Digital Signal Processing 59 (2016) 76–85

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

On multiple-model extended target multi-Bernoulli filters

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ARTICLE INFO

Article history:
Available online 18 August 2016

Keywords:
Random finite set
Multiple-model
Multi-Bernoulli filters
Maneuvering extended targets
Gaussian mixture
Sequential Monte Carlo

ABSTRACT

In this paper, we propose a multiple-model (MM) version of the extended target multi-Bernoulli (ET-MB) filter for estimating multiple maneuvering extended targets. A Gaussian mixture (GM) implementation of the MM-ET-MB filter for linear Gaussian models and a sequential Monte Carlo (SMC) implementation of the MM-ET-MB filter for nonlinear models are presented. Two numerical examples are provided to verify the effectiveness of the MM-ET-MB filter for estimating multiple maneuvering extended targets.

1. Introduction

The objective of multi-target tracking is to simultaneously estimate the number of targets and their states from a sequence of noisy measurements. Generally, each target is assumed to be a point target which produces at most one measurement per scan. This assumption is valid when the target is far away from the sensor or when the resolution of sensors is low. However, when the distance between the target and sensor is small, or when the resolution of sensors is high, the sensor may be able to resolve individual features on the target. Each target may generate more than one measurement per scan, and the assumption of point targets is not appropriate. Hence extended target tracking arises. An extended target is defined as a target which potentially generates more than one measurement per scan [1].

With multiple measurements, an inhomogeneous Poisson point process measurement model was proposed for tracking extended targets [2]. For this measurement model, the measurements are distributed around the target, and the number of measurements follows a Poisson distribution. Except for the target kinematical state, the target's extension (i.e. size and shape) can also be estimated with multiple measurements. The random matrix approach for modeling target's extension has been proposed to tracking an ellipsoidal target [3]. Some improved random matrix approaches appeared in [4,5]. Extension of the random matrix approach to non-ellipsoidal extended target tracking has been suggested in [6,7]. Other approaches to modeling the target's extension were given in [8–10]. An overview of the group and extended target tracking approaches can be found in [11].

Among various multi-target tracking approaches, we are interested in the random finite set (RFS) approach. Compared with the traditional target tracking approaches [12], the RFS approach avoids explicit associations between measurements and targets [13]. Hence, the RFS approach provides another kind of methods for target tracking [14–16]. In the RFS approach, the states and measurements are treated as RFSs. With RFS models, Mahler has proposed the multi-target Bayes filter which propagates the multi-target posterior density recursively [17,14]. Since the optimal multi-target Bayes filter is generally intractable, some approximate multi-target Bayes filters were proposed, such as the probability hypothesis density (PHD) filter [17] which propagates the first order moment of the multi-target density, the cardinality PHD (CPHD) filter [18] which propagates the first order moment and cardinality distribution of the multi-target density, and the multi-Bernoulli (MB) filter [14,19] which propagates the parameters of an MB distribution that approximate the multi-target density. These filters have been implemented by using Gaussian mixture (GM) and sequential Monte Carlo (SMC) techniques [13,20,21,19]. Using a Poisson model of extended target measurements [2], Mahler has derived the PHD filter for extended targets. The GM implementation of the ET-PHD filter was presented in [22,1]. A Gaussian inverse Wishart (GIW) implementation of the ET-PHD filter was proposed to jointly estimate the kinematic states and extensions of multiple extended targets [23]. The CPHD filter for extended targets was derived in [24], and the GM implementation of the ET-CPHD filter was proposed in [25]. By integrating the ET-CPHD filter with the random matrix approach, a Gamma Gaussian in-

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http://dx.doi.org/10.1016/j.dsp.2016.08.002
1051-2004/

verse Wishart (GIWW) implementation of the ET-CPHD filter was proposed in [26]. The latest development is the GIWW implementation of the generalized labeled MB filter which is able to estimate the number of targets and their trajectories, kinematic states, measurement rates, and extents [27].

Recently, the MB filter for extended targets was proposed in [28], and a GM implementation of the ET-MB filter for linear Gaussian models was presented in [29]. For nonlinear non-Gaussian models, we have proposed an SMC implementation of the ET-MB filter [30]. Notice that, the ET-MB filter for maneuvering extended targets has not been considered so far. Maneuvering extended targets may switch between a set of models, and a single model is not general enough to accommodate maneuvering extended targets. The multiple-model (MM) (or jump Markov models) approach has proven to be an effective approach for maneuvering target tracking [31,32]. The standard MM-MB filter and its extensions for point targets have been proposed in [33–35]. Inspired by [33,34], in this paper, we extend the ET-MB filter to accommodate multiple maneuvering extended targets, and propose an MM version of the ET-MB filter. Then the GM and SMC implementations of the MM-ET-MB filter for linear Gaussian and nonlinear models are presented. Simulation results demonstrate that the MM-ET-MB filter is effective for estimating multiple maneuvering extended targets, and has high estimation accuracy than both the single model ET-MB and the standard MM-MB filters.

To summarize, the main contributions of this paper are summarized as follows:

- propose an MM version of the ET-MB filter;
- give a GM implementation of the MM-ET-MB filter for linear Gaussian models;
- give an SMC implementation of the MM-ET-MB filter for nonlinear models;
- compare the MM-ET-MB filter with the single model ET-MB and MM-MB filters.

The rest of this paper is organized as follows. The MM version of the ET-MB filter is provided in Section 2. A GM implementation of the MM-ET-MB filter is given in Section 3. An SMC implementation of the MM-ET-MB filter is given in Section 4. Numerical results for two simulation scenarios are provided in Section 5. Finally, the conclusion is drawn in Section 6.

2. The MM-ET-MB filter

The MB filter propagates the parameters of an MB distribution that approximate the multi-target density. It propagates a time-varying number of target tracks in time. Initially, the MB filter was proposed for handling point targets. Recently, based on a Poisson measurement model proposed by Gilholm [2], Zhang [28] has derived the MB filter for extended targets, for more details see [28]. To date, the ET-MB filter for maneuvering extended targets has not been considered. In this section, we give a brief review of the MM approach and present an MM version of the ET-MB filter.

2.1. A brief review of the MM approach

The MM approach has proven to be an effective method for maneuvering target tracking. In the MM approach [32], the target can switch between a set of motion models according to a Markovian process. Let $x_k \in \mathbf{R}^n$ denote the kinematic state, $z_k \in \mathbf{R}^m$ denote the measurement, and $o_k \in \mathcal{O}$ denote the motion model at time k, where $\mathcal{O}$ denotes the discrete set of all models. Assume that the models follow a discrete Markovian chain process with transition probability $t_{k|k-1}$, then the transition probability of the augmented state $\mathbf{x}_k = (x_k, o_k) \in \mathbf{R}^n \times \mathcal{O}$ can be described by [36]

$$\begin{aligned} &f_{k|k-1}(\mathbf{x}_k|\mathbf{x}_{k-1}) \\ &= f_{k|k-1}(x_k, o_k|x_{k-1}, o_{k-1}) \\ &= f_{k|k-1}(x_k|x_{k-1}, o_k) t_{k|k-1}(o_k|o_{k-1}) \end{aligned} \tag{1}$$

The measurement likelihood is described by

$$g_k(z_k|\mathbf{x}_k) = g_k(z_k|x_k, o_k) \tag{2}$$

2.2. The MM-ET-MB filter

Mahler has introduced the jump-Markov version of the multi-target Bayes filter for maneuvering targets, and discussed several approaches for RFS-based filters in [37]. Some implementations of the MM RFS-based filters were presented in [36,38,33,34]. The estimation performance of the MM-PHD, MM-CPHD, and MM-MB filters for multiple maneuvering point targets has been compared in [33]. Following [37], a discrete random variable representing the motion model is augmented to the multi-target state under the RFS framework, i.e.

$$X = \{\mathbf{x}_1, \cdots, \mathbf{x}_n\} = \{(x_1, o_1), \cdots, (x_n, o_n)\} \tag{3}$$

Similar to the description of a Bernoulli RFS in [19], the probability density of a Bernoulli RFS is

$$\pi(X) = \begin{cases} 1-r & X = \emptyset \\ r \cdot p(x, o) & X = \{x, o\} \end{cases} \tag{4}$$

where r denotes the existence probability and p denotes the probability density of a track.

An MB-RFS X is a union of a fixed number of independent Bernoulli RFSs $X^{(i)}, i = 1, \cdots, M$, i.e., $X = \bigcup_{i=1}^{M} X^{(i)}$. The MB-RFS is described by $\{(r^{(i)}, p^{(i)})\}_{i=1}^{M}$, where $r^{(i)}$ denotes the existence probability of the ith hypothesized track, $p^{(i)}$ denotes the probability density of the ith hypothesized track, and M is the total number of hypothesized tracks. Following the MM approach, the probability density of the ith hypothesized track is described by a joint distribution $p^{(i)}(x, o)$. Hence the MM version of the MB-RFS is $\{(r^{(i)}, p^{(i)}(x, o))\}_{i=1}^{M}$. The MM-ET-MB filter is an extension of the ET-MB filter. The key of the MM-ET-MB filter is that the model variable is augmented to the probability density of each hypothesized track. The prediction and update of the MM-ET-MB filter are presented as follow.

Proposition 1. *If at time $k-1$, the posterior multi-target density*

$$\pi_{k-1} = \{(r_{k-1}^{(i)}, p_{k-1}^{(i)}(x', o'))\}_{i=1}^{M_{k-1}} \tag{5}$$

is given, then the predicted multi-target density is described by

$$\pi_{k|k-1} = \{(r_{P,k|k-1}^{(i)}, p_{P,k|k-1}^{(i)}(x, o))\}_{i=1}^{M_{k-1}} \cup \{(r_{\Gamma,k}^{(i)}, p_{\Gamma,k}^{(i)}(x, o))\}_{i=1}^{M_{\Gamma,k}} \tag{6}$$

where

$$r_{P,k|k-1}^{(i)} = r_{k-1}^{(i)} \langle p_{k-1}^{(i)}(x', o'), p_{S,k}(x', o') \rangle \tag{7}$$

$$p_{P,k|k-1}^{(i)}(x, o) = \frac{\langle f_{k|k-1}(x|x', o) t_{k|k-1}(o|o'), p_{k-1}^{(i)}(x', o') p_{S,k}(x', o') \rangle}{\langle p_{k-1}^{(i)}(x', o'), p_{S,k}(x', o) \rangle} \tag{8}$$

$\langle \cdot, \cdot \rangle$ is the inner product defined between two real-valued functions α and β by $\langle \alpha, \beta \rangle = \int \alpha(x)\beta(x)dx$ (or $\langle \alpha, \beta \rangle = \sum_{i=0}^{\infty} \alpha(i)\beta(i)$, when α and β are sequences), $f_{k|k-1}(\cdot|x', o)$ denotes a single target transition density given state x' conditioned on model o at time k, $p_{S,k}(x', o')$ is the survival probability of a target conditioned on model o' at time k, and $\{(r_{\Gamma,k}^{(i)}, p_{\Gamma,k}^{(i)}(x, o))\}_{i=1}^{M_{\Gamma,k}}$ are the parameters of birth targets at time k.