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Constrained Multiple Model Bayesian Filtering for Target Tracking in Cluttered Environment

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Abstract: This paper proposes a composite Bayesian filtering approach for unmanned aerial vehicle trajectory estimation in cluttered environments. More specifically, a complete model for the measurement likelihood function of all measurements, including target-generated observation and false alarms, is derived based on the random finite set theory. To accommodate several different manoeuvre modes and system state constraints, a recursive multiple model Bayesian filtering algorithm and its corresponding Sequential Monte Carlo implementation are established. Compared with classical approaches, the proposed method addresses the problem of measurement uncertainty without any data associations. Numerical simulations for estimating an unmanned aerial vehicle trajectory generated by generalised proportional navigation guidance law clearly demonstrate the effectiveness of the proposed formulation.

Keywords: Unmanned aerial vehicle, Trajectory estimation, Random finite set, Multiple model filtering, System state constraint, Sequential Monte Carlo implementation.

1. INTRODUCTION

The large scale of Unmanned Aerial Vehicle (UAV) applications has proliferated vastly within the last few years. The operational experience of UAVs has proven that their technology can bring a profound impact to the civilian and military arenas. This includes obtaining real-time, relevant situational awareness information before making contact; helping operators to lead appropriate decision making; and reducing risk to the mission and operation. The potential applications are wide, e.g surveillance, border patrol, search and rescue, convoy protection Grocholsky et al. (2006).

Despite of these advantages, UAV operations might pose serious risks: insertion of them to the non-segregated airspace could pose the risk of collision with other objects and hostile UAVs could raise a serious security concern. One of key technologies in reducing such a risk is the target tracking technology. The issue is that these UAVs could be operated in complex environments such as an urban environment.

Target tracking, in complex and or clustered environments is challenging since the sensor received measurements may include target-generated observation, clutters as well as spurious targets (decoys). Traditional way to address such measurement uncertainty is the well-known data association, such as nearest neighbour filter (NNF) Singer et al. (1974), probability data association (PDA) Bar-Shalom and Tse (1975), joint PDA Fortmann et al. (1983), multiple hypothesis tracking (MHT) Reid (1979). Unlike data association technique, the recently proposed random finite set (RFS) theory Mahler (2007); Vo et al. (2005); Ristic et al. (2016) results in elegant and rigorous mathematical formulation to solve this issue and provides a different view on filtering without data association. RFS-based algorithms, where system states and measurements are represented by RFSs, are joint decision and estimation approaches.

In the absence of measurement-origin uncertainty, UAV trajectory estimation faces another two interrelated issues: UAV manoeuvre mode uncertainty and system nonlinearity. The mainstream approach for target tracking under motion uncertainty is multiple model filtering Mazor et al. (1998); Li and Jilkov (2005). At each filtering cycle, multiple model approach runs a bank of nonlinear filters corresponding to each mode with the same measurement and fuses the output of these filters to find an overall estimate.

By combining the interacting multiple model approach and RFS theory, this paper proposes a new recursive Bayesian filtering algorithm for UAV trajectory estimation. Since the key of nonlinear filtering is to obtain the measurement likelihood function for the set-valued case, a simple but complete model is derived using RFS theory, where the target-generated observation and false alarms are represented by two different RFSs. Using the proposed measurement likelihood function obtained, a rigorous recursive multiple model Bayesian filtering is presented. Instead of generic Bayesian framework, system state constraints are also considered due to the existence of physical limits. Since analytic closed-form solution for such Bayesian filter is intractable due to nonlinearity, a Sequential Monte Carlo (SMC) implementation is presented to approximate the posterior density function. Simulation results show

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that the estimation accuracy can be significantly improved compared with a classical PDA filter for highly cluttered environments

The remainder of this paper is organized as follows. Some backgrounds and preliminaries are presented in Sec. 2. In Sec. 3, the proposed constrained multiple model Bayesian filtering algorithm is derived in detail, followed by Sequential Monte Carlo implementation introduced in Sec. 4. Finally, a case study and some conclusions are offered.

2. BACKGROUNDS AND PRELIMINARIES

2.1 Bayesian Filtering

Suppose that the state vector $x_k \in \mathbb{R}^n$ provides the complete information of the system state of a target at time t_k, and let $z_k \in \mathbb{R}^m$ be the measured information. Typically, only partial system state can be observed, that is, $m < n$. Then, the general target dynamics can be formulated as

$$\begin{aligned} x_k &= f_{k-1}\left(x_{k-1}\right) + v_{k-1} \\ z_k &= h_k\left(x_k\right) + w_k \end{aligned} \tag{1}$$

where f_{k-1} is a nonlinear transition function governing the temporal evolution of first-order Markov target state, v_{k-1} the independent identically distributed (IID) process noise. Function h_k is used to define the relationship between system state and sensor measurement and w_k is the IID measurement noise. The term IID means that each variable that belongs to a collection of random variables has the same probability distribution as the others and all variables are mutually independent.

In the formulation of Bayesian filtering, two different probability density functions need to be specified, e.g. the transitional density function $\pi\left(x_k \left| x_{k-1}\right.\right)$ and the measurement likelihood function $g\left(z_k \left| x_k\right.\right)$. Under these conditions, Bayesian filter propagates the posterior density $p\left(x_k \left| z_{1:k}\right.\right)$ according to

$$\begin{aligned} p\left(x_k \left| z_{1:k-1}\right.\right) &= \int \pi\left(x_k \left| x\right.\right) p\left(x \left| z_{1:k-1}\right.\right) dx \\ p\left(x_k \left| z_{1:k}\right.\right) &= \frac{g\left(z_k \left| x_k\right.\right) p\left(x_k \left| z_{1:k-1}\right.\right)}{\int g\left(z_k \left| x\right.\right) p\left(x \left| z_{1:k-1}\right.\right) dx} \end{aligned} \tag{2}$$

where $z_{1:k} = [z_1, z_2, \ldots, z_k]$ stands for the measurement sequence.

2.2 Random Finite Set Probability Density

Recursion procedure (2) is formulated based on the assumption that at most one measurement can be generated at each time step. Typically, sensor detection is imperfect, leading to the fact that the target may not be observed at some time. Moreover, complex cases, such as electronic counter measures, multi-path effect, may generate unknown spurious measurements or decoys. In addition to decoys, clutters are also needed to be considered in severe conditions. Since each sensor measurement at any given time step has no physical importance, the unordered measurements at time t_k can be modelled by a RFS on Z, e.g. $Z_k \in \Xi(\mathrm{Z})$ with $\Xi(\mathrm{Z})$ being the set of finite subsets of Z. Obviously, the key to implement Bayesian recursion (2) is to extend the measurement likelihood function $g\left(z_k \left| x_k\right.\right)$ to set-valued multiple measurement case. To make this paper self-contained, some preliminaries of RFS probability density are reviewed in this subsection.

A RFS is defined as that a random set that takes values as unordered finite sets, which means that both the number of elements and the individual state values of each element in Z are both random. To fully characterize the probability density of a RFS variable, it is necessary to define the discrete cardinality (the number of elements) distribution and a group of joint distributions conditioned on the cardinality. The cardinality distribution $\rho\left(n_z\right) = \Pr\left\{\left|Z_k\right| = n_z\right\}$ specifies the cardinality of the RFS, while the joint probability distributions $p_{n_z}\left(z_{k,1}, z_{k,2}, \ldots, z_{k,n_z}\right)$ model the distribution of the elements. Naturally, the value of $p_{n_z}\left(z_{k,1}, z_{k,2}, \ldots, z_{k,n_z}\right)$ remains unchanged for all $n!$ possible element permutations due to the unordered property of a RFS. With these two definitions, the rigorous mathematical representation of the probability density function of a RFS can be derived as Ristic et al. (2016)

$$\begin{aligned} f\left(\left\{z_{k,1}, z_{k,2}, \ldots, z_{k,n_z}\right\}\right) = \rho\left(n_z\right) \\ \times p_{n_z}\left(z_{k,1}, z_{k,2}, \ldots, z_{k,n_z}\right) n_z! \end{aligned} \tag{3}$$

3. CONSTRAINED MULTIPLE MODEL FILTERING IN A CLUTTERED ENVIRONMENT

This section details the proposed estimation algorithm in two parts: set-valued measurement likelihood function derivation, constrained multiple model Bayesian recursion.

3.1 Multiple Measurements Likelihood Function

To distinguish the target-generated observation and false alarms, the measurement set Z_k is represented as

$$Z_k = \Theta_k \cup \Omega_k \tag{4}$$

where Θ_k denotes the target-generated measurement, and Ω_k stands for the false measurements, including decoys and clutters.

Since sensor measurement is usually imperfect, we model Θ_k as a Bernoulli RFS Ristic et al. (2016), which can either be empty or has target-generated measurement. Let $p_{D,k}(x_k)$ be the probability of target detection, then, the probability of miss detection is $1 - p_{D,k}(x_k)$, and in contrast, supposed that there exists a target-generated observation in the measurement set, the probability of obtaining such a measurement is $p_{D,k}\left(x_k\right) g_k\left(z_k \left| x_k\right.\right)$. In conclusion, the probability density function of Θ_k can be obtained as

$$f_1\left(\Theta_k\right) = \begin{cases} 1 - p_{D,k}\left(x_k\right), & \Theta_k = \emptyset \\ p_{D,k}\left(x_k\right) \cdot g_k\left(z_k^t \left| x_k\right.\right), & \Theta_k = \left\{z_k^t\right\} \end{cases} \tag{5}$$

where z_k^t denotes the target-generated observation.

Suppose that each element of Ω_k is independent of one another and is identically distributed according to probability density function $c_k\left(z_k \left| x_k\right.\right)$, then the false alarm measurement Ω_k in complex environments can be modelled as a Poisson RFS and the cardinality distribution $\rho\left(\left|\Omega_k\right|\right)$ is Poisson with parameter λ, that is

$$\rho\left(\left|\Omega_k\right|\right) = \frac{e^{-\lambda}}{\left|\Omega_k\right|!} \lambda^{\left|\Omega_k\right|} \tag{6}$$