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Hybrid-driven Gaussian process online learning for highly maneuvering multi-target tracking

Key words: Target tracking; Gaussian process; Data-driven; Online learning; Model-driven; Probabilistic data association

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Motivation

1. The performance of existing maneuvering target tracking methods for highly maneuvering targets in cluttered environments is unsatisfactory.
2. Traditional model-driven methods face several application limitations: (1) poor tracking ability and environmental adaptability; (2) state estimation delay; (3) high computational complexity.
3. In response to the constraints of the model-driven approaches, data-driven methods have been proposed, but they also have some problems: (1) poor interpretability; (2) estimation instability.

Method

•The fundamental idea is to integrate the time-varying constant velocity (CV) model into Gaussian process motion tracker (GPMT), thereby enhancing predictive abilities to effectively track extremely maneuverable targets amidst cluttered surroundings.

Algorithm 1 Hybrid-driven GPMT

Input: $\boldsymbol{X}_t$, $\boldsymbol{T}_t$, θ

Output: $\hat{\boldsymbol{\mu}}_t^f$, $\hat{\boldsymbol{C}}_t^f$, $\boldsymbol{\mu}_t^f$, $\boldsymbol{C}_t^f$, $\boldsymbol{C}_t$

1: Hyperparameter θ is learned via Eq. (11)
2: Compute the predicted state $\tilde{\boldsymbol{S}}_t$ via Eq. (13) and the predicted covariance $\tilde{\boldsymbol{P}}_t$ via Eq. (14)
3: Compute the associated measurement $\boldsymbol{Z}_t$ according to inequality (15) and Eqs. (16)–(20)
4: Compute mean $\hat{\boldsymbol{\mu}}_t^f$ and covariance $\hat{\boldsymbol{C}}_t^f$ of the estimated state via Eqs. (21) and (22), respectively
5: Compute cross-covariance $\boldsymbol{C}_t$ via Eq. (23)
6: Compute mean $\boldsymbol{\mu}_t^f$ and covariance $\boldsymbol{C}_t^f$ of the training set by Eqs. (26) and (27), respectively

$$V_{x_{t-1}} = \left(x_{t-1} - x_{t-2}\right)/T_{\mathrm{d}}$$

$$\tilde{\boldsymbol{S}}_t = \boldsymbol{F}\boldsymbol{S}_{t-1},$$

$$\tilde{\boldsymbol{P}}_t = \boldsymbol{F}\boldsymbol{P}_{t-1}\boldsymbol{F}^{\mathrm{T}} + \boldsymbol{Q},$$

$$\boldsymbol{Z}_t = \sum_{i=0}^{m} \beta_{ij}\boldsymbol{Z}_{ij}$$

$$\hat{\boldsymbol{\mu}}_t^f = \tilde{\boldsymbol{x}}_t + \boldsymbol{K}_t\left(\boldsymbol{x}_t - \tilde{\boldsymbol{x}}_t\right), \qquad \boldsymbol{\mu}_t^f = \boldsymbol{\mu}_{t-1}^f + \tilde{\boldsymbol{K}}_t\left(\boldsymbol{x}_t - \tilde{\boldsymbol{\mu}}_t^f\right),$$

$$\hat{\boldsymbol{C}}_t^f = \tilde{\boldsymbol{C}}_t^f - \boldsymbol{K}_t\tilde{\boldsymbol{C}}_t^f, \qquad \boldsymbol{C}_t^f = \boldsymbol{C}_{t-1}^f - \tilde{\boldsymbol{K}}_t\boldsymbol{J}_t\boldsymbol{C}_{t-1}^f,$$

$$\boldsymbol{C}_t = \boldsymbol{C}_{t-1}^f\boldsymbol{J}_t^{\mathrm{T}}\left(\tilde{\boldsymbol{C}}_t^f\right)^{-1}\hat{\boldsymbol{C}}_t^f, \quad \tilde{\boldsymbol{K}}_t = \boldsymbol{L}_t\boldsymbol{K}_t = \boldsymbol{C}_{t-1}^f\boldsymbol{J}_t^{\mathrm{T}}\left(\tilde{\boldsymbol{C}}_t^f + \sigma_n^2\boldsymbol{I}\right)^{-1},$$

Method

Major results

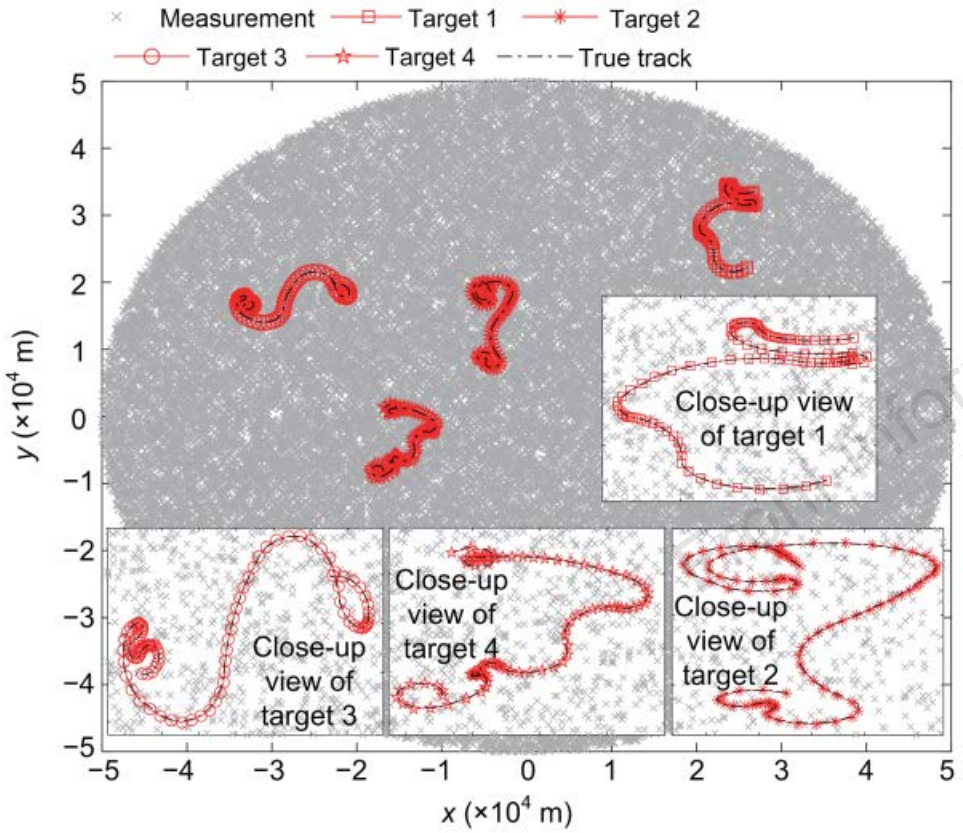

Fig. 1 True target tracks and position estimates

Table 1 Mean root mean square error

Method	x (m)	y (m)	V_x (m/s)	V_y (m/s)
IMM	4622.23	3893.82	242.07	217.04
GPMT	7518.37	7234.40	238.78	243.84
Ours	297.48	297.44	215.36	227.07

Table 2 Processing time

Method	Time (s)
IMM	0.0219
GPMT	0.1829
Ours	0.1816

Conclusions

1. This paper proposes a hybrid-driven approach for tracking multiple highly maneuvering targets, leveraging the advantages of both data-driven and model-based algorithms.
2. The time-varying constant velocity model is integrated into the Gaussian process (GP) of online learning to improve the performance of GP prediction.
3. This integration is further combined with a generalized probabilistic data association algorithm to realize multi-target tracking.
4. The proposed hybrid-driven method outperforms existing techniques such as IMM and GPMT under challenging scenarios involving highly maneuvering targets in cluttered environments.

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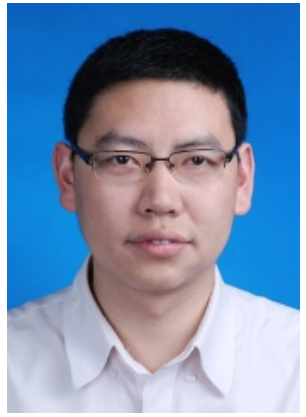

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