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Particle filters for probability hypothesis density filter with the presence of unknown measurement noise covariance

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Abstract In Bayesian multi-target filtering, knowledge of measurement noise variance is very important. Significant mismatches in noise parameters will result in biased estimates. In this paper, a new particle filter for a probability hypothesis density (PHD) filter handling unknown measurement noise variances is proposed. The approach is based on marginalizing the unknown parameters out of the posterior distribution by using variational Bayesian (VB) methods. Moreover, the sequential Monte Carlo method is used to approximate the posterior intensity considering non-linear and non-Gaussian conditions. Unlike other particle filters for this challenging class of PHD filters, the proposed method can adaptively learn the unknown and time-varying noise variances while filtering. Simulation results show that the proposed method improves estimation accuracy in terms of both the number of targets and their states.

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1. Introduction

In multi-target filtering, the states of the targets are unknown and the number of targets will vary with time. Most traditional multiple-target tracking methods, such as the nearest neighbour (NN), multiple hypothesis tracking (MHT),[1] joint probabilistic data association (JPDA),[2] etc., involve explicit associations between measurements and targets. However, these methods require a great amount of computation and hence are not of practical interest when the number of targets is large. A promising alternative solution to multiple-target tracking (MTT) that can avoid data association is the probability hypothesis density (PHD) filter.[3]

The PHD filter is the first-order statistical moment of the multitarget posterior distribution, which operates on the single-target state space and can avoid measurement association.[4] However, there are no closed-form solutions for the PHD filter in general. Sequential Monte Carlo (SMC) implementations with closed-form solutions have been proposed and the performance guarantees can be found in the surveys.[5,6] The PHD filter is shown to be a computationally tractable method for unified tracking and classification,[7] cluster tracking[8] and group target detection.

In order to achieve better performance for the PHD filters, a modeling problem and an estimation problem need to be considered. While the former refers to the development of

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better dynamic models that describe more accurately the motion trajectory, the latter refers to the achievement of better state estimates through the proper use of available process and measurement information. The optimality of the PHD algorithm is closely connected to the quality of the priori information about the statistics of measurement noise. For convenience, the terminology "noise statistics" is used to represent the mean or the variance when measurement noise is subject to the Gaussian distribution. Conceptually, insufficiently known a priori statistics will either reduce the precision of the estimated states or introduce biases to their estimates.[9] In addition, wrong a priori noise information or frequently changing environment may lead to weight estimation problems of the PHD filter.[10] However, a good knowledge of noise parameters depends on many factors, such as the type of application and the process dynamics, which are difficult to obtain.

This paper addresses the related challenges of adaptive noise learning and state estimation for multi-target tracking. Previous work has examined these issues for target tracking via parameters learning approximations. Their problems can be summarized as: (i) slow and inefficient due to the use of multiple model approach[11,12]; or (ii) limited to only static parameters, which is not practicable.[13] Compared to the mulitple-model approximations, the selected models are often far more structurally complex due to their limited gating abilities, which makes it more expensive and difficult for them to learn the time-varying parameters. In contrast, variational Bayesian (VB) methods have not yet been applied to parameter estimation for the PHD filter, due to their recent development.

This paper derives a new particle filter for the PHD algorithm without the prior knowledge of measurement noise. We first extend the standard PHD filter to accommodate unknown noise parameters. Then we assume that the posterior distribution of unknown noise parameters are dependent on certain sufficient statistics, and a new variational Bayesian approximation for the posterior distribution of the parameters is derived. The proposed variational Bayesian methods yield computationally efficient approximate intensity for noise parameters and multi-target states. The number of targets and the time-varying noise variances are jointly estimated on-line via the SMC-PHD implementations, which are demonstrated here experimentally on application data.

2. Extended PHD filter with unknown noise parameters

In an MTT problem, the number of targets and their states vary with time because of the process of spontaneous birth, death and spawning. Consider each target follows the general system model:

$$\begin{cases} \boldsymbol{x}_k = f(\boldsymbol{x}_{k-1}) + \boldsymbol{w}_k \\ z_k = g(\boldsymbol{x}_k) + \boldsymbol{v}_k \end{cases} \tag{1}$$

where $f(\cdot)$ is the transition density and $g(\cdot)$ the translational measurement model; $\boldsymbol{w}_k \sim N(\boldsymbol{0}, \boldsymbol{Q}_k)$ is the Gaussian distribution process noise and $\boldsymbol{v}_k \sim N(\boldsymbol{0}, \boldsymbol{R}_k)$ the Gaussian measurement noise. Assume that the measurement z_k and the process noise $\boldsymbol{w}_k$ are known a priori, while the state $\boldsymbol{x}_k$ and measurement noise variance $\boldsymbol{R}_k$ are unknown. In addition, the target states, measurement noise, process noise are independent of each other.

Assume that at time step k, there are n_k target states $\boldsymbol{x}_{k,1}, \boldsymbol{x}_{k,2}, \ldots, \boldsymbol{x}_{k,n_k}$ in a state space $\boldsymbol{\chi}$ and m_k measurements $z_{k,1}, z_{k,2}, \ldots, z_{k,m_k}$ are received in an observation space $\boldsymbol{Z}$. The multi-target states and observations are then naturally represented by the finite sets:

$$\begin{cases} \boldsymbol{X}_k = \{\boldsymbol{x}_{k,1}, \boldsymbol{x}_{k,2}, \ldots, \boldsymbol{x}_{k,n_k}\} \in \boldsymbol{\chi} \\ \boldsymbol{Z}_k = \{z_{k,1}, z_{k,2}, \ldots, z_{k,m_k}\} \in \boldsymbol{Z} \end{cases} \tag{2}$$

Assumed that the measurement noise variance $\boldsymbol{R}_k = \{\boldsymbol{R}_{k,1}, \boldsymbol{R}_{k,2}, \ldots, \boldsymbol{R}_{k,m_k}\} \in \boldsymbol{R}$ is unknown at time k, where the capital letter $\boldsymbol{R}$ represents the unknown measurement noise variance space. The challenge for the PHD filter is to estimate the augmented state $(\boldsymbol{X}_k, \boldsymbol{R}_k)$ while filtering. The Bayesian recursions for MTT systems with unknown noise variance $\boldsymbol{R}_k$ are determined via the following prior and posterior calculations:

$$\begin{cases} p_{k|k-1}(\boldsymbol{X}_k, \boldsymbol{R}_k|\boldsymbol{Z}_{1:k-1}) = \int f_{k|k-1}(\boldsymbol{X}_k, \boldsymbol{R}_k|\boldsymbol{X}_{k-1}, \boldsymbol{R}_{k-1}) \\ \quad (\cdot)p(\boldsymbol{X}_{k-1}, \boldsymbol{R}_{k-1}|\boldsymbol{Z}_{1:k-1})\boldsymbol{\mu}_s \mathrm{d}\boldsymbol{X}_{k-1}\mathrm{d}\boldsymbol{R}_{k-1} \\ p_{k|k}(\boldsymbol{X}_k, \boldsymbol{R}_k|\boldsymbol{Z}_{1:k}) = \dfrac{g_k(\boldsymbol{Z}_k|\boldsymbol{X}_k, \boldsymbol{R}_k)p(\boldsymbol{X}_k, \boldsymbol{R}_k|\boldsymbol{Z}_{1:k-1})}{\int g_k(\boldsymbol{Z}_k|\boldsymbol{X}_k, \boldsymbol{R}_k)p(\boldsymbol{X}_k, \boldsymbol{R}_k|\boldsymbol{Z}_{1:k-1})\boldsymbol{\mu}_s \mathrm{d}\boldsymbol{X}_k \mathrm{d}\boldsymbol{R}_k} \end{cases} \tag{3}$$

where $\boldsymbol{\mu}_s$ is constructed from the Lebesgue measure.[3] All information about the state at time k is encapsulated in the posterior density $p_{k|k}(\boldsymbol{X}_k, \boldsymbol{R}_k|\boldsymbol{Z}_{1:k})$, and the unknown parameters of the targets at time k can be obtained using a PHD filter.

The PHD filter is the first order statistical moment of the Random finite sets (RFS) of a multi-target posterior distribution.[8] In order to derive the extended PHD filter for joint target states and measurement noise variances, we first treat $(\boldsymbol{x}_k, \boldsymbol{R}_k)$ as the augmented state at time k. Assume that the multi-target states $\boldsymbol{x}_k$ are independent of the variance parameters $\boldsymbol{R}_k$ and the system dynamics of variance $\boldsymbol{R}_k$ is Markovian, the state transition density $f_{k|k-1}(\boldsymbol{x}_k, \boldsymbol{R}_k|\boldsymbol{x}_{k-1}, \boldsymbol{R}_{k-1})$ can be denoted by

$$f_{k|k-1}(\boldsymbol{x}_k, \boldsymbol{R}_k|\boldsymbol{x}_{k-1}, \boldsymbol{R}_{k-1}) = f_{\boldsymbol{x},k|k-1}(\boldsymbol{x}_k|\boldsymbol{x}_{k-1}) f_{\boldsymbol{R},k|k-1}(\boldsymbol{R}_k|\boldsymbol{R}_{k-1}) \tag{4}$$

where the transition density of target states $f_{\boldsymbol{x},k|k-1}(\boldsymbol{x}_k|\boldsymbol{x}_{k-1})$ comes from Eq. (1), and $f_{\boldsymbol{R},k|k-1}(\boldsymbol{R}_k|\boldsymbol{R}_{k-1})$ is the transition density of noise variance, which is usually unknown.

The spawn transition density $\beta_k(\boldsymbol{x}_k, \boldsymbol{R}_k|\boldsymbol{x}_{k-1}, \boldsymbol{R}_{k-1})$ and the survival probability $p_{\mathrm{S},k|k-1}(\boldsymbol{x}_{k-1}, \boldsymbol{R}_{k-1})$ with the augmented state can be decomposed analogously as follows:

$$\begin{cases} \beta_k(\boldsymbol{x}_k, \boldsymbol{R}_k|\boldsymbol{x}_{k-1}, \boldsymbol{R}_{k-1}) = \beta_{\boldsymbol{x},k}(\boldsymbol{x}_k|\boldsymbol{x}_{k-1})\beta_{\boldsymbol{R},k}(\boldsymbol{R}_k|\boldsymbol{R}_{k-1}) \\ p_{\mathrm{S},k|k-1}(\boldsymbol{x}_{k-1}, \boldsymbol{R}_{k-1}) = p_{\mathrm{S},k|k-1}(\boldsymbol{x}_{k-1})p_{\mathrm{S},k|k-1}(\boldsymbol{R}_{k-1}) = p_{\mathrm{S},k|k-1}(\boldsymbol{x}_{k-1}) \end{cases} \tag{5}$$

The noise variance is coupled with target states, therefore $p_{\mathrm{S},k|k-1}(\boldsymbol{R}_{k-1}) = 1$.

By extending the standard-PHD filter with the augmented state,[3] the recursions for the extended PHD filter are given as follows:

The time-update step is

$$\begin{aligned} v_{k|k-1}(\boldsymbol{x}_k, \boldsymbol{R}_k|\boldsymbol{Z}_{k-1}) = {} & b_k(\boldsymbol{x}_k, \boldsymbol{R}_k) \\ & + \int [p_{\mathrm{S},k} f_{\boldsymbol{R},k|k-1}(\boldsymbol{R}_k|\boldsymbol{R}_{k-1}) f_{\boldsymbol{x},k|k-1}(\boldsymbol{x}_k|\boldsymbol{x}_{k-1}) \\ & + \beta_{\boldsymbol{x},k}(\boldsymbol{x}_k|\boldsymbol{x}_{k-1})\beta_{\boldsymbol{R},k}(\boldsymbol{R}_k|\boldsymbol{R}_{k-1})] \\ & \cdot v_{k-1|k-1}(\boldsymbol{x}_{k-1}, \boldsymbol{R}_{k-1})\mathrm{d}\boldsymbol{x}_{k-1}\mathrm{d}\boldsymbol{R}_{k-1} \end{aligned} \tag{6}$$

where $p_{\mathrm{S},k}$ is probability that a target exists from time $k-1$ to k, $f_{\boldsymbol{x},k|k-1}(\boldsymbol{x}_k|\boldsymbol{x}_{k-1})$ single target Markov transition density from $k-1$ to time k, $f_{\boldsymbol{R},k|k-1}(\boldsymbol{R}_k|\boldsymbol{R}_{k-1})$ Markov transition den-

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