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Penalized Gaussian mixture probability hypothesis density filter for multiple target tracking

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ABSTRACT

Bayesian multi-target filter develops a theoretical framework for estimating the full multi-target posterior which is intractable in practice. The probability hypothesis density (PHD) is a practical solution for Bayesian multi-target filter which propagates the first order moment of the multi-target posterior instead of the full version. Recently, the Gaussian Mixture PHD (GM-PHD) has been proposed as an implementation of the PHD filter which provides a close form solution. The performance of this filter degrades when targets are moving near each other such as crossing targets. In this paper, we propose a novel approach called penalized GM-PHD (PGM-PHD) filter to improve this drawback. The simulation results provided for various probabilities of detection, clutter rates, targets velocities and frame rates indicate that the proposed method achieves better performance compared to the GM-PHD filter.

1. Introduction

Multiple target tracking (MTT) is defined as a joint estimation of the number of targets and their states based on noisy observations in the presence of spurious targets (clutter) and uncertainty in detection. The traditional methods such as nearest neighbor standard filter (NNSF), joint probabilistic data association filter (JPDAF) [1–3] and multiple hypothesis tracking filter (MHTF) [1–2,4] utilize a measurement-to-track association approach, to track multiple targets. Actually, these methods map the multiple target tracking into a single target tracking by assigning one measurement to one trajectory, at each time step.

Recently, the PHD filter has been proposed as an alternative for multiple target tracking which propagates the first order moment of the Bayesian multi-target posterior as an approximation of the full multi-target posterior density [5,6]. This filter estimates the number and the state of the targets, simultaneously, without doing the measurement-to-track association. The set of targets are defined as a random finite set (RFS) [7,8] that the cardinality of which may change over time as well as its individual elements [5]. At each time step, the RFS of the targets may alter according to the born, spawned, survived and dead targets.

The sequential Monte Carlo PHD (SMC-PHD) filter has been proposed as a practical implementation of PHD filter which constructs the PHD density using a weighted sum of particles [9,10]. Besides, the GM-PHD filter has also suggested as another alternative for MTT which provides a closed form solution of the PHD filter [11]. This filter estimates the PHD distribution as a mixture of Gaussian densities.

In the PHD filter a data association mechanism is needed to keep the continuity of the targets' trajectories across frames. The data association is discussed for SMC-PHD filter in [12–14] and for GM-PHD filter in [15–17].

The GM-PHD filter has recently been applied on different applications such as passive target tracking

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[18], sonar image tracking [19] and multiple objects tracking in video [20]. The tracking of maneuvering targets has been studied in [21,22] using this filter.

The classical methods such as JPDA filter [1–3] and MHT filter [1,2,4] suppose a 'one-to-one' constraint in the association step. This constraint expresses that at each time step one target can only generate one measurement and one measurement can only be assigned to one target. However, the GM-PHD filter does not check the one-to-one assumption; because it does not explicitly associate one measurement to one track. Indeed, this filter implicitly considers all possible associations between each measurement and all targets. In practice, the GM-PHD filter is prone to violate the one-to-one assumptions when targets are moving near each other such as crossing targets [23]. As the result, the performance of the GM-PHD filter dramatically decreases and the estimation is lost in its trajectory.

In this paper, we propose a novel approach called penalized GM-PHD (PGM-PHD) filter to improve the above mentioned limitation of the GM-PHD filter. The suggested method considers the weight of the targets created in the update step recursion of the GM-PHD filter. It employs a penalization scheme to refine the weights of the targets whenever a target is prone to violate the one-to-one assumption.

The performance of the proposed PGM-PHD filter is compared with GM-PHD filter in several experiments by simulating closely spaced targets as well as crossing targets with various uncertainties in the probability of detection and clutter rate. The effect of different targets velocities and data rates are also studied. The simulation results show that our suggested method improves the performance of GM-PHD filter in most cases when targets are moving near each other.

The rest of this paper is organized as follows. In Section 2 a brief background of MTT is provided. In addition, the PHD and GM-PHD filters are reviewed and the drawback of the GM-PHD filter is illustrated by a simple example. The proposed PGM-PHD method is explained in Section 3. The simulation results and discussions are given in Section 4 and finally, we conclude the work in Section 5.

2. Background

2.1. Multiple target tracking review

Multiple target tracking (MTT) is the estimation of both number and location of a number of targets based on noisy observations. The number of targets is a variable changing over time, i.e. some targets may die, some are born, etc. The dynamic of a target on the state space X and the measurements space Z is modeled as a transition density $f(x_k|x_{k-1})$ and the likelihood function $g(\mathbb{Z}_k|x_k)$, respectively.

In MTT the targets and observations constitute a random finite set. The RFS of the target's states and measurements are defined as $X_k=\{x_k^1,\ldots,x_k^{N_k}\}\epsilon \mathrm{X}$ and $Z_k=\{\mathbb{Z}_k^1,\ldots,\mathbb{Z}_k^{W_k}\}\epsilon Z$, where x_k^n and $\mathbb{Z}_k^m$ show the nth target state and the mth measurement at time step k with N_k targets and W_k measurements at this time. Some observations in Z_k may be due to clutter. The number of clutter points is assumed to be Poisson distributed with a mean of λ_c [6].

The prediction and update equations for a multiple-sensor, multiple-target system expressed as (1) and (2), respectively:

$$P_{k|k-1}(X_k|Z_{1:k-1}) = \int f_{k|k-1}(X_k|X)P_{k-1}(X|Z_{1:k-1})\mu_s(dX) \quad (1)$$

$$P_k(X_k|Z_{1:k}) = \frac{g_k(Z_k|X_k)P_{k|k-1}(X_k|Z_{1:k-1})}{\int g_k(Z_k|X)P_{k|k-1}(X|Z_{1:k-1})\mu_s(dX)} \quad (2)$$

where the parameter μs takes the place of the Lebesgue measure [24].

2.2. PHD filter formulations

The PHD filter jointly estimates the time varying number of targets and their state from noisy observations. This filter has the ability of tracking multiple objects in presence of noise or spurious target (clutter) and uncertain detection, and it can track multiple objects without data association. Computation of joint multi-target posterior distribution is intractable in real problems. The PHD filter propagates the first-order statistical moment of multiple target posterior distribution. It provides a framework for tracking multiple objects in practice. The prediction and update equations in (1) and (2) are modeled as the following (3) and (4) in the PHD filter recursion, respectively, as

$$\begin{aligned} \upsilon_{k|k-1}(x) = &\int P_{S,k}(\zeta) f_{k|k-1}(x|\zeta)\upsilon_{k-1}(\zeta)d\zeta \\ &+ \int \beta_{k|k-1}(x|\zeta)\upsilon_{k-1}(\zeta)d\zeta + \gamma_k(x) \end{aligned} \quad (3)$$

$$\begin{aligned} \upsilon_k(x) = &\left[1-P_{D,k}(x)\right]\upsilon_{k|k-1}(x) \\ &+\sum_{z\in Z}\frac{P_{D,k}(x)g_k(\mathbb{Z}|x)\upsilon_{k|k-1}(x)}{\mathcal{K}_k(\mathbb{Z})+\int P_{D,k}(\zeta)g_k(\mathbb{Z}|\zeta)\upsilon_{k|k-1}(\zeta)d\zeta} \end{aligned} \quad (4)$$

where γ_k,$\beta_{k|k-1}$,$P_{S,k}$,$P_{D,k}$ and $\mathcal{K}_k$ are the intensity of the birth model, the intensity of spawned target, the survival probability, the probability of detection and the intensity of clutter, respectively.

2.3. GM-PHD filter

Linear Gaussian multi-target assumption proposes a closed-form solution for the PHD filter [11]. The state and observation models follow a linear Gaussian model as

$$f_{k|k-1}(x|\zeta) = \mathcal{N}(x;F_{k-1}\zeta,Q_{k-1}) \quad (5)$$

$$g_k(\mathbb{Z}|x) = \mathcal{N}(\mathbb{Z};H_k x,R_k) \quad (6)$$

where $\mathcal{N}(x;\ m;\ S)$ denotes a Gaussian density with mean m and covariance S. The parameter F_{k-1} is the state transition matrix, Q_{k-1} is the process noise covariance, H_k is the observation model matrix and R_k is the observation noise covariance.

The prediction and update formula in (3) and (4) are expressed as a Gaussian mixture of

$$\upsilon_{k|k-1}(x) = \sum_{i=1}^{J_{k|k-1}} w_{k|k-1}^{(i)}\mathcal{N}(x;m_{k|k-1}^{(i)},S_{k|k-1}^{(i)}) \quad (7)$$