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Structure modeling and estimation of multiple resolvable group targets via graph theory and multi-Bernoulli filter ☆

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ABSTRACT

This paper considers multiple resolvable group target estimation under clutter environment. The proposed algorithm involves two aspects: target estimation and group state (group size, shape, etc.) estimation. First, we propose dynamic models and observation function for the group targets. Second, we derive the connection relation of individual targets through the predicted target states. In the following step, we combine the graph theory with the group targets and build the adjacency matrix of the estimated state set. The connection information is used to correct the collaboration noise and estimate the target states. For group estimation, we focus on the number of subgroups, the group states and the group sizes. Finally, several examples are given to verify the proposed algorithm, respectively.

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1. Introduction

Group target tracking has been received much attention in recent years. The main reason is due to the rapid development of new sensor technology, which results in the rich information collected from targets. In traditional radar tracking community, it is well known that a target is assumed to be a point source, called a point source target (Bar-Shalom, 1978; Bar-Shalom & Tse, 1975; Reid, 1979). As the limited ability of detection, the target is naturally shown as a point source on radar screen due to the hundreds, even thousands of kilometers away. For a point source target, we focus on its moving point states such as acceleration, velocity and position. With the progress of the advanced sensor technologies, higher resolution and more sensitive capabilities can be available. For instance, modern infrared sensor using superconductive technology may receive much more shape information from a target. This means that multiple measurements may be gotten from a point source target. In this case, tracking and data association under the "one target one detection" assumption is no longer hold (Feldmann, Fränken, & Koch, 2011; Koch, 2008; Koch & Keuk, 1997; Oliver, 1995). These measurements not only reflect the target state but also its shape. We call the target as an extended target. Another scenario is when multiple targets forming a formation with a close distance between any two targets, coined as the group targets.

The extended targets and group targets are usually confronted with the same problems in dynamic modeling, state and shape estimation. Specifically, first, they have certain shapes and thus produce multiple measurements. Second, these measurements have close distance compared to the detection gate, which results in the traditional association based approaches intractable. Thus, estimating the states of individual targets in group or the parts in extended target become difficult. For simplicity, we call these two kinds of targets as group targets and do not make any distinctions.

To the best knowledge of authors, Koch proposed the group target tracking in the classic Bayesian framework (Koch & Keuk, 1997). A key conception of symmetric and positively definite (SPD) matrix described by a random matrix is adopted to show the shape of group targets. The SPD is in essentially an ellipsoidal shape. The core problem of the research is to estimate the random matrix from the received measurements. It has been shown that if the prior distribution of the random matrix is assumed to follow inverted Wishart related distributions and the transition density of the target extension (shape) is with Wishart distribution, then the updated extension can be approximated by an inverted Wishart distribution. Further work focused on non-ellipsoidal extended target by combinated of multiple ellipsoidal sub-objects (targets) where each target is represented by a random matrix (Lan & Li, 2011). Baum et al. described the extended target using the random super-surface model (Baum & Hanebeck, 2011; Baum, Noack, &

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Hanebeck, 2010; Hanebeck & Baum, 2009). E. Richter et al. tracks multiple extended target using Markov chain Monte Carlo approaches (Richter, Obst, Noll, & Wanielik, 2011). In classic estimation theory, most existing algorithms assume that the number of targets in the groups is fixed.

Another kind of approaches can be categorized as the random finite set (RFS) based algorithm. Mahler proposed the group target tracking algorithm in the finite set statistics (FISST) paradigm (Mahler, 2009a,b). Refs. Lundquist, Granström, and Orguner (2011) and Orguner, Lundquist, and Granström (2011) proposed the CPHD filter approaches. Ref. Granström and Orguner (2012) combined the SPD matrix with the PHD filter and generalized the PHD filer to the group target tracking. The key of the extended PHD filter is to partition the measurement set. Lian, Han, and Liu (2010) proposed the PHD filtering algorithm for group targets by using the MCMC sampling method. Swain and Clark (2011) proposed a first-moment recursion for a single-group filter. Ref. Gning, Mihaylova, Maskell, Pang, and Godsill (2011) combined the graph to the group tracking by learning the evolving graph model for the groups and estimate the group state by using a Monte Carlo method, but it does not deal with the uncertain number of targets. Ref. Ristic and Sherrah (2009) achieved a Bernoulli filter for an extended object. The approach proposed in Ref. Beard et al. (2015) is based on modeling the multi-target state as a generalized labeled multi-Bernoulli (GLMB), combined with the gamma Gaussian inverse Wishart distribution for a single extended target. The RFS theory has a splendid paradigm and tackles these two issues together. The RFS based algorithms can avoid the association step. In our idea, this characteristic is more suitable to group target tracking.

Basically, the above group targets are assumed to be unresolvable. This means the group targets is located in the same resolution unit, so it is very difficult to discriminate individual targets and estimate the dependent relation between them. For existing algorithms, the core idea is to adopt the random matrix to describe the shape of group targets. Nevertheless, if the group targets are close to sensors or sensors have higher resolution ability, they may become resolvable. Thus, estimating the dependent relation of targets becomes available and even necessary.

In this paper, we focus on multiple resolvable group targets. That is, individual targets are in different resolution units of the sensor. Besides, we consider multiple subgroups (in a big group) using multi-Bernoulli RFS filter and graph theory. We classify the issue of group target estimation into target estimation and group estimation. The former includes estimation of the number of targets, individual target states, and the dependent relation. The latter group estimation includes the number of subgroups, the subgroup states (centroid), the sizes and the structures of individual subgraphs.

The challenge is that the group targets are dependent, while most existing results of the RFS algorithms are given under the independent condition. A basic problem is to consider the problem of whether the multi-Bernoulli filter still available in this condition. This is the second part of the paper. We show that under the given dynamic models and some assumptions. The multi-Bernoulli filter for dependent group targets is equivalent to original multi-Bernoulli filter under independent case. In sum up, our main contributions are listed as follows.

- We build dynamic model for the resolvable group targets. The movement of group targets not only depends on individual member states, but also the target birth and spawned models. We propose the linear model and nonlinear for multiple subgroups, respectively. Moreover, several propositions are given to be used to estimate individual target states. Besides, under some condition, we show the original multi-Bernoulli still can be available.
- By combining graph theory to the group targets, we derive the group states and structures. The relationship between group targets is expressed by an adjacency matrix which reflects the dependent relation of the members in the group targets. We also use the adjacency matrix to recover the structures of individual subgroups.
- We estimate the number of targets and subgroups by importing the conception of connected graph from the estimated adjacency matrix. Besides, we also consider the dependent relation of each subgroup. This work is rarely given in the existing work.

The structure of this paper is listed as follows. Section 2 is background for random finite sets and related graph theory. Section 3 gives the graphical structure and dynamic model for group targets. In Section 4, we focus on the target estimation and group estimation. By combining the graph theory to group targets and building adjacency matrix, we consider the estimation algorithm for the group targets based on the multi-Bernoulli filter and graph theory. Two propositions are proposed in this section. Section 5 proposed two experiments of linear and nonlinear systems to verify the our provided algorithm. Section 6 concludes this paper.

2. Background

2.1. Random finite sets

The theory of RFS considers the multi-target tracking systems using the conception of sets. Specifically, the states of multi-target and measurements from a sensor can be modeled by the state RFS and measurement RFS. Here the meaning of the finite implies that the number of members in the RFS is with a limited number. Besides, the number of members is random in a discrete space of integers, while the state is usually defined in a continuous space. So we can describe the two RFSs in the following forms (Mahler, 2007):

$$X_k = \{x_{k,1}, \ldots, x_{k,N_k}\} \in \mathcal{F}(\mathcal{X}) \tag{1}$$

$$Z_k = \{z_{k,1}, \ldots, z_{k,M_k}\} \in \mathcal{F}(\mathcal{Z}) \tag{2}$$

where X_k and Z_k are the state RFS and measurement RFS, respectively. $\mathcal{X} \subseteq \mathbb{R}^{n_x}$ and $\mathcal{Z} \subseteq \mathbb{R}^{n_z}$ are the state space and observation space. $\mathcal{F}(\mathcal{X})$ and $\mathcal{F}(\mathcal{Z})$ show the spaces of all finite subsets of $\mathcal{X}$ and $\mathcal{Z}$.

The state RFS can be modeled by Mahler (2007):

$$X_k = [\cup_{x\in X_{k-1}} S_{k|k-1}(x)] \cup [\cup_{x\in X_{k-1}} B_{k|k-1}(x)] \cup \Gamma_k \tag{3}$$

where $S_{k|k-1}(x)$, $B_{k|k-1}(x)$, and Γ_k are respectively the RFSs of target surviving, spawned, and birth. With the RFS variables, our next task is to model the probability distribution function (pdf) for the RFSs. In Bayesian framework, two pdfs of the state RFS and the measurement RFS are needed. Let $f(X_k|X_{k-1})$ be the transition function of the state RFS. Different from the general transition, which shows the state transition in a continuous state space, the RFS transition function involves much more information. For example, targets disappear (death), and new targets may be born.

Suppose that the target surviving, spawned, and birth are mutually independent. Then, the probability density of the multi-target state RFS can be given by Mahler (2007):

$$f_{k|k-1}(X_k|X_{k-1}) = \sum_{W\subseteq X_k} \pi_{T,k|k-1}(W|X_{k-1})\pi_{\Gamma,k}(X_k - W) \tag{4}$$

where RFS $T_{k|k-1}(x) \triangleq S_{k|k-1}(x)\cup B_{k|k-1}(x)$, $\pi_{T,k|k-1}(W|X_{k-1})$, $\pi_{\Gamma,k}(\cdot)$ are respectively the probability densities of surviving RFS and spontaneous birth RFS Γ_k. The equation incorporate the underlying

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