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Generalized labeled multi-Bernoulli filter with signal features of unknown emitters

Key words: Multi-target tracking; Generalized labeled multi-Bernoulli; Signal features of emitter; Fuzzy C-means; Dynamic clustering

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Motivation

1. The objective of multi-target tracking is to transform uncertain measurement information into deterministic target state information.

2. However, as the number of clutters in the target tracking scene increases, the differentiation between the target measurement and the clutter gradually decreases. The tracking performance of the random finite set (RFS) filters will be degraded to different degrees.

3. To improve the anti-clutter performance of RFS filters, some algorithms integrate multi-dimensional independent information into the RFS filters.

Main idea

1. Generalized labeled multi-Bernoulli (GLMB) filter with signal features is effective for multi-target tracking.

2. The state and measurement of the target are extended, and the emitter feature (EF) identification method based on dynamic clustering of the data field is proposed to solve the problem of unknown EFs.

3. An improved fuzzy C-means (FCM) algorithm is proposed which can approximately calculate the time-varying EF likelihood.

4. The EFs are integrated into the GLMB filter to improve the multi-target tracking performance, especially in heavy clutter environments.

Method

1. A novel algorithm that combines the GLMB filter with signal features of the unknown emitter is proposed.

2. Aiming at the unknown feature problem, we propose a method for identifying EFs based on dynamic clustering of data fields.

3. Because EFs are time-varying and the probability distribution is unknown, an improved fuzzy C-means algorithm is proposed to calculate the correlation coefficients between the target and measurements, to approximate the EF likelihood function.

Method

GLMB filter with EFs

$$x=\left[x_c;x_e\right],z=\left[z_c;z_e\right]$$

$$\pi_{Z_+}\left(\boldsymbol{X}\right)\propto\Delta\left(\boldsymbol{X}\right)\sum_{I,\xi,I_+,\theta_+}\omega^{(I,\xi)}\omega_{Z_+}^{(I,\xi,I_+,\theta_+)}\delta_{I_+}\left[\mathcal{L}\left(\boldsymbol{X}\right)\right]\left[p_{Z_+}{}^{(\xi,\theta_+)}\right]^{\boldsymbol{X}}$$

$$\omega_{Z_+}{}^{(I,\xi,I_+,\theta_+)}=1_{\Theta_+(I_+)}\left(\theta_+\right)\left[1-\bar{P}_S^{(\xi)}\right]^{I-I_+}\left[\bar{P}_S^{(\xi)}\right]^{I\cap I_+}\times\left[1-r_{B,+}\right]^{\mathbb{B}_+-I_+}r_{B,+}^{\mathbb{B}_+\cap I_+}\left[\bar{\psi}_{Z_+}^{(\xi,\theta_+)}\right]^{I_+}$$

$$\bar{P}_S^{(\xi)}\left(\ell\right)=\left\langle p^{(\xi)}\left(\cdot,\ell\right),P_S\left(\cdot,\ell\right)\right\rangle$$

$$\bar{\psi}_{Z_+}^{(\xi,\theta_+)}\left(\ell_+\right)=\left\langle\bar{p}_+^{(\xi)}\left(\cdot,\ell_+\right),\psi_{Z_+}^{(\theta_+(\ell_+))}\left(\cdot,\ell_+\right)\right\rangle$$

$$\bar{p}_+^{(\xi)}\left(x_+,\ell_+\right)=1_{\mathbb{L}}\left(\ell_+\right)\frac{\left\langle P_S\left(\cdot,\ell\right)f_+\left(x_+\middle|\cdot,\ell_+\right),p^{(\xi)}\left(\cdot,\ell_+\right)\right\rangle}{\bar{P}_S^{(\xi)}\left(\ell_+\right)}+1_{\mathbb{B}_+}\left(\ell_+\right)p_{B,+}\left(x_+,\ell_+\right)$$

$$p_{Z_+}^{(\xi,\theta_+)}\left(x_+,\ell_+\right)=\frac{\bar{p}_+^{(\xi)}\left(x_+,\ell_+\right)\psi_{Z_+}^{(\theta_+(\ell_+))}\left(x_+,\ell_+\right)}{\bar{\psi}_{Z_+}^{(\xi,\theta_+)}\left(\ell_+\right)}$$

$$\psi_{Z_+}\left(x,\ell\right)=\begin{cases}\dfrac{P_D\left(x,\ell\right)g_+\left(z_{\mathrm{c},+}^{\theta(\ell)}\middle|x,\ell\right)g_+\left(z_{\mathrm{e},+}^{\theta(\ell)}\middle|x,\ell\right)}{\lambda c\left(z_{\mathrm{c},+}^{\theta(\ell)}\right)c\left(z_{\mathrm{e},+}^{\theta(\ell)}\right)}, & \theta\left(\ell\right)>0\\ 1-P_D\left(x,\ell\right), & \theta\left(\ell\right)=0\end{cases}$$

$$g_k\left(e\right)=\frac{\mu_{ij}^{rf}\,\mu_{ij}^{prf}\,\mu_{ij}^{pw}}{\sum_{l=0}^{J_k}\mu_{il}^{rf}\,\mu_{il}^{prf}\,\mu_{il}^{pw}}\qquad c_k\left(e\right)=\frac{\mu_{i0}^{rf}\,\mu_{i0}^{prf}\,\mu_{i0}^{pw}}{\sum_{l=0}^{J_k}\mu_{il}^{rf}\,\mu_{il}^{prf}\,\mu_{il}^{pw}}$$

Major results

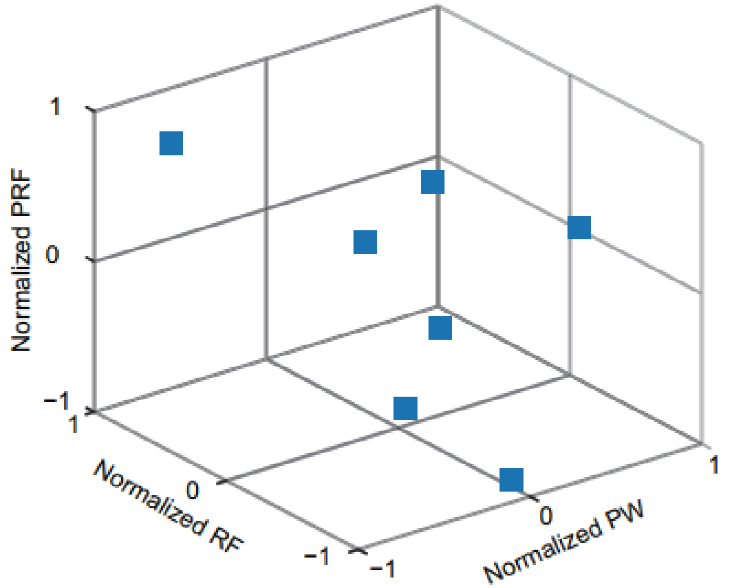

Fig. 2 Dynamic clustering based on the data field

PW: pulse width; RF: radio frequency; PRF: pulse repetition frequency

Table 2 Features of each cluster center

Cluster center	PW (μs)	RF (MHz)	PRF (kHz)
1	252.62	2257.74	42.61
2	293.13	1251.42	21.06
3	300.10	1553.09	36.39
4	339.00	1446.63	25.92
5	339.20	1055.36	12.64
6	375.65	1803.17	36.91
7	441.85	1509.07	31.48

PW: pulse width; RF: radio frequency; PRF: pulse repetition frequency

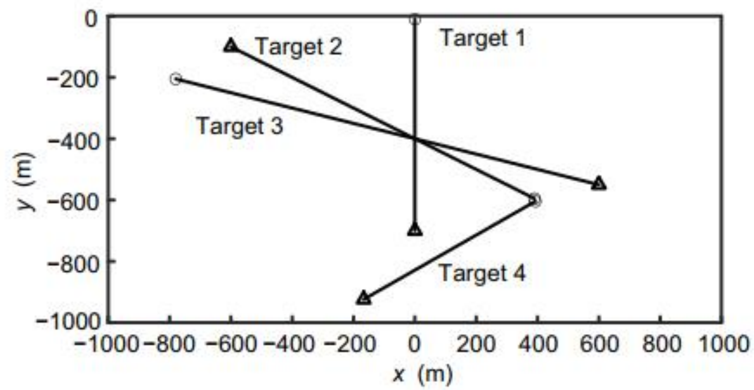

Fig. 3 Target trajectories

At "○" locations, targets are born and at "△" locations, targets die

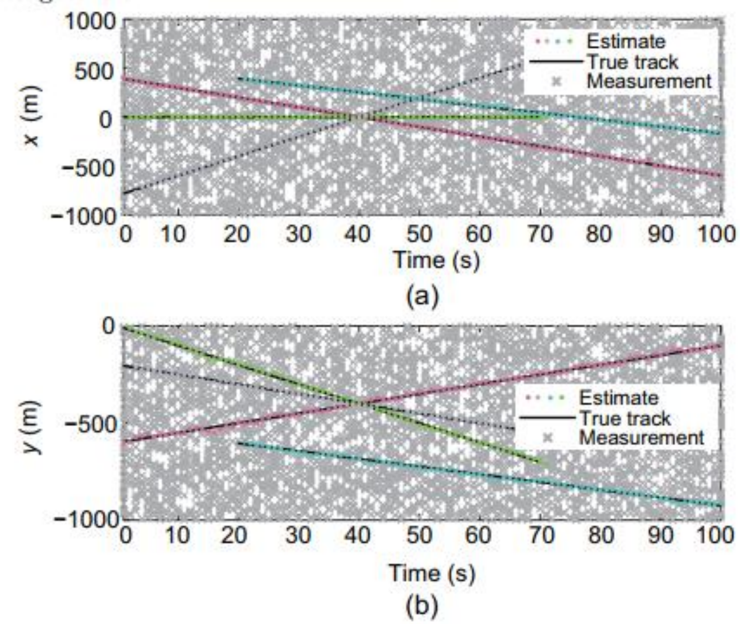

Fig. 4 True target positions and position estimates on x (a) and y (b) coordinates

Major results

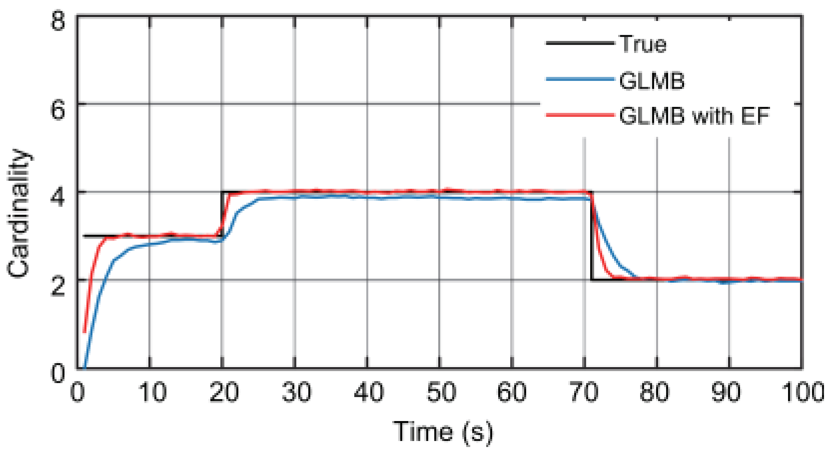

Fig. 5 Cardinality estimation of the GLMB and the GLMB with the EF filter

GLMB: generalized labeled multi-Bernoulli; EF: emitter feature

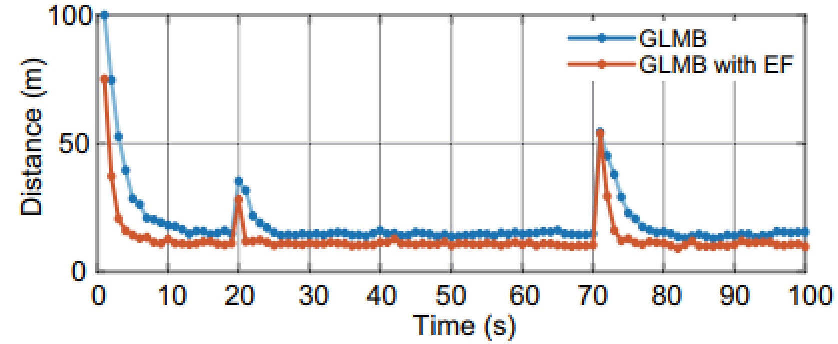

Fig. 6 OSPA distance of the GLMB and GLMB with the EF filter

OSPA: optimal subpattern assignments; GLMB: generalized labeled multi-Bernoulli; EF: emitter feature

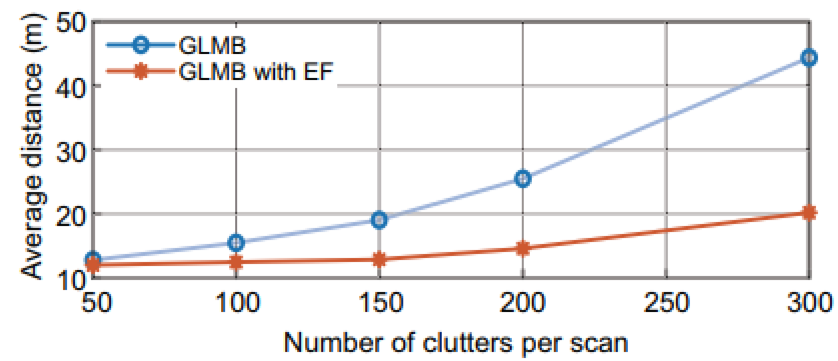

Fig. 7 Average OSPA distance vs. the number of clutters per scan

EF: emitter feature; GLMB: generalized labeled multi-Bernoulli; OSPA: optimal subpattern assignments

Conclusions

In this paper we propose an improved GLMB filter that integrates unknown and time-varying features of the emitter signals. It employs the feature information of the emitter to enhance the discrimination between the target and the clutter. It can be seen from the simulation results that the proposed method has significant performance advantages compared with the GLMB filter in heavy clutter scenarios.

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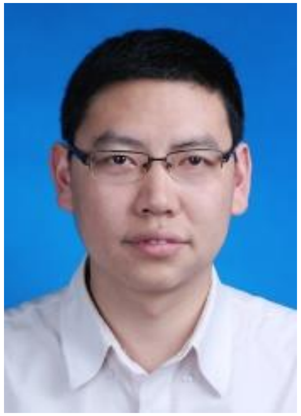

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