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Probability hypothesis density filter with imperfect detection probability for multi-target tracking

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ABSTRACT

Probability hypothesis density (PHD) filter is an effective means to track multiple targets in that it avoids explicit data association between measurements and targets. However, the PHD filter cannot be directly applied to track targets in imperfect detection probability conditions. Otherwise, the performance of almost all the PHD-based filters significantly decreases. Aiming at improving the estimate accuracy as for target states and their number, a multi-target tracking algorithm using the probability hypothesis density filter is proposed, where a novel multi-frame scheme is introduced to cope with estimates of undetected targets caused by the imperfect detection probability. According to the weights of targets at different time steps, both the previous weight array and state extraction identifier of individual targets are constructed. When the targets are undetected at some times, the states of the undetected targets are extracted based on previous weight arrays and state extraction identifiers of correlative targets. Simulation results show that the proposed algorithm effectively improves the performance of the existing relevant PHD-based filters in imperfect detection of probability scenarios.

1. Introduction

Random finite set (RFS) [1] theory-based multi-target tracking as an alternative to classical data association-based target tracking algorithm has attracted considerable attention. To obtain computational tractable solution, three suboptimal approximations are probability hypothesis density (PHD) [2], cardinality PHD (CPHD) [3], and multi-target multi-Bernoulli (MeMBer) [4]. Two implementations of the three suboptimal approximations are via Sequence Monte Carlo (SMC) [5] and Gaussian mixture (GM) [4,6]. More recently, the concept of labeled RFS has been introduced to cope with the multi-target tracking problem, and its implementations include labeled multi-Bernoulli [7] and generalized labeled multi-Bernoulli (GLMB) [8,9]. These analytic approximations of the multi-target Bayes filter via RFS and labeled RFSs have various scopes of applications such as radar target tracking [10,11], computer vision [12,13], and sensor networks [14,15].

With the linear Gaussian model assumption, the Gaussian mixture PHD as one of the closed-form implementations for the PHD recursion has been extensively applied in the multi-target tracking field because of the advantage of target state extraction and track generation. Unfortunately, inaccurate estimates of targets would be obtained when directly applied the GM-PHD filter (GM-PHDF) to track multiple targets in inferior detection probability scenarios. Especially, the tracking performance of the GM-PHD filter is confronted with the substantial decline when tracking closely spaced targets in imperfect

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detection probability environments. In [16] and [17], Yazdian-Dehkordi et al. proposed a penalized GM-PHD filter (PGM-PHDF) to track multiple close proximity targets, where a penalized weight update method is introduced to refine the weights of closely spaced targets in the update step of the GM-PHD filter. Compared with the GM-PHD filter, the PGM-PHD filter achieves relatively accurate estimates in the number of targets and their states when targets move closely to each other. However, the PGM-PHD filter has a disadvantage that the number of targets may be over-estimated in dense clutter rate environments. Moreover, the PGM-PHD filter is unable to generate continuous trajectories of closely spaced targets. To estimate the continuous tracks of close proximity targets, Wang et al. reported a collaborative penalized GM-PHD filter (CPGM-PHDF) [18], which distinguishes the individual targets by assigning a unique label to each target. In addition, the penalized weight update method adopted in the PGM-PHD filter has been revised with target identity. The CPGM-PHD filter improves the tracking performance of the close proximity targets compared to the PGM-PHD filter. For the problem of higher false alarms in both the PGM-PHDF and CPGM-PHDF in dense clutter scenarios, the reference [19] reported an irregular window smoother-based Gaussian mixture probability hypothesis density filter (IRGM-PHDF), which effectively improves the estimate accuracy in closely spaced target scenarios. Unfortunately, the PGM-PHDF, CPGM-PHDF and IRGM-PHDF are only proposed to track closely spaced targets. The three improved filters along with the original GM-PHDF will suffer from performance significantly decrease when the detection probability is not good in multi-target tracking scenarios.

For the problem of tracking multiple targets in imperfect detection probability scenarios, an improved PHD filter based on multi-frame scheme within Gaussian mixture implementation is proposed. Three auxiliary parameters, named target label, previous weight array and state extraction identifier, are added to each target. When some persistent targets cannot be detected at some time steps during the process of tracking, the states of undetected targets can be estimated by the proposed multi-frame scheme, which makes full use of the previous weight array and state extraction identifier of related targets. Simulation results illustrate that the proposed algorithm can improve the tracking performance in terms of the number of targets and their states compared to the relevant PHD-based filters.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the PHD and GM-PHD filters. The multi-frame based probability hypothesis density filter is detailed in Section 3. In Section 4, the performance comparisons of different algorithms are presented in several tracking scenarios. Finally, the conclusions are presented in Section 5.

2. The Gaussian Mixture PHD Filter

Within the framework of RFS, the respective collections of multi-target states and measurements at time k can be denoted as

$$X_k = \left\{x_{k,1}, x_{k,2}, \ldots, x_{k,N_k}\right\} \in \mathcal{F}(\mathcal{X}) \tag{1}$$

$$Z_k = \left\{z_{k,1}, z_{k,2}, \ldots, z_{k,M_k}\right\} \in \mathcal{F}(\mathcal{Z}) \tag{2}$$

where N_k and M_k are the respective cardinalities of multi-target state set and measurement set. $\mathcal{F}(\mathcal{X})$ and $\mathcal{F}(\mathcal{Z})$ denote the sets of all finite subsets in multi-target state and measurement spaces, respectively.

The PHD filter jointly estimates target states and their number by iteratively propagating first-order statistical moment of the multi-target posterior density. Let $\mathcal{V}_{k-1}\left(x|Z^{(k-1)}\right)$ be the multi-target posterior intensity at time $k-1$, the prediction equation of the PHD filter the can be given by

$$\mathcal{V}_{k|k-1}\left(x|Z^{(k-1)}\right) = \int \left[p_{S,k} f_{k|k-1}(x|\zeta) + \beta_{k|k-1}(x|\zeta)\right] \mathcal{V}_{k-1}\left(\zeta|Z^{(k-1)}\right) d\zeta + \gamma_k(x) \tag{3}$$

where x and $p_{S,k}$ are the target states and survival probability, respectively. $Z^{(k-1)}$ is the union of the measurement sets during the time interval $[1\ k-1]$, $f_{k|k-1}(x|\zeta)$ is the transition probability of target states, $\gamma_k(x)$ is the newborn target intensity, and $\beta_{k|k-1}(x|\zeta)$ is the spawn target predicted intensity.

By using the latest obtained measurement set Z_k at time k, the update equation of the PHD filter can be approximated as

$$\mathcal{V}_k\left(x|Z^{(k)}\right) = \left[1 - p_{D,k}\right] \mathcal{V}_{k|k-1}\left(x|Z^{(k-1)}\right) + \sum_{z \in Z_k} \frac{p_{D,k} g_k(z|x) \mathcal{V}_{k|k-1}\left(x|Z^{(k-1)}\right)}{\mathcal{K}_k(z) + \int p_{D,k} g_k(z|x) \mathcal{V}_{k|k-1}\left(x|Z^{(k-1)}\right) dx} \tag{4}$$

where $g_k(z|x)$ is the single target likelihood function, $p_{D,k}$ is the detection probability, and $\mathcal{K}_k(z)$ is the clutter intensity.

Given the assumptions of linear Gaussian target motion model and linear Gaussian measurement model as

$$f_{k|k-1}(x|\zeta) = \mathcal{N}(x; F_{k-1}\zeta, Q_{k-1}) \tag{5}$$

$$g_k(z|x) = \mathcal{N}(z; H_k x, R_k) \tag{6}$$

where $\mathcal{N}(\cdot; m, P)$ denotes a Gaussian density with mean m and covariance P, F_{k-1} is the state transition matrix, H_k is the observation matrix, Q_{k-1} is the state Gaussian noise covariance, and R_k is the observation Gaussian noise covariance.

The Gaussian mixture PHD filter represents a closed-from solution of the PHD recursion as a weighted sum of mixing Gaussian components. The main iteration process of the GM-PHD filter consists of prediction and update steps.