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Improved measurement-driven Gaussian mixture probability hypothesis density filter

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ABSTRACT

The probability hypothesis density (PHD) is an effective method for tracking the time-varying number of targets in multi-target tracking. Gaussian mixture is an approximation method to obtain the closed solution of PHD. However, the tracking performance of the Gaussian mixture PHD filter will decline sharply when multiple targets born and disappear in closely spaced target tracking scenarios. In addition, real-time performance of multi-target tracking cannot be met in heavy clutter scenario. To solve these problems, an improved measurement-driven Gaussian mixture PHD algorithm is proposed in this paper. First, the multi-target measurement set at each time step is divided into non-intersect measurement subset, where only survival and birth measurement set are used to update targets. Due to most clutter measurements do not used to update targets in the update step, better real-time performance can be achieved. Second, for the purposed of further improve the performance or multiple target tracking, a backward smoothing based on varied length window is utilized to reduce the possibility of wrong tracking of targets. In numerical experiments, the results demonstrate that the proposed approach can achieve better performance compared to the other existing methods.

1. Introduction

Recent years, the random finite set (RFS) theory [1,2] for multi-target tracking has attracted considerable attention, which offers an elegant representation of a finite, time-varying number of targets and measurements. The probability hypothesis density (PHD) [3] and the cardinalized PHD (CPHD) [4] are two suboptimal approximations but more tractable alternative to the RFSs Bayesian multiple target filtering. The Sequence Monte Carlo PHD (SMC-PHD) [5] and Gaussian mixture PHD (GM-PHD) [6] are two major implementations of the PHD filter, which have been widely applied in various fields such as visual tracking [7], radar targets [8], and robotics [9]. Moreover, there are some modified versions of both SMC-PHD and GM-PHD in [10,11].

The real-time multi-target tracking has been demanded increasingly in recent years [12,13]. For the problem of real-time tracking, there are some approaches reported in the literature. In [14], an efficient data-driven particle PHD filter for multi-target tracking is proposed by Zheng. In Zheng's algorithm, clutters are eliminated by using historic states of targets, and the remainder measurements are classified as survival and birth measurements. The real-time performance of Zheng's algorithm is better than the original particle PHD filter. Unfortunately, the method proposed in [14] is specialized to the class of one newborn target during a sampling period, otherwise, the performance of the algorithm will decline. Moreover, the algorithm may underestimate the number of targets when multiple targets appear closely to each other. The similar idea is utilized in the sequential Monte Carlo multi-Bernoulli filter (SMC-MB filter) in [15,16], and the real-time performance of the SMC-MB filter also can be achieved. However, the update scheme for targets proposed in the SMC-MB filter may overestimate target number under the closely spaced targets scenario, in that some targets may be updated repeatedly by using one measurement. Although, the methods mentioned above can improve the performance of original PHD filter to some extent, and achieve better real-time performance than that of the latter. However, the performance of these filters is also disturbed by clutter measurements, and the drawback of multiple newborn targets in closely spaced targets scenario is not solved yet.

In this paper, an improved measurement-driven Gaussian Mixture PHD filtering algorithm for multiple target tracking is proposed. The original measurements are divided into survival, birth and clutter measurements at each time step. The survival measurements are used to update the survival targets and the birth measurements are adopted to update the birth targets. Owning to the fact that most clutter measurements do not participate in

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updating the targets in the update step, better real-time performance can be achieved. To further improve the performance of multiple target tracking, a backward smoothing based on varied length window is utilized to reduce the possibility of wrong tracking of targets.

The remainder of this paper is organized as follows. Section 2 explains the background of multi-target tracking. The proposed multi-target tracking algorithm is discussed in Section 3. In Section 4, we study the performance of the proposed approach via different Monte Carlo simulations. Finally, the conclusions are given in Section 5.

2. The PHD and GM-PHD filter

In RFS framework, the multi-target state and multi-target observation defined as random finite sets are $X_k = \left\{x_{k,1}, x_{k,2}, \ldots, x_{k,N_k}\right\}$ and $Z_k = \left\{z_{k,1}, z_{k,2}, \ldots, z_{k,M_k}\right\}$, where the N_k and M_k denote the target number and measurement number at time k, respectively. The PHD is a suboptimal alternative to multi-target Bayesian filter [17], which propagates the first order statistical moment of the posterior multi-target states. The PHD filter recursive calculation consists of prediction step and update step. The prediction equation is

$$\nu_{k|k-1}(x) = \int p_{S,k}(\zeta) f_{k|k-1}(x|\zeta)\nu_{k-1}(\zeta)d\zeta + \int \beta_{k|k-1}(x|\zeta)\nu_{k-1}(\zeta)d\zeta + \gamma_k(x) \quad (1)$$

when the measurement is available at time k, the PHD update equation can be described as

$$\nu_k(x) = \left[1 - p_{D,k}(x)\right]\nu_{k|k-1}(x) + \sum_{z\in Z_k} \frac{p_{D,k}(x) g_k(z|x)\nu_{k|k-1}(x)}{\kappa_k(z) + \int p_{D,k}(\zeta) g_k(z|\zeta)\nu_{k|k-1}(\zeta)d\zeta} \quad (2)$$

where $p_{s,k}$ is the survival probability, $p_{D,k}$ is the detection probability, and $\kappa_k(z)$ is the clutter intensity. $\gamma_k(x)$ is the intensity function of the newborn targets, and $\beta_{k|k-1}(x|\zeta)$ is the spawn target intensity. $f_{k|k-1}(x|\zeta)$ is the state transition probability density function of the multi-target, $g_k(z|\zeta)$ is the multi-target likelihood function.

The GM-PHD filter provides a closed-form solution via the summation of mixing weights of Gaussian components to approximate the PHD function. Assume that $\mathcal{N}(\cdot; m, P)$ is a Gaussian density with mean m and covariance P. Based on some assumptions [18] hold, assume the posterior intensity at time $k-1$ is expressed as a Gaussian mixture with J_{k-1} components as

$$\nu_{k-1}(x) = \sum_{i=1}^{J_{k-1}} w_{k-1}^{(i)} \mathcal{N}\left(x; \quad m_{k-1}^{(i)}, P_{k-1}^{(i)}\right) \quad (3)$$

where $w_{k-1}^{(i)}$ is the weight of ith Gaussian mixture at time $k-1$. Then, the predicted intensity at time k is also a Gaussian mixture with $J_{k|k-1}$ components calculated as

$$\nu_{k|k-1}(x) = \sum_{i=1}^{J_{k|k-1}} w_{k|k-1}^{(i)} \mathcal{N}\left(x; \quad m_{k|k-1}^{(i)}, P_{k|k-1}^{(i)}\right) \quad (4)$$

When the measurement set Z_k is available at time k, the posterior intensity is a Gaussian mixture and can be described as

$$\nu_k(x) = \left(1 - p_{D,k}\right)\nu_{k|k-1}(x) + \sum_{z\in Z_k}\sum_{i=1}^{J_{k|k-1}} w_k^{(i)}(z)\mathcal{N}\left(x; \quad m_{k|k}^{(i)}(z), \quad P_{k|k}^{(i)}\right) \quad (5)$$

where $w_k^{(i)}$ denotes the weight of ith target computed as

$$w_k^{(i)}(z) = \frac{p_{D,k} w_{k|k-1}^{(i)} g\left(z|x^{(i)}\right)}{\kappa_k(z) + p_{D,k}\sum_{j=1}^{J_{k|k-1}} w_{k|k-1}^{(i)} g\left(z|x^{(j)}\right)} \quad (6)$$

For the purpose of keeping the efficient of the GM-PHD filter, the pruning and merging method of Gaussian mixture is needed [18].

3. The improved measurement-driven GM-PHD algorithm

In this section, the Gate technique is introduced to partition the multi-target measurement set at each time step, and a backward smoothing based on varied length window is utilized to reduce the possibility of wrong tracking of targets. The proposed method is referred to as a MD–BS–GMPHD filter, which is explained in detail as follows.

3.1. Measurement-driven scheme

According to the RFS theory, multi-target observation set Z_k is a union at time k, which is composed of both target measurements and clutter measurements. Because the original GM-PHD filter utilizes Z_k to update all the targets, the performance of the GM-PHD filter not only affected by clutter measurements, but also interfered by the measurement originated from survival targets and birth targets. The motivation behind the measurement-driven scheme is to reduce the disturbance between measurements in the update step, where newborn targets are update by birth measurements and survival targets are update by survival measurements, respectively.

The validation gating method is an effective approach to eliminate the clutters applied in different filters [19,20]. Based on the predicted target states, the measurements can be divided into survival measurements, birth measurements and clutter measurements at each time step by using the gating method. Under the linear Gaussian assumption, the elliptical gating technique is incorporated into the GM-PHD filter to partition the current measurements. An elliptical region can be described as

$$\Xi(k,\eta) = \left\{z : \left(z - H_k m_{k|k-1}\right)^T S_k^{-1}\left(z - H_k m_{k|k-1}\right) \le \eta\right\} \quad \forall z \in Z_k \quad (7)$$

$$\eta = -2\ln(1 - P_G) \quad \text{if } \nu_z = 2 \quad (8)$$

where η is the gating threshold, and P_G is the probability of target-originated measurements in the elliptical region. H_k is the measurement matrix, and S_k is the measurement residual covariance matrix. The dimension of the measurement and predicted target state are denoted by n_z and $m_{k|k-1}$, respectively.

Assuming that, at time k, the predicted multi-target intensity is represented by Eq. (4), and the spawned targets are not considered in tracking scenario, therefore, the predicted multi-target intensity can be calculated as

$$\nu_{k|k-1}(x) = \nu_{S,k|k-1}(x) + \gamma_k(x) \quad (9)$$

$$\nu_{S,k|k-1}(x) = p_{S,k}\sum_{i=1}^{J_{k|k-1}} w_{k-1}^{(i)}\mathcal{N}\left(x; \quad m_{S,k|k-1}^{(i)}, \quad P_{S,k|k-1}^{(i)}\right) \quad (10)$$

$$\gamma_k(x) = \sum_{j=1}^{J_{\gamma,k}} w_{\gamma,k}^{(j)}\mathcal{N}\left(x; \quad m_{\gamma,k}^{(j)}, \quad P_{\gamma,k}^{(j)}\right) \quad (11)$$

where $\nu_{k|k-1}$ is the predicted multi-target intensity, $\nu_{S,k|k-1}$ is the predicted survival target intensity.