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Multi-target Bayesian filter for propagating marginal distribution

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ABSTRACT

The Bayesian filter and its approximation, the probability hypothesis density (PHD) filter, propagate joint distribution of the multi-target state and the first-order moment of the joint distribution, respectively. However, these two filters fail to distinguish multiple distinct targets when these targets are closely spaced. To efficiently distinguish closely spaced targets according to a sequence of measurements, we (1) use the individual state distributions to model the uncertainties of individual target states caused by the target dynamic uncertainty and measurement uncertainty, (2) use the existence probabilities of individual targets to characterize the randomness of target appearance and disappearance, and (3) propose a novel multi-target Bayesian filter. Instead of maintaining the joint state distribution, the proposed filter jointly propagates the marginal distributions and existence probabilities of each target. An implementation of the proposed filter for linear and Gaussian models is also presented to deal with an unknown and variable number of targets. The simulation results demonstrate that the proposed filter is better at distinguishing distinct targets and tracking multiple targets than the Gaussian mixture PHD filter.

1. Introduction

Detection and tracking of multiple targets are crucial for distinguishing multiple distinct targets and estimating their states according to a set of uncertain measurements that consist of observations corrupted by both noise and clutter. This scenario describes a very challenging problem in a cluttered environment when targets have a small separation compared with measurement error [1]. The most commonly used multi-target tracking technique is multi-target Bayesian filter, which propagates joint posterior distribution through target dynamics, measurement likelihood, and the Bayesian rule [1–3]. However, due to the integrals of high dimensions and the requirement that the target number is known, the optimal Bayesian filter is intractable in many tracking applications. Principled approximation strategies must be developed to make the Bayesian filter practical [1,4–7]. Existing approximations of the multi-target Bayesian filter include fixed grid approximation, sequential Monte Carlo (SMC) approximation, and probability hypothesis density (PHD) approximation [1,2]. The fixed grid filter approximates the multi-target state numerically by using a fixed grid and applies numerical integration for filter recursion. However, the large associated computational cost makes this filter impractical and inherently intractable [1,2]. The SMC filter represents target distribution by using particles and importance weights, and propagates them in the filter recursion [1,2]. The SMC filter requires less computational load than the fixed grid filter. However, this difference in computational load is not enough to allow the use of the SMC filter in real-time applications [2]. Importantly, both fixed grid and SMC filters require a known number of targets. The PHD filter proposed by Mahler alleviates computational

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intractability of the multi-target Bayesian filter and can estimate the instantaneous target number [2,4]. Instead of maintaining joint posterior distribution of the multi-target state, the PHD filter propagates the first-order moment of multi-target posterior density. With the development of two numerical solutions of the PHD filter, namely, SMC [8–14] and Gaussian mixtures (GM) [15–22], the PHD filter has received increasing research interest from scholars and researchers. Many extensions of the PHD filter have also been proposed to improve the performance of the PHD filter. PHD filters with observation-driven birth intensity were independently proposed in [21,23,24] to obviate the need for exact knowledge of birth intensity. Methods for maintaining track continuity were proposed in [8,25] for the SMC-PHD filter and in [26] for the GM-PHD filter. To improve the accuracy and stability of the target number estimate, the cardinalized PHD filter, which jointly propagates the moment and cardinality, was proposed in [27]. Methods for estimating an unknown clutter rate, which is an important parameter of the PHD filter, were proposed in [28,29]. In [17], the GM-PHD filter was extended to linear jump Markov multi-target models for use in tracking maneuvering targets. A GM-based PHD filter for sequentially handling the received measurement was proposed by Liu et al. [18].

The efficiency, simplicity of implementation, and success of the PHD filter in avoiding the combinatorial problem that arises from data association has made it more appealing than other filters. Given its advantages, the PHD filter is used in passive localization [13], passive radar target tracking [14], visual tracking [30], target tracking in sonar images [31], group target tracking [32], and so on. However, the PHD filter cannot distinguish multiple distinct targets when they are closely spaced. A simple example in [4] shows that when two targets are well separated, the multi-target posterior intensity of the PHD filter is bimodal, and the maxima are near the states of the two targets, but it is unimodal with a maximal value at the mean of the two target states if the two distinct targets have a sufficiently small separation. In this case, the state estimate given by the PHD filter is that of the target group, not that for either of the two targets. The same problem occurs when using the multi-target Bayesian filter, but a PHD-based multi-target tracker experiences more difficulty with closely spaced targets [2,4].

In this paper, we derive and propose a new multi-target Bayesian filter to efficiently distinguish closely spaced targets according to a sequence of measurements. The proposed filter sufficiently considers the independences of individual targets. Instead of maintaining the joint posterior density of the multi-target state, the filter propagates the marginal distributions of each target. Similar to the PHD filter, the proposed filter operates on the single-target state space, hence avoiding the combinatorial problem that arises from data association. In the proposed filter, the uncertainties of individual target states caused by the target dynamic uncertainty and measurement uncertainty are modeled by individual state distributions, and the randomness of target appearance and disappearance is characterized by the existence probabilities of individual targets. Filter recursion jointly propagates individual distributions and their existence probabilities. An implementation of the proposed filter for linear and Gaussian models is also developed. Simulation results are obtained by comparing the proposed filter and the PHD filter in terms of optimal subpattern assignment (OSPA) distance [33], which demonstrates that the proposed filter is better than the PHD filter at distinguishing distinct targets and tracking multiple targets. The similarity between the two filters ensures that some improvements to the PHD filter can be applied to the proposed filter.

The joint integrated probabilistic data association filter (JIPDAF) proposed in [34] is also a multi-target filter used to propagate marginal posterior distribution. However, the proposed filter and JIPDAF are different in nature. JIPDAF handles the possible presence of multiple targets in a joint PDAF [35] manner, where joint events are formed by creating all possible combinations of track-measurement assignments. The combinatorial nature of this data association-based approach makes it computationally intensive in general [17], whereas the proposed method does not need data association.

The main contributions of this paper focus on two points. First, we propose a new method for computing marginal posterior distribution and existence probability. Second, we present a novel implementation of the proposed filter for linear and Gaussian models.

The rest of this paper is organized as follows. Section 2 briefly introduces the multi-target Bayesian filter and PHD filter. The multi-target Bayesian filter used to propagate marginal distribution is proposed in Section 3. The implementation of the proposed filter for linear and Gaussian models is presented in Section 4. The performance of the proposed filter is evaluated by simulations in Section 5. Conclusions are drawn in Section 6.

2. Multi-target Bayesian filter and PHD filter

2.1. Multi-target Bayesian filter

Given that the proposed filter is a multi-target Bayesian filter, we first describe the multi-target Bayesian filter briefly [1]. In a multi-target Bayesian filter, the distribution of interest is the joint posterior $f(\boldsymbol{x}_t|\boldsymbol{y}_{1:t})$, which is also known as the filtering distribution, where t denotes the discrete time index, $\boldsymbol{x}_t=(\boldsymbol{x}_{1,t}\cdots\boldsymbol{x}_{K,t})$ is the multi-target state at time t, K is the target number, and $\boldsymbol{y}_{1:t}=(\boldsymbol{y}_1\cdots\boldsymbol{y}_t)$ represents all the observations from time 1 to time t. The filtering distribution of a multi-target Bayesian filter can be computed by using two-step recursion.

Prediction step

$$f(\boldsymbol{x}_t|\boldsymbol{y}_{1:t-1})=\int f(\boldsymbol{x}_t|\boldsymbol{x}_{t-1})f(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{1:t-1})d\boldsymbol{x}_{t-1} \tag{1}$$

Update step

$$f(\boldsymbol{x}_t|\boldsymbol{y}_{1:t})=\frac{g(\boldsymbol{y}_t|\boldsymbol{x}_t)f(\boldsymbol{x}_t|\boldsymbol{y}_{1:t-1})}{f(\boldsymbol{y}_t|\boldsymbol{y}_{1:t-1})} \tag{2}$$

where $f(\boldsymbol{x}_t|\boldsymbol{x}_{t-1})$ denotes the Markov transition probability from state $\boldsymbol{x}_{t-1}$ at time $t-1$ to state $\boldsymbol{x}_t$ at time t, $g(\boldsymbol{y}_t|\boldsymbol{x}_t)$ is the probability density that state $\boldsymbol{x}_t$ at time t generates