Signal Processing 144 (2018) 352–363

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

A standard PHD filter for joint tracking and classification of maneuvering extended targets using random matrix

Qi Hu, Hongbing Ji*, Yongquan Zhang

School of Electronic Engineering, Xidian University, P.O. BOX 229, Xi'an, 710071, PR China

ARTICLE INFO

Article history:
Received 12 April 2017
Revised 22 September 2017
Accepted 27 October 2017
Available online 28 October 2017

Keywords:
Joint tracking and classification
Probability hypothesis density
Extended target tracking
Prior information

ABSTRACT

This paper presents a novel filter for jointly tracking and classification (JTC) of maneuvering extended targets using the standard probability hypothesis density (PHD) framework. For an extended target, the extended state that describes the target size, shape and orientation is also estimated, in addition to the kinematic state. Assuming that the target size information is known in advance, the presented filter can classify the extended target based on different sizes, instead of based on different kinematic motion modes in point target tracking. By utilizing the known target size information, the presented filter can contribute to a better extended state estimation while classifying, and how a good classification result can improve the estimation is mathematically analyzed. Simulation results show that the presented filter simultaneously provides a superior tracking performance and the correct classification of multiple extended targets, compared to the gamma Gaussian inverse Wishart PHD (GGIW-PHD) filter.
© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Tracking and classification of multiple maneuvering targets with unknown and time-varying number are the two basic procedures of a surveillance system. The tracking procedure refers to estimating the target state, while the classification procedure refers to classifying targets into given categories based on target prior information. However, the two procedures may be coupled [1] and the results of the tracking and classification can affect each other. For example, the estimation of the target state can be used to classify targets based on the prior information stored in the database of a system, in turn, a right classification of the target can contribute to a more accurate state estimation in the tracking procedure by utilizing the target prior information. In view of this, a possible solution is to simultaneously achieve the two procedures for the better performances of both the tracker and classifier, and the strategy used in this solution is called the joint tracking and classification (JTC) approach.

Traditional target tracking assumes that each target generates at most one measurement [2–8] at each time step, which is called the point target tracking. It is worth noting that this assumption is true only when the size of a target is smaller than a resolution cell of the sensor. Many literatures focus on the JTC of point targets [9–11], and they mainly utilize the prior motion models or attributes to classify targets. However, with the development of modern sensors or the small distance between the target and the sensor, a target may occupy several resolution cells and potentially generates multiple measurements per time step, which is called the extended target [12–25]. Unlike the JTC of point targets, more prior information on extended targets could be used into classification and this poses a new challenge for JTC of extended targets.

For extended target tracking, the kinematic state can be described by a Gaussian probability distribution [13]. The extended state of an extended target, describing the size, shape and orientation, can also be estimated by introducing the random matrix model [14–23] or random hypersurface model [24–25]. Especially the random matrix model, initialed by Koch [14], draws great attention in recent years. It models the extended state of the extended target as an ellipse that is represented by a symmetric positive define (SPD) random matrix, and the random matrix is described by an inverse Wishart distribution. In addition to the kinematic and extended states, a more general method attempts to estimate the measurement rate, which describes the number of measurements generated by an extended target at each time step. The measurement rate state is modeled as a scale random variable and described by a gamma probability density function (pdf). This model, firstly appeared in [16], is called the gamma Gaussian inverse Wishart (GGIW) method and describes the kinematic, extension and measurement rate of an extended target using Gaussian, inverse Wishart and gamma distributions, respectively.

The key for JTC of the extended target is how to incorporate the prior information into tracking procedure. Provided that the size prior information on extended targets is known, one possi-

* Corresponding author.
E-mail addresses: huqi_xidian@163.com (Q. Hu), hbji@xidian.edu.cn (H. Ji), zhangyq@xidian.edu.cn (Y. Zhang).

https://doi.org/10.1016/j.sigpro.2017.10.026
0165-1684/© 2017 Elsevier B.V. All rights reserved.

ble solution is to transfer the size prior information into pseudo-measurements (generated by prior information) and treat psuedo-measurements equally to the true-measurements (generated by targets) [26]. Then, the tracking of extended targets can use the measurements that include the target prior and real-time information, and the classification procedure can simultaneously be achieved according to the target extended state estimation in the tracking procedure. However, the algorithm for JTC of extended target proposed in [26] is a prototype, and many situations are not fully considered, such as orientation mismatch, target maneuvering, etc. Otherwise, to the best of our knowledge, the problem of JTC of extended target has previously not been explored in the random finite set (RFS) framework that is designed for multiple target tracking, which obviously does not meet the requirement of a system in complicated surveillance areas. Based on the RFS framework and finite set statistics (FISST) tool, lots of filtering frameworks are developed for multi-target tracking and those can be divided into two categories in our opinion. The first category is the suboptimal Bayesian framework that does not propagate full posterior multi-target RFS, such as probability hypothesis density (PHD) [5], cardinalized PHD (CPHD) [30] and cardinality-balanced multi-target multi-Bernoulli (CBMeMBer) [31] frameworks. The second category is the optimal Bayesian framework that propagates full posterior multi-target RFS. The representative example of the second category is the generalized labeled multi-Bernoulli (GLMB) [32–35] framework. Initialed by Vo [32], it theoretically propagates full posterior RFS of which unique and static labels are assigned to targets.

In this paper, based on the extended target PHD (ET-PHD) framework, we expand the JTC of the extended target into multiple maneuvering targets tracking and present a JTC-GGIW-PHD filter, which is capable of joint tracking and classification of an unknown and time-varying number of maneuvering extended targets in the presence of clutter, newborn targets and missed detections. The main contributions of this work are listed as follows: First, we present a JTC-GGIW implementation method, where the orientation mismatch and target maneuvering problems are considered. As an expanded version of the GGIW method, the JTC-GGIW method can simultaneously estimate the kinematic, extension, measurement rate and classification states of an extended target. Second, the JTC-GGIW method is applied in the ET-PHD framework, thus the resulting filter is called the JTC-GGIW-PHD filter. Third, we mathematically analyze how a good classification result of the presented filter can improve the performance of tracking in extended state estimation. Finally, the presented filter is demonstrated on simulated data from real scenarios, compared to the original GGIW-PHD filter [16].

The rest of this paper is organized as follows: Based on the original GGIW approach, Section 2 introduces the JTC-GGIW implementation method. We expand the JTC-GGIW method into the ET-PHD framework and the presented JTC-GGIW-PHD filter will be described in Section 3, and the performance of the presented filter are mathematically analyzed in Section 4. Section 5 demonstrates the simulation results of the presented filter, compared to the GGIW-PHD filter. Conclusions and future work are presented in Section 6.

2. JTC-GGIW

For a whole surveillance system, it contains a sequence of procedures, such as detection, tracking, classification and trajectory management. Due to coupling relationships of those procedures, the joint estimation strategy can be used to simultaneously achieve the two or more procedures for a better performance. That jointly achieving the tracking and classification procedures is called the JTC approach, which is a well-known application of the joint estimation strategy.

In this section, to improve the readability, the distributions and notations used in original GGIW method are summarized first. Then, we present a Bayesian inference for JTC of an extended target. Finally, the constant turn model with unknown turn rate [27] is introduced into the JTC of extended target framework, and the JTC-GGIW implementation method is described.

2.1. Distributions and notations

As the foundation of the presented JTC-GGIW method, a brief background on the GGIW method [16] will be introduced, especially for the used distributions and notations. In the GGIW method, the measurement rate, kinematic, and extended states of an extended target can be, respectively, modeled as follows:

$$(\gamma, \boldsymbol{x}, \boldsymbol{X}) \tag{1}$$

where measurement rate γ, kinematic state $\boldsymbol{x}$ and extended state $\boldsymbol{X}$ can be described using the gamma, Gaussian and inverse Wishart distributions, respectively. For a close form of iterative estimation in Bayesian framework, the pdfs for describing the prior and measurement likelihood distributions must follow the conjugate principle. The exponential family is a well-known conjugate prior class, and the conjugate pairs used in this method are Gaussian-Gaussian, gamma-Poisson and Wishart-inverse Wishart. The definitions of those distributions and some notations used in the GGIW method are summarized in Table 1.

2.2. Bayesian inference

Considering jointly processing the tracking and classification procedures, an extended target at time k can be remodeled as

$$(\gamma_k, \boldsymbol{x}_k, \boldsymbol{X}_k, \mathcal{C}) \tag{2}$$

where $\mathcal{C} = (\mathcal{C}^1, ..., \mathcal{C}^c, ..., \mathcal{C}^{n_c})$, n_c denotes the number of models in database and indicates that there are n_c different prior classes stored in database, and $\mathcal{C}^c$ represents the *cth* class. Usually, the states within different classes are independent of each other, and it is worth noting that the number of models can be assumed to be a constant for sake of simplification. Then, the probability function of the target state at time k is given by

$$\begin{aligned} p(\gamma_k, \boldsymbol{x}_k, \boldsymbol{X}_k, \mathcal{C}|Z^k) &= p(\gamma_k, \boldsymbol{x}_k, \boldsymbol{X}_k|\mathcal{C}, Z^k) \cdot p(\mathcal{C}|Z^k) \\ &= \sum_{c=1}^{n_c} p(\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c|\mathcal{C}^c, Z^k) p(\mathcal{C}^c|Z^k) \end{aligned} \tag{3}$$

where $Z^k = (Z_1, ..., Z_k)$ denotes all measurements up to time k and Z_k is the measurement set received at time k, and γ_k^c, $\boldsymbol{x}_k^c$ and $\boldsymbol{X}_k^c$ denotes the kinematic, extended and measurement rate states of the extended target in the *cth* class, respectively. The pdf $p(\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c|\mathcal{C}^c, Z^k)$ represents the tracking part. Due to the discreteness definition of the class, the probability function $p(\mathcal{C}|Z^k) = \{p(\mathcal{C}^1|Z^k), ..., p(\mathcal{C}^c|Z^k), ..., p(\mathcal{C}^{n_c}|Z^k)\}$ is called the probability mass function (pmf), which represents the classification part. Then, Using Bayesian formulas and under the one-order Markov state transition assumption, the inference of the tracking part can be obtained, i.e.

$$\begin{aligned} & p\left(\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c|\mathcal{C}^c, Z^k\right) \\ &= \left(\Delta_k^c\right)^{-1} p\left(Z_k|\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c, \mathcal{C}^c, Z^{k-1}\right) p\left(\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c|\mathcal{C}^c, Z^{k-1}\right) \\ &= \left(\Delta_k^c\right)^{-1} p\left(Z_{r,k}, Z_{p,c,k}|\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c, \mathcal{C}^c, Z^{k-1}\right) p\left(\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c|\mathcal{C}^c, Z^{k-1}\right) \\ &= \left(\Delta_k^c\right)^{-1} p\left(Z_{r,k}|\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c, \mathcal{C}^c, Z^{k-1}\right) p\left(Z_{p,c,k}|\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c, \mathcal{C}^c, Z^{k-1}\right) \\ & \cdot \int p\left(\gamma_k^c, \boldsymbol{x}_k^c, \boldsymbol{X}_k^c|\gamma_{k-1}^c, x_{k-1}^c, X_{k-1}^c\right) p\left(\gamma_{k-1}^c, x_{k-1}^c, X_{k-1}^c|\mathcal{C}^c, Z^{k-1}\right) \\ & d\gamma_{k-1}^c dx_{k-1}^c dX_{k-1}^c \end{aligned} \tag{4}$$

Download English Version:

https://daneshyari.com/en/article/6957946

Download Persian Version:

https://daneshyari.com/article/6957946

Daneshyari.com