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An efficient approximate implementation for labeled random finite set filtering

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ABSTRACT

In this paper, we propose an approximate implementation for labeled random finite set filtering with low computational cost. In contrast to the earlier implementations of the generalized labeled multi-Bernoulli (GLMB) filter and the labeled multi-Bernoulli (LMB) filter, the proposed approach adopts a sampler based on marginaling the joint association probability that can generate the components of the GLMB density from marginal probabilities with high parallel level. Additionally, this marginal probability approximation results in an efficient implementation of the LMB filter, which calculates the parameter set of the filtering LMB density from the marginal probabilities. Furthermore, we exploit a simplified belief propagation algorithm to obtain approximate marginal probabilities with linear complexity in the number of measurements and objects. Simulations show that the proposed implementation can handle both linear and non-linear scenarios and is more efficient against the existing implementations.

1. Introduction

1.1. Background and motivation

Multi-object tracking (MOT) techniques deal with the problem of estimating an unknown and time-varying number of objects and trajectories [1]. As an important technology in diverse applications [2,3], MOT has been developed for over 50 years. The intrinsic challenges in MOT include detection uncertainty caused by non-ideal sensors, spurious measurements (clutter) not originating from any real target, and measurement-origin uncertainty [4]. There are three major algorithms, namely, multiple hypothesis tracking (MHT), joint probabilistic data association (JPDA), and recently, random finite set (RFS) are used to address these problems [3,5–9].

The RFS approach provides general systematic treatment of multi-object systems and recursive Bayesian formulation of multi-object filtering/tracking problems. Under the RFS framework, the probability hypothesis density (PHD) filter [10], the cardinalized PHD filter [11], and the multi-target multi-Bernoulli (MeMBer) filter [7,12] have been developed as tractable approximations to intractable Bayes multi-object filter. Without explicit data association, sequential Monte Carlo (SMC) and Gaussian mixture (GM) implementations [13–15] of RFS based filters are well suited for parallelism on multi-core and cluster platforms [16,17]. These algorithms successfully applied to many fields including radar/sonar [18–20], computer vision [4,21], and sensor management [22–24].

However, these RFS-based filters are not multi-object trackers, which only estimate object states at individual time instants as opposed to object trajectories and their uniqueness. To overcome this limitation, the notion of labeled RFS is introduced in [25,26], which appended a unique label to RFS to distinguish different objects. The generalized labeled multi-Bernoulli (GLMB) RFS leads to an analytic solution to the Bayes multi-object tracker, namely the GLMB filter. This tractable multi-object tracker is based on the GLMB family of conjugate priors that are closed under the Chapman–Kolmogorov equation. An approximate version of the GLMB filter introduced in [27], called the labeled multi-Bernoulli filter (LMB) filter, is a computationally cheaper multi-object tracker by approximating the GLMB density to a LMB density that matches the unlabeled PHD. In these two filters, a major challenge is the intractable implementation of the GLMB recursion in closed form, because the number of components in the GLMB prediction and filtering densities grows exponentially with time. Hence, implementing the GLMB filter and the LMB filter efficiently is very important in the applications of the labeled RFS.

1.2. Brief survey of related work

The first implementation [26] of the GLMB filter and the LMB filter discards the smallest weighted components in the GLMB den-

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sity to minimize the L_1-error. The prediction and the update densities are truncated by using the K-shortest path and ranked assignment algorithms, respectively. This separated implementation leads to solving a large number of ranked assignment problems that require computations with cubic complexity in the number of measurements at best. Alternatively, by using a single joint prediction and update stage, a more efficient technique proposed in [28] truncates the densities once in each recursion of the GLMB filter and reduces the number of ranked assignment problems. Based on the joint prediction and update, a Markov chain Monte Carlo (MCMC) method is proposed in [29], which considers the data association problem as a statistic inference and constructs a Gibbs sampler to generate the valid association set with significant weights. This Gibbs sampling based implementation has a linear complexity in the number of measurements and quadratic in the number of objects. The LMB filter can also be achieved by using the sampling method to efficiently obtain object states and labels [30]. Although these two implementations can be parallelized with respect to the components of the GLMB density, performing the ranked assignment algorithm and Gibbs sampler in each component is still serial, for the association hypothesis depends on the previous assignments or samples.

Besides, in order to solve the data association problem efficiently, Williams et al. use a loopy belief propagation (BP) based approximate method [31–33]. This method utilizes graphical model to describe joint association event and a simplified BP algorithm to estimate marginal association probability. For most multi-object tracking problems, this algorithm is proved [32] to converge to an accurate approximation with low computational complexity and is applied to JPDA filter and association-based MeMBer filter [34]. Hence, we incorporate this method to an approximate implementation of the labeled RFS filter, which can be performed parallel with respect to the association samples and has low complexity.

1.3. Main contributions

The major contributions of this paper are as follows:

i) We provide a marginal probability sampler and a modified version, based on marginal probability approximation, to generate association hypotheses with significant weights in the GLMB density filtering. In contrast to Gibbs sampler [29,30] that serially samples from Markov Chain of association hypothesis, the proposed marginal probability sampler and the modified version have lower computational cost and can be implemented parallel with respect to the tracks within each association hypothesis and the association hypotheses, respectively.

ii) We prove that marginal probability approximation results in an efficient implementation of the LMB filter [27]. Since the propagated parameter set of LMB density can be calculated from the marginal probabilities, our implementation does not need to enumerate all possible association hypotheses or find a certain number of the significant hypotheses as [27,30] do. Without exhaustive enumeration or solving the ranked assignment problem, the proposed LMB filter has much lower complexity than the previous methods [27,30].

iii) We calculate the marginal probability by exploiting an extended version of the simplified BP algorithm, which can also estimate the existence probabilities of objects. It has a linear complexity in the number of measurements and hypothesized objects, leading to an efficient implementation of the proposed method.

The rest of the paper is organized as follows. In Section 2, we present some background on labeled RFS and the Bayes multi-object filter. The joint prediction and update formulation and the BP marginal probability sampler based implementation for the labeled RFS filtering are provide in Section 3. Simulation results are given in Section 4. Finally, in Section 5, conclusions are discussed.

2. Preliminary

This section provides brief background materials on labeled RFS and multi-object filtering. For further details, we refer the reader to the original works [25,26].

Throughout this article, we denote single-object states by small letters (e.g. x) and multi-object states by capital letters (e.g. X). The labeled states and distributions are denoted by bold face letters to distinguish them from the unlabeled one (e.g. $\mathbf{x}, \mathbf{X}, \boldsymbol{\pi}$). Additionally, spaces are denoted by blackboard bold (e.g. $\mathbb{X}, \mathbb{Z}, \mathbb{L}, \mathbb{N}$), and the collection of all finite subsets of a space $\mathbb{X}$ is represented by $\mathcal{F}(\mathbb{X})$. For notational convenience, we denote the inner product $\int f(x)g(x)dx$ as standard notation $\langle f, g\rangle$, and the following product $\prod_{x\in X} f(x)$ as the multi-object exponential notation f^X, with $f^{\emptyset}=1$.

The generalized Kroneker delta function is defined as

$$\delta_Y(X) \triangleq \begin{cases} 1 & \text{if } X = Y \\ 0 & \text{otherwise} \end{cases}$$

where X and Y may be arbitrary types such as sets, vectors, integers etc. And the inclusion function is given by

$$\mathbf{1}_Y(X) \triangleq \begin{cases} 1 & \text{if } X \subseteq Y \\ 0 & \text{otherwise} \end{cases}$$

We also use the notation $X_{m:n}$ to abbreviate the list of variables $X_m, X_{m+1}, \ldots, X_n$, and $|X|$ to represent the cardinality of a finite set X.

2.1. Labeled random finite set

An RFS is a finite-set-valued random variable [10], or a simple-finite point process, which can model the multi-object state and multi-object observation. In the paper, we characterize RFSs by using Mahler's Finite Set Statistics (FISST) notion of integration/density [7,8].

A labeled RFS $\mathbf{X}$ is an RFS on the Cartesian product space $\mathbb{X}\times\mathbb{L}$, where $\mathbb{X}$ is the state space and $\mathbb{L}$ is the discrete label space, such that the labels within each realization are distinct. The set of labels of $\mathbf{X}$ is given by $\mathcal{L}(\mathbf{X}) = \{\mathcal{L}(\mathbf{x}), \mathbf{x}\in\mathbf{X}\}$, where $\mathcal{L}:\mathbb{X}\times\mathbb{L}\to\mathbb{L}$ is the projection defined by $\mathcal{L}((x,l)) = l$ and the distinct label indicator function is given by

$$\triangle(\mathbf{X}) \triangleq \delta_{|\mathbf{X}|}(|\mathcal{L}(\mathbf{X})|)$$

Thus, for each realization $\mathbf{X}$ of a labeled RFS, $\triangle(\mathbf{X})$ is always equal to one.

The integral of a function f on $\mathbb{X}\times\mathbb{L}$ is given by

$$\int f(\mathbf{x})d\mathbf{x} = \sum_{l\in\mathbb{L}} \int f(x,l)dx$$

2.1.1. Generalized labeled multi-Bernoulli (GLMB)

An GLMB [25,26] is a labeled RFS on $\mathbb{X}\times\mathbb{L}$ with the probability distribution

$$\pi(\mathbf{X}) = \triangle(\mathbf{X}) \sum_{c\in\mathbb{C}} w^{(c)}(\mathcal{L}(\mathbf{X}))\left[p^{(c)}\right]^{\mathbf{X}} \tag{1}$$

where c is an arbitrary discrete index set, each $p^{(c)}(\cdot, l)$ is a probability density on $\mathbb{X}$ with $\int_{x\in\mathbb{X}} p^{(c)}(x,l)dx = 1$, and each $w^{(c)}(L)$ is non-negative with $\sum_{c\in\mathbb{C}}\sum_{L\in\mathcal{F}(\mathbb{L})} w^{(c)}(L) = 1$.

The cardinality distribution and intensity function of a GLMB are given by

$$Pr(|\mathbf{X}| = n) = \sum_{c\in\mathbb{C}} \sum_{I\in\mathcal{F}(\mathbb{L})} \delta_n(|I|) w^{(c)}(I) \tag{2}$$