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A measurement-driven adaptive probability hypothesis density filter for multitarget tracking

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Abstract This paper studies the dynamic estimation problem for multitarget tracking. A novel gating strategy that is based on the measurement likelihood of the target state space is proposed to improve the overall effectiveness of the probability hypothesis density (PHD) filter. Firstly, a measurement-driven mechanism based on this gating technique is designed to classify the measurements. In this mechanism, only the measurements for the existing targets are considered in the update step of the existing targets while the measurements of newborn targets are used for exploring newborn targets. Secondly, the gating strategy enables the development of a heuristic state estimation algorithm when sequential Monte Carlo (SMC) implementation of the PHD filter is investigated, where the measurements are used to drive the particle clustering within the space gate. The resulting PHD filter can achieve a more robust and accurate estimation of the existing targets by reducing the interference from clutter. Moreover, the target birth intensity can be adaptive to detect newborn targets, which is in accordance with the birth measurements. Simulation results demonstrate the computational efficiency and tracking performance of the proposed algorithm.

1. Introduction

Multiple target tracking (MTT) solves the problem of estimations for the time-varying number of targets and the corresponding target states in cluttered environments, which involves complex filtering and estimate algorithms.[1–3] And the data association[4,5] is also a challenge due to the uncertainty between the targets and measurements. Recently, the random finite sets (RFS) approach has been presented as a mechanism to develop methods for MTT,[6] and a novel RFS-based probability hypothesis density (PHD) filter was proposed by Mahler. Particularly, the PHD filter propagates the intensity function of the multitarget posterior, which is also known as PHD. This approximation allows the PHD filter to operate on the single-target state space and hence the combinatorial problem caused by data association is completely avoided.

However, the closed-form solutions for the PHD filter are not available since the PHD recursion involves multiple integrals. At present, one of the well-known implementations of the PHD filter is sequential Monte Carlo (SMC-PHD) filter[7,8] and the other is Gaussian mixtures (GM-PHD) filter.[9] The

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cardinalized PHD (CPHD) filter[10] was introduced subsequently, which additionally considered the cardinality distribution. Although a significant improvement in the estimate of cardinality can be achieved, the computational cost is quite high.[11] Multitarget filters based on the PHD/CPHD recursion have shown favorable performance in MTT and significant research has been carried out to develop this method.[12–16]

When the PHD filter is used, the detection and tracking of new targets are highly dependent on the target birth intensity function. However, the standard formulation of the PHD/CPHD filter requires priori information of the target birth intensity,[6,10] and this leads to many limitations in terms of practical applications of the algorithm. Especially when the newborn targets can appear anywhere in the monitoring region, the target birth intensity function is required to cover the whole state space of interest. Although a large number of Gaussian components can be used to approximate an arbitrary density, this method is potentially computationally inefficient.[14] As the CPHD filter is insensitive to changes in the number of targets,[15] it is not suitable for the rapid detection of new targets. While the GM-PHD/CPHD filter is computationally efficient for real-time implementation, it is only applicable for linear Gaussian systems. By contrast, the SMC-PHD filter can handle the situation where dense clutter exists and can also be applied to non-linear, non-Gaussian systems. The existing data-driven PHD filters[17,18] are also based on the SMC method. The idea of adaptively building target birth models according to measurements[16,19] has also been proposed for the PHD filter. A more general method known as the adaptive target birth intensity PHD (ABI-PHD) filter can be found in Ref.[16]. This method places the newborn target particles based on the measurements to avoid the need for prior knowledge of the target birth intensity.

In this paper, a novel measurement-driven adaptive PHD filter is presented for MTT. As the measurements are represented by the RFS, a measurement-driven mechanism is introduced to classify current measurements for the existing and newborn targets. Subsequently, the two kinds of measurement are used for the update steps of the existing targets and exploring new targets, respectively. All of these benefits from the proposed gating strategy that based on the measurement likelihood function of the target state space. An SMC implementation of the proposed PHD filter is investigated in this paper, where the target birth intensity is adapted according to the measurements of newborn targets at each processing step instead of selecting newborn targets using the priori expected mean of the target states. Thus, a more efficient and accurate estimate for the existing targets can be obtained and the processing requirements of the filtering computation can be simplified by the measurement-driven mechanism. In addition, a heuristic state estimation algorithm based on the gating strategy is also presented to extract the target states from the particles representing the intensity function of the state set, in which the measurements and particle distribution information are considered to guide the particle clustering. Extensive simulations show the tracking performance of the proposed PHD filter.

2. Formulation of tracking model

The problem addressed in this paper involves a single sensor, and bearing and range measurements are used for MTT. The individual target state at time k is modeled in the following dynamic model

$$\boldsymbol{x}_k = \boldsymbol{f}(\boldsymbol{x}_{k-1}) + \boldsymbol{\xi}_k \tag{1}$$

where $\boldsymbol{x}_k = [x_k, v_k^x, y_k, v_k^y]^{\mathrm{T}}$ is the target state vector, with $[x_k, y_k]^{\mathrm{T}}$ and $[v_k^x, v_k^y]^{\mathrm{T}}$ the position and velocity in Cartesian coordinates respectively; $\boldsymbol{\xi}_k$ is the process noise vector; $\boldsymbol{f}(\cdot)$ is the dynamic equation of the target.

Each target generated measurement is obtained by

$$\boldsymbol{z}_k = \boldsymbol{h}(\boldsymbol{x}_k) + \boldsymbol{\varepsilon}_k \tag{2}$$

where $\boldsymbol{\varepsilon}_k \sim \mathcal{N}(\cdot; \boldsymbol{0}, \boldsymbol{R})$ represents Gaussian random noise with zero-mean and measurement error covariance $\boldsymbol{R} = \mathrm{diag}(\delta_\theta^2, \delta_{\mathrm{r}}^2)$, with δ_θ and δ_{r} representing the angle standard deviation and range standard deviation respectively. The position of the sensor platform is assumed to be known at $[x_{\mathrm{s}}, y_{\mathrm{s}}]^{\mathrm{T}}$, so the invertible measurement function $\boldsymbol{h}(\cdot)$ is specified as

$$\boldsymbol{h}(\boldsymbol{x}_k) = \begin{bmatrix} \arctan\left(\dfrac{\begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}\boldsymbol{x}_k - y_{\mathrm{s}}}{\begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}\boldsymbol{x}_k - x_{\mathrm{s}}}\right) \\ \left\| \boldsymbol{H}\boldsymbol{x}_k - \begin{bmatrix} x_{\mathrm{s}} \\ y_{\mathrm{s}} \end{bmatrix} \right\| \end{bmatrix} \tag{3}$$

where

$$\boldsymbol{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

As the multitarget state changes with time, the dynamic system model can be represented using the RFS theory.[6] For example, suppose that there are n_k targets which are located at $\boldsymbol{x}_{k,1}, \boldsymbol{x}_{k,2}, \ldots, \boldsymbol{x}_{k,n_k}$ in the single-target state space E_{S} at time k, and then they are measured and a set of measurements $\boldsymbol{z}_{k,1}, \boldsymbol{z}_{k,2}, \ldots, \boldsymbol{z}_{k,m_k}$ that taking values in the single-target observation space E_{O} are collected. It is natural that some clutter generated measurements may be collected and some of the existing and newborn targets may not be detected due to the imperfect detectors. The target states and measurements are respectively represented by the finite sets as $X_k = \{\boldsymbol{x}_{k,1}, \boldsymbol{x}_{k,2}, \ldots, \boldsymbol{x}_{k,n_k}\} \in \mathcal{F}(E_{\mathrm{S}})$ and $Z_k = \{\boldsymbol{z}_{k,1}, \boldsymbol{z}_{k,2}, \ldots, \boldsymbol{z}_{k,m_k}\} \in \mathcal{F}(E_{\mathrm{O}})$, where $\mathcal{F}(E_{\mathrm{S}})$ and $\mathcal{F}(E_{\mathrm{O}})$ are the finite subsets of E_{S} and E_{O}.[7] The goal of the algorithm considered here is to recursively estimate the true target sets X_k conditioned on all the measurement sets received up to time k.

3. Decomposition of PHD filter

3.1. Standard PHD filter

The inherent combinatorial nature of multitarget densities makes it intractable to implement the multitarget Bayes filter directly.[15] To obtain practical solutions, the PHD filter has been derived via the first moment approximation. The standard PHD filter recursion contains the prediction and the update steps[6,16] as

$$D_{k|k-1}(\boldsymbol{x}) = \gamma_{k|k-1}(\boldsymbol{x}) + \langle p_{\mathrm{S}}\pi_{k|k-1}(\boldsymbol{x}|\cdot) + b_{k|k-1}(\boldsymbol{x}|\cdot), D_{k-1|k-1} \rangle \tag{4}$$

$$D_{k|k}(\boldsymbol{x}) = (1 - P_{\mathrm{D}}(\boldsymbol{x}))D_{k|k-1}(\boldsymbol{x}) + \sum_{\boldsymbol{z} \in Z_k} \frac{P_{\mathrm{D}}(\boldsymbol{x}) g_k(\boldsymbol{z}|\boldsymbol{x}) D_{k|k-1}(\boldsymbol{x})}{\kappa_k(\boldsymbol{z}) + \langle P_{\mathrm{D}} g_k(\boldsymbol{z}|\cdot), D_{k|k-1} \rangle} \tag{5}$$