k+1}^{s}(x_{k+1}, l) = \gamma_{k}^{s}(l) p_{G}^{s}(x_{k+1}, l) + (1 - \gamma_{k}^{s}(\xi)) p_{k}^{s}(x_{k+1}, l)
$$

(18)

$$
p_{G}^{s}(x, l) = \int f(x_{k+1}|(x, l)) p_{S}(x, l) dx
$$

(19)

In combination with the formula (13), the state update equation is also a GLMB RFS

$$
\pi(X|Z) = \Delta(X) \sum_{s \in S} \sum_{p \perp Z} \sum_{W \subseteq P} \omega_{W}^{s} (\xi(X)) \cdot \left[ p_{s,\theta}(W) \right]^{X}
$$

(20)

$$
\omega_{W}^{s,\theta} (\xi) = \sum_{s \in S} \sum_{J \subseteq Z} \sum_{p \perp Z} \sum_{W \subseteq P} \omega_{J}^{s} (\xi) [\mu_{W}^{s,\theta}]^{l}
$$

(21)

$$
p_{s,\theta}(x, l|W) = \frac{p_{s}(x, l) \cdot \phi_{W}(x, l; \theta)}{\mu_{W}^{s,\theta}(l)}
$$

(22)

$$
\mu_{W}^{s,\theta}(l) = \frac{p_{D}(x, l) \mu_{s} \mu_{s}}{\lambda c(x, l) \chi^{W_{\theta,l}}}
$$

(23)

$\mu_{s}$ and $\mu_{s}$ both are the normalized constant.
Simulation Experiment and Analysis

A two-dimensional observation area for x~[-600m, 800m], y~[-1000m, 600m], three kinds of filtering algorithms are used to track the target modeling with Star-Convex extension, the sampling period is T=1s, The measurement last for 100s, four extended targets have emerged. We achieved 200 times Monte-Carlo simulation.

Figure 2, figure 3 and Figure 4 indicate the result of state estimation by ET-PHD, ET-CPHD and ET-GLMB in once experiment respectively. By contrast can be seen from the visual observation, in the low SNR scenario, the ET-GLMB filter can effectively suppress the clutter measurement and maintain a better performance. In contrast, the filtering accuracy of ET-PHD algorithm is poor, especially with the increase of target number, the suppression towards clutter measurement is obviously weakened, and the estimation error is serious in the later period.

The contrast of target number estimation is shown in Figure 5. We can see that ET-GLMB and ET-CPHD can effectively estimate the targets number, however the stability of ET-GLMB is better. We use Optimal Sub Pattern Assignment (OSPA) distance to evaluate the performance of different algorithms. Figure 6 dedicates the OSPA distance comparison.

Conclusion

In this paper, an extended target filter based on generalized labeled multi-Bernoulli filter is proposed. In low SNR detection scenario, the proposed algorithm can effectively output target trajectory and estimate the extension information accurately, the tracking accuracy and stability of extended target number estimation and state estimation are better than the traditional algorithm, so that the stability and effectiveness of the filter can be improved.
Acknowledgement

The research was financially supported by the National Science Foundation: Research on the key technology of multi-target tracking based on interval analysis (61571458).

References


