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Adaptive Gaussian mixture probability hypothesis density for tracking multiple targets

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ABSTRACT

The probability hypothesis density (PHD) filter is a promising method for multi-target tracking problem. The Gaussian mixture PHD filter is an analytic solution to the PHD filter for linear Gaussian multi-target models. However, the PHD filter is inapplicable to the multi-target tracking scenario with unknown newborn target intensity. To overcome the problem, an adaptive Gaussian mixture probability hypothesis density algorithm for multiple target tracking is proposed, where the Dirichlet distribution with negative exponent parameters and target maximum velocity constraint-based schemes are introduced to recursively estimate the newborn target intensity at each time step. The simulation results illustrate that the proposed algorithm has better performance under the unknown newborn target intensity in the multi-target tracking systems.

1. Introduction

In 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], Cardinalized PHD (CPHD) [4], and Multi-Bernoulli (MeMBer) [5] are three suboptimal approximations but more tractable alternative to the RFSs Bayesian multiple target filtering. Two major implementations of the PHD filter are Sequence Monte Carlo PHD (SMC-PHD) [6,7] and Gaussian mixture PHD (GM-PHD) [8,9], which have been widely applied in various fields such as visual tracking [10,11], radar targets [12,13], and robotics [14]. Moreover, there are some modified versions of both SMC-PHD and GM-PHD in [15–17]. More recently, Labeled Multi-Bernoulli (LMB) [18] and generalized Labeled Multi-Bernoulli (δ-GLMB) [19,20] have been developed as novel analytic solutions to the Bayes multi-target tracking filter by labeled RFS.

The conventional PHD filter cannot be applied directly to multi-target tracking when the newborn target intensity is unknown. For the problem of estimating newborn target intensity, there are some methods reported in the literature. In [21], Ristic proposed an extended PHD filter for estimating target birth intensity, which used both the position and likelihood information of measurements to initialize newborn target intensity at each time step, and the survival targets and birth targets are predicted and updated at the same time. However, the adaptive algorithm may overestimate the number of targets in dense clutter scenario. In [22], Wang proposed an improved multi-target Bayesian filter, where the track initiation approach based on sequential probability ratio test is introduced to form the newborn target intensity. Unfortunately, the performance of the Wang's algorithm may decline in closely spaced target scenario in that some measurements are not used for initializing new track hypotheses. In [23], a new implementation of the GM-PHD filter to estimate newborn target intensity is proposed, which reserves at least one Gaussian component corresponding to each measurement in the improved Gaussian component pruning and merging scheme. However, the proposed algorithm requires nearly double computational burden than that of the original GM-PHD filter, and the computational load of the proposed algorithm increases largely in dense clutter scenario. In [24], a multi-target visual tracking algorithm that combines object detection and the PHD filter is proposed to track birth targets in noisy videos. Unfortunately, Zhou's algorithm is specialized to visual target tracking due to the fact that the weight of each newborn target depends on both intersection rate and area rate of different birth targets. In addition, the bounding box size of individual target must be known as a prior, otherwise, the performance of the Zhou's algorithm will decrease.

In this paper, an adaptive Gaussian mixture probability hypothesis density algorithm for multiple target tracking is proposed. First, the Dirichlet distribution with negative exponent parameters is utilized to model prior distribution of Gaussian component

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parameters of initialized newborn target intensity, and the Gaussian components of initialized target birth intensity related to clutter measurements are removed. Afterward, the remainder newborn target intensity is again purified by target maximum velocity constraint-based scheme, and the most likely newborn target intensity can be ultimately approximated. Simulation results demonstrate that the proposed algorithm has better performance of tracking unknown newborn targets compared to the Extended GM-PHD filter [21].

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. Backgrounds

In RFS theoretical framework, the collection of individual target states and the corresponding observations are model as finite sets at time k, which are represented by $X_k = \{x_{k,1}, x_{k,2}, \ldots, x_{k,N_k}\}$ and $Z_k = \{z_{k,1}, z_{k,2}, \ldots, z_{k,M_k}\}$, respectively. N_k and M_k denote the target number and measurement number. If X_{k-1} is the multi-target state set at time $_{k-1}$, then the multi-target state set X_k and the measurement set Z_k, at time k, can be modeled as follows

$$X_k = \left[\bigcup_{\zeta e X_{k-1}} S_{k|k-1}(\zeta)\right] \cup \left[\bigcup_{\zeta e X_{k-1}} B_{k|k-1}(\zeta)\right] \cup \Gamma_k \tag{1}$$

$$Z_k = \kappa_k \cup \left[\bigcup_{x \in X_k} \Theta_k(x)\right] \tag{2}$$

where $S_{kk-1}(\zeta)$ and $B_{kk-1}(\zeta)$ are the RFSs of the surviving targets and the spawned targets that evolved from a target with previous state ζ at time k–1, respectively. At time k, Γ_k denotes the RFS of spontaneous birth, κ_k represents the RFS of clutter, and $\Theta_k(x)$ is the RFS of the measurements from targets.

The PHD propagates first order statistical moment of the posterior multi-target states. Based on linear Gaussian assumption, the PHD filter can be efficiently approximated by mixed Gaussian components. Let $\mathcal{N}(\cdot; m, P)$ illustrate a Gaussian density with mean m and covariance P. At time $k-1$, assume the posterior intensity is given in Gaussian mixture form with J_{k-1} components as

$$\upsilon_{k-1}(x) = \sum_{i=1}^{J_{k-1}} w_{k-1}^i \mathcal{N}((x; m_{k-1}^i), P_{k-1}^i) \tag{3}$$

The predicted intensity at time k is also a Gaussian mixture with $J_{k|k-1}$ components calculated as

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

Then the posterior intensity at time k is a Gaussian mixture and can be described as

$$\upsilon_k(x) = (1 - p_{D,k})\upsilon_{k|k-1}(x) + \sum_{z \in Z_k} \sum_{i=1}^{Jk|k-1} w_k^i(z) \mathcal{N}(x; m_{k/k}^i(z), P_i^{k|k}) \tag{5}$$

where w_k^i denotes the weight of ith target described as

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

The posterior PHD is propagated by the PHD recursion similar to Kalman filter. Detail process of the GM-PHD filter can be referred to [25].

3. Adaptive GM-PHD algorithm for newborn target intensity

3.1. Newborn target intensity estimation scheme

For multi-target tracking system with unknown newborn target intensity, each measurement might be a birth target. However, owing to the disturbance of clutters, and the measurement originated uncertainly in clutter scenario, some measurements originated from clutters cannot be adopted to model newborn target intensity. To eliminate the disturbance of these clutters, a novel newborn target intensity estimation approach is introduced based on Dirichlet distribution [26] and target maximum velocity constraint-based schemes, where false birth targets, originated from clutter measurements, are removed from the newborn target intensity.

Each target is assigned with an unique label ℓ to distinguish each other, and all the Gaussian components of each individual target has the same label. An estimated target state set $\vartheta_{E,k-1}$ and its label set $\Xi_{E,k-1}$, where weights of these targets are greater than a preset multi-target state extraction threshold w_{th}, can be obtained at time k–1 as

$$\vartheta_{E,k-1} = \{m_{k-1}^i : w_{k-1}^i > w_{th}, \quad i = 1, \ldots J_{k-1}\} \tag{7}$$

$$\Xi_{E,k-1} = \{\ell_{k-1}^i : w_{k-1}^i > w_{th}, \quad i = 1, \ldots J_{k-1}\} \tag{8}$$

where J_{k-1} denotes the number of Gaussian components.

When the observation set $Z_k = \left\{z_k^j\right\}_{j=1}^{M_k}$ is available at time k, a possible multi-target measurement set $Z_{E,k}$ associated with estimated target state set $\vartheta_{E,k-1}$ can be calculated as

$$Z_{E,k} = \{z_k^j : arg \min_j (z_k^j - H_k m_{E,k|k-1}^i)^T (S_{E,k}^i)^{-1} (z_k^j - H_k m_{E,k|k-1}^i)\},$$

$$z_k^j \in Z_k, j \in \{1 \ldots M_k\} \tag{9}$$

$$m_{E,k|k-1}^i = F_{k-1} m_{E,k-1}^i \tag{10}$$

$$S_{E,k}^i = H_k P_{E,k|k-1}^i H_k^T + R_k \tag{11}$$

$$P_{E,k|k-1}^i = Q_{k-1} + F_{k-1} P_{E,k-1}^i F_{k-1}^T \tag{12}$$

$$M_{E,k} = numel(Z_{E,k}) \tag{13}$$

where H_k is the observation matrix, and F_{k-1} is the state transition matrix. Q_{k-1} is the process noise covariance, and R_k is the observation noise covariance. $Numel(\bullet)$ is a function that can count the number of elements in a set. $M_{E,k}$ is the cardinality of $Z_{E,k}$.

After extracting the measurements of estimated target state set $\vartheta_{E,k-1}$ from the measurement set Z_k, a residual measurement set $Z_{R,k}$, composed of the residual measurements in Z_k, can be formed. The residual measurement set $Z_{R,k}$ and its cardinality $M_{R,k}$ can be approximated by

$$Z_{R,k} = Z_k - Z_{E,k} \tag{14}$$

$$M_{R,k} = M_k - M_{E,k} \tag{15}$$

Each measurement in $Z_{R,k}$ is utilized to model an unknown newborn target in that birth targets may randomly appear in any