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A box-particle implementation of standard PHD filter for extended target tracking

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ABSTRACT

This paper presents a box-particle implementation of the standard probability hypothesis density (PHD) filter for extended target tracking, called the extended target box-particle PHD (ET-Box-PHD) filter. The proposed filter can dynamically track multiple extended targets and estimate the unknown number of extended targets, in the presence of clutter measurements, false alarms and missed detections, where the extended targets are described as a Poisson model developed by Gilholm et al. To get the PHD recursion of the ET-Box-PHD filter, a suitable cell likelihood function for one given reliable partition is derived, and the main filter steps are presented along with the necessary box manipulations and approximations. The capabilities and limitations of the proposed ET-Box-PHD filter are illustrated both in linear simulation examples and in nonlinear ones. The simulation results show that the proposed ET-Box-PHD filter can effectively avoid the high number of particles and obviously reduce computational burden, compared to a particle implementation of the standard PHD filter for extended target tracking.

1. Introduction

Early classical target tracking can be characterized as the processing of a time-sampling sequence of measurements collected from a target for the sake of maintaining an estimate of the target's current state, see, e.g., [1–3]. In this context, the target is defined as a point target which is assumed to generate at most one measurement at a given time step. However, with increased resolution of modern and more accurate sensors (e.g., phased array radar), the target may occupy the sensor's multiple resolution cells, thus potentially generating a strongly fluctuating number of measurements at a given time step. In this case, this target is preferably defined as an extended target [4], which provides not only the target's kinematic information but also the target-extension information as the size, shape and orientation of the target. Extended target tracking is valuable for many actual applications including ground-based radar stations tracking airplanes in the near field of the radar, vehicles tracking other road-users using radar sensors, and mobile robotics tracking pedestrians using laser range sensors. Additionally, closely related to extended target is group target, defined as a group of closely-spaced point targets which cannot be tracked individually and can only be treated as a single object [5].

Unlike the point target, each extended target can generate multiple measurements at a given time step, thus a model of the measurements' number for each target is needed. Gilholm and Salmond in [6] for extended target tracking developed an approach under the assumption that the number of the measurements generated by each extended target at a given time step is Poisson distributed. A measurement model was presented in [7], which is characterized as an inhomogeneous Poisson point process. In this model, a Poisson distributed random number of measurements at each time step are produced and distributed around the extended target. This measurement model implies that the extended target is sufficiently far from the sensor so that the measurements generated by it resemble a cluster rather than a geometric structure.

Multiple measurements generated by each extended target may raise the possibility of estimating its extension. For this purpose, several approaches for the extended target tracking have been proposed. The random matrix model for extended target and group target tracking was introduced by Koch in 2008 [8], which decomposes the extended target state at each time step into a kinematical state and an extension. The kinematical state and the target extension are modeled as Gaussian distributed and inverse Wishart distributed, respectively. Modifications and developments to the random matrix model [8] have been found in [9–11]. Another model for extended target is the random hypersurface model (RHM) [12], which is a specific measurement source model under the assumption that each measurement source lies on a scaled version of the true ellipse describing the extended target. The elliptic RHMs' development for extended target tracking is inspired by the idea estimating the smallest enclosing ellipse of

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the extended target [13]. The other approaches to estimating the target extensions, as rectangles, ellipses, non- ellipses, or more general shapes, are given in [14–18].

With finite set statistics (FISST), Mahler developed a set theoretic approach in which both states and measurements of targets are modeled using random finite sets (RFS). This approach allows the problem of dynamically estimating multiple targets in the presence of clutter and with uncertain association to be cast in a Bayesian filtering framework [19,20], which in turn results in a theoretically optimal multi-target Bayesian filter. However, the novel RFS-based approach, introduced by Mahler [19], is usually intractable in most practical applications [21,22] except for simple examples. To alleviate this intractability, for the point target tracking [23–25], Mahler proposed the standard probability hypothesis density (PHD) [21] by FISST. The standard PHD filter in time propagates the posterior intensity of the targets' RFS as a first moment approximation of the multi-target Bayesian filter. Compared to the traditional association-based approaches, the standard PHD filter has the distinct advantage that it operates only on the single-target state space and avoids data association [26]. The practical Gaussian mixture (GM) and sequence Monte Carlo (SMC) implementations of the PHD filter were given in [27] and [22], respectively. Recently, for the extended target tracking, Mahler in [28] proposed an extended version of the standard PHD filter, called the extended target PHD (ET-PHD) filter. In [28], Mahler only gave the optimal theoretical derivation of the ET-PHD filter's PHD recursion, but no corresponding closed-form solution.

Under linear and Gaussian assumptions, a GM implementation of the ET-PHD filter [28], called the ET-GM-PHD filter, has been derived by Granström et al. in [29] and [30], and it has been used to track the extended targets with laser measurements [14]. In order to improve the precision in estimating the number of extended targets, Orguner et al. derived a CPHD filter for extended targets and gave its GM implementation, i.e., the ET-GM-CPHD filter [31]. In the works [29,30] and [31], only the kinematic properties of the extended targets' centroids are estimated. Estimation of the targets' extensions is omitted to reduce the complexity. To solve this problem, an implementation of the ET-PHD filter using the random matrix introduced by Koch [8] was presented in [32], and the resulting filter is called the extended target Gaussian inverse Wishart PHD (ET-GIW-PHD) filter. Subsequently, an implementation of the ET-CPHD filter [31] using the random matrix was derived by Lundquist et al. [33], called the extended target Gamma Gaussian inverse Wishart CPHD (ET-GGIW-CPHD) filter. Another implementing way of the ET-PHD filter [28] is the SMC form, or particle filter (PF) form. To the best of our knowledge, the SMC implementation of [28] has not been reported except the algorithm, introduced by Li et al. [34], called the extended target particle PHD (ET-P-PHD) filter.

Most of the current researches on implementations of the ET-PHD filter [28] are still limited to linear and Gaussian problems. Implementations of [28] under nonlinear and non-Gaussian assumptions need further exploration. Recently, to reduce the number of particles in PF, Abdallah, Gning, Ristic, and Mihaylova in [35–37] developed a box-particle filter, where a box particle represents a random sample occupying a small, controllable and nonzero-volume rectangular region in the target state space. In 2012, A box-particle implementation of the standard PHD filter [21], called the box-particle PHD filter, was presented by Schikora et al. [38,39]. Additionally, to handle the extended target tracking, several modified versions have been suggested in [40] and [41]. However, for the extended-target box-particle implementation of the standard PHD filter, at present there are no related reports.

The main contribution of this work is a derivation of the box-particle implementation of the standard PHD filter, referred to as the extended target box-particle PHD (ET-Box-PHD) filter, in the context of multiple extended target tracking with clutter, false alarms and an unknown number of targets. The key of deriving the ET-Box-PHD filter is the definition of the cell likelihood function. In this work, we simplify this problem by introducing all cells from only one reliable partition into computation of the cell function. In addition, the proposed ET-Box-PHD filter can deal with nonlinear and non-Gaussian problems, and is suitable for the strong clutter surveillance areas, compared to the ET-GM-PHD filter introduced by Granström et al. in [30]. Besides, since the ET-Box-PHD filter's new born box particles of the current time step are generated by the measurement set from the previous time step, its tracking results appear the lag phenomenon. Finally, we validate the effectiveness of the ET-Box-PHD filter via linear and nonlinear examples.

The remainder of the paper is organized as follows. Section 2 describes a problem formulation. The details of our algorithm, i.e., the ET-Box-PHD filter, are given in Section 3, including the definition of cell likelihood for the ET-Box-PHD filter and details for the box-particle implementation of the standard PHD filter. The simulation results are presented in Section 4. Finally, the conclusions and the future work are given in Section 5.

2. Problem formulation

This section first gives the partitioning problem of the extended target tracking, based on ET-PHD filter [28], in Section 2.1. Then, a short introduction to interval analysis is given in Section 2.2. Finally, within the interval analysis framework, the extended-target dynamic motion model and measurement model are defined by Sections 2.3 and 2.4, respectively.

2.1. Measurement partitioning problem

In the RFS-based extended target filters, as the ET-PHD filter [28], the ET-GM-PHD filter [30], the ET-GM-CPHD filter [31], the ET-GIW-PHD filter [32], the ET-GGIW-CPHD filter [33], etc., an important part of obtaining the closed-form solution to the filters is the measurement partitioning. Theoretically, the above filters require all possible partitions of the current measurement set for its update. For the purpose of illustration, the process of partitioning with a measurement set containing three individual measurements, $\mathbf{Z}_k = \{\mathbf{z}_k^{(1)}, \mathbf{z}_k^{(2)}, \mathbf{z}_k^{(3)}\}$, is considered at time step k. This set can be partitioned as follows [28],

$$\begin{aligned}
&\wp_1 : W_1^1 = \{\mathbf{z}_k^{(1)}, \mathbf{z}_k^{(2)}, \mathbf{z}_k^{(3)}\},\\
&\wp_2 : W_1^2 = \{\mathbf{z}_k^{(1)}, \mathbf{z}_k^{(2)}\}, W_2^2 = \{\mathbf{z}_k^{(3)}\},\\
&\wp_3 : W_1^3 = \{\mathbf{z}_k^{(1)}, \mathbf{z}_k^{(3)}\}, W_2^3 = \{\mathbf{z}_k^{(2)}\},\\
&\wp_4 : W_1^4 = \{\mathbf{z}_k^{(2)}, \mathbf{z}_k^{(3)}\}, W_2^4 = \{\mathbf{z}_k^{(1)}\},\\
&\wp_5 : W_1^5 = \{\mathbf{z}_k^{(1)}\}, W_2^5 = \{\mathbf{z}_k^{(2)}\}, W_3^5 = \{\mathbf{z}_k^{(3)}\}
\end{aligned} \tag{1}$$

where $\wp_i$ is the ith partition, and W_j^i is the jth cell of partition $\wp_i$. Obviously, the number of possible partitions becomes very large as the total number of measurements increases, hence considering using a subset that contains the most likely partitions approximates all possible partitions is necessary. Thus, the choice of the partitioning methods for approximating all possible partitions directly impacts on the tracking performance. A partition is a division of the measurement set into a few of non-empty subsets called cells [33]. The measurements contained in each cell all stem from the same source, either a target or a clutter source.

There have been several attempts to solve the problem of the measurement partitioning. In [30] and [31], distance partition and distance partition with sub-partition were adopted. In addition, in order to handle a densely cluttered environment with high accuracy, Zhang and Wu suggested an affinity propagation clustering