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Improved Iterated-corrector PHD with Gaussian mixture implementation

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ABSTRACT

Many filter algorithms based on the probability hypothesis density (PHD) filter have been proposed to solve the multi-target tracking (MTT) problem. Most of them are applied to single-sensor case. As a simple and feasible multi-sensor filter algorithm, the Iterated-PHD filter is influenced by the order of the sensor updates and the probability of detection. In this paper, an improved algorithm with a modified update formula is proposed to deal with the above problems. In this algorithm, the original detection probability is divided into two parts: the improved miss-detection probability and the improved detection probability, which take the order of the sensor updates and the original detection probability of each sensor into consideration simultaneously. The effectiveness of the proposed algorithm is verified by the simulation results.

1. Introduction

Target tracking plays a significant role in military and civilian fields. However, the uncertainty of the measurement information, such as miss detection and the false alarm, results in great difficulties in multi-target tracking. Moreover, the number of targets may vary over time when a target appears or disappears. How to track multiple targets with varying numbers has been a difficult research issue in both academic and engineering fields for a long time. Traditional multi-target tracking algorithms mainly include multiple hypothesis tracking (MHT) [1], joint probabilistic data association (JPDA) [2], multi-target particle filter [3] and their variances, etc. Although the above algorithms work well in multi-target tracking, they are time consuming in data association between targets and measurements.

In recent years, the random finite set (RFS) theory [4] has become an important and effective approach for the multi-target tracking (MTT) problem. Based on this theory, Mahler proposed three methods: the probability hypothesis density (PHD) filter [5]; the cardinalized probability hypothesis density (CPHD) filter [6]; and the multi-target multi-Bernoulli (MeMBer) filter [4]. The CPHD filter does not assume that the number of targets is a Poisson distribution, and it estimates the number of targets while updating their states. Although the CPHD filter is more accurate than the PHD filter in estimating the cardinality, its computational complexity is higher. Unlike the PHD filter, which propagates the first-order moment, the MeMBer filter propagates the multi-target posterior density. The MeMBer filter is usually applied to handle the target tracking in a low clutter density condition; however, it has a significant cardinality bias caused by a particular updating approximation. To deal with the problem, the cardinality-balanced MeMBer (CBMeMBer) is proposed in [7]. Taking the computation cost and applicability into account, the PHD filter is the most common method for target tracking. To implement the PHD filter, Vo et al. presented two approaches, namely the Sequential Monte Carlo PHD (SMC-PHD) [8] and the Gaussian mixture PHD (GM-PHD) [9]. In the SMC implementation, a large number of weighted particles are used to approximate the

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intensity function. Compared to the SMC implementation, the GM implementation with less weighted Gaussian components saves more running time.

The multi-target tracking algorithms mentioned above are mainly applied to the case of single sensor. To deal with multi-sensor multi-target tracking, the Iterated-PHD filter is proposed in [5]. Its performance is influenced by the order of the sensor updates and low probability of detection. Compared to the Iterated-PHD filter, the product multi-sensor PHD (PM-PHD) filter proposed by Mahler in [10] has a better performance in both cardinality estimation and stability. The PM-PHD filter requires calculating the quotient of two infinite sums, because it works on the assumption that the predicted number of targets obeys the Poisson distribution. Thus, the PM-PHD filter cannot be supplied in practical situations. A new multi-sensor PHD filter algorithm is proposed in [11], which gives a theoretical proof for a special case, called the 'true' two-sensor PHD filter. This algorithm treats the measurement set collected by each sensor as a unit and divides the joint measurement sets into different partitions. The difficulty to implement the 'true' two-sensor PHD filter is how to traverse all possible partitions. The computational complexities of the PM-PHD filter and the 'true' two-sensor PHD filter are approximate to $O\left(\overset{1}{m}{}^3 \cdots \overset{s}{m}{}^3 \cdot n\right)$ and $O(M! \cdot n)$, respectively, where $M = \sum_{i=1}^{s} m^i$, m^i is the measurement numbers of the ith sensor, s is the number of sensors and n is the current target numbers. Obviously, the computational complexities of the two algorithms are affected by the measurement numbers, which limits their application in target tracking. Comparatively, the Iterated-corrector solution seems easier to implement. In addition, several modified algorithms are proposed to apply in actual applications. The problem of multi-sensor registration errors is discussed in [12,13] and its Gaussian Mixture (GM) and Sequential Monte Carlo (SMC) implementation are given in [14,15]. A joint partition method based on the configuration of the sensors' field of views (FOVS) is described in [16,17]. This method can reduce the computation burden of the update step significantly.

In this paper, a heuristic method is proposed to reduce the influences of the order of the sensor updates and low probability of detection on the Iterated-PHD filter. By considering the order of sensor updates and the detection probability of each sensor simultaneously, the probabilities of detection and miss detection are modified in the improved algorithm. The improved algorithm can deal with the common problem arising in the Iterated-PHD filter effectively, and it has a good stability.

The rest of this paper is organized as follows. The RFS theory is described in Section 2. The motivation is described in Section 3. The improved Iterated-PHD filter and its Gaussian mixture implementation are presented in Section 4. Simulation results are performed in Section 5. Finally, Section 6 gives conclusions and future work.

2. Random finite set

In multi-target tracking, the dimensions of the state space vary with the number of targets. Since the number of targets and the number of measurements are a random process, the state set and the observation set can be represented by the RFSs of state space and observation space, respectively,

$$\mathbf{X}_k = \{\mathbf{x}_k^1, \ldots, \mathbf{x}_k^{N_k}\} \in \boldsymbol{F}(\mathbf{X}) \tag{1}$$

$$\mathbf{Z}_k = \{\mathbf{z}_k^1, \ldots, \mathbf{z}_k^{M_k}\} \in \boldsymbol{F}(\mathbf{Z}) \tag{2}$$

where $\boldsymbol{F}(\mathbf{X})$ and $\boldsymbol{F}(\mathbf{Z})$ are the sets of the state space $\mathbf{X}$ and the observation space $\mathbf{Z}$, respectively. N_k and M_k denote the number of targets and the number of measurements at time k, respectively.

If the state RFS at time $k-1$ is $\mathbf{X}_{k-1}$, and the state RFS $\mathbf{X}_k$ at time k can be expressed by

$$\mathbf{X}_k = \left(\cup_{\xi \in X_{k-1}} \mathbf{S}_{k|k-1}(\boldsymbol{\xi})\right) \cup \left(\cup_{\xi \in X_{k-1}} \mathbf{B}_{k|k-1}(\boldsymbol{\xi})\right) \cup \boldsymbol{\Gamma}_k \tag{3}$$

where $\mathbf{S}_{k|k-1}(\boldsymbol{\xi})$ is the RFS of targets which still survive at time k from a multi-target state $\boldsymbol{\xi} \in \mathbf{X}_{k-1}$. $\mathbf{B}_{k|k-1}(\boldsymbol{\xi})$ is the RFS of targets spawned by a previous multi-target state $\boldsymbol{\xi} \in \mathbf{X}_{k-1}$. $\boldsymbol{\Gamma}_k$ is the RFS of birth targets which appear instantly at time k.

Taking both the miss detection and the false alarm into account, and given a state $\mathbf{x} \in \mathbf{X}_k$, the observation RFS $\mathbf{Z}_k$ can be expressed by

$$\mathbf{Z}_k = \mathbf{K}_k \cup \left(\cup_{\xi \in \mathbf{X}_k} \boldsymbol{\Theta}_k(\boldsymbol{\xi})\right) \tag{4}$$

where $\mathbf{K}_k$ represents the observation set generated by the clutter, and $\boldsymbol{\Theta}(\boldsymbol{\xi})$ represents the observation set generated by the true targets.

To deal with the heavy computational burden in processing the joint probability density function of $\mathbf{X}_k$ and $\mathbf{Z}_k$ directly, Mahler proposed the probability hypothesis density (PHD) filter which can approximate the probability density of multi-target RFS with its first-order moment.

For an RFS $\mathbf{X}$ on the state space $\mathbf{X}$, its probability hypothesis density $D(\mathbf{X})$, also known as the intensity, is defined as

$$D(\mathbf{x}) = E\left[\sum_{\xi \in \mathbf{X}} \delta_\xi(\mathbf{x})\right] = \int \sum_{\xi \in \mathbf{X}} \delta_\xi(\mathbf{x}) p(\mathbf{X}) d\mathbf{X} \tag{5}$$

and for each region $\mathbf{S} \subseteq \mathbf{X}$, it satisfies

$$\int |\mathbf{X} \cap \mathbf{S}| P(d\mathbf{X}) = \int_{\mathbf{S}} D(\mathbf{x}) d\mathbf{x} \tag{6}$$

where $p(\mathbf{X})$ and $P(\mathbf{X})$ are probability density function and probability distribution function, respectively. In Eq. (6), the integral of D is equal to the mean number of elements of $\mathbf{X}$ that are in $\mathbf{S}$. Hence, the total number of elements in $\mathbf{X}$ can be obtained by rounding $\int D(\mathbf{x}) d\mathbf{x}$. The state of elements can be estimated by the local maximum points of D.

3. Motivation

3.1. Iterated-corrector PHD (Iterated-PHD)

The Iterated-corrector PHD filter [5] is an approximate solution to multi-sensor PHD filter by iterating the updated PHD of each sensor. The Iterated-corrector solution described in the Iterated-PHD filter can be applied in multi-sensor Bernoulli filter [18] and sensor bias estimation [14,19]. The Iterated-PHD filter consists of a prediction step and all sensors update equations, and it can degenerate to