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Probability hypothesis density filter for radar systematic bias estimation aided by ADS-B

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ABSTRACT

This paper provides a solution for systematic bias estimation of radar without priori information of data association based on the probability hypothesis density (PHD) filter aided by automatic dependent surveillance broadcasting (ADS-B). Novel dynamics model and measurement model of systematic bias are developed by using ADS-B surveillance data as the high-accuracy reference source. The Gaussian mixture probability hypothesis density (GM-PHD) filter is applied for recursive estimation of systematic bias by introducing the novel dynamics model and measurement model of systematic bias into the filter. Numerical results are provided to verify the effectiveness and improved performance of the proposed method for systematic bias estimation.

1. Introduction

The surveillance report of radar always comes along with errors. These errors consist two components: the random component (e.g. noise), and the systematic component (e.g. bias) (shown in Fig. 1). Stand-alone sensors are integrated into a single one in order to obtain improved performance in modern tracking systems. Therefore, systematic bias estimation and registration play key roles in multi-sensor tracking systems both in civilian and military applications. Many approaches have been introduced for solving this problem, and they can be classified into two categories: One is the offline estimation methods, e.g. the least squares bias estimation algorithm (LSE) [1], the generalized least squares bias estimation algorithm (GLSE) [2], and the maximum likelihood bias estimation algorithm (MLE) [3], etc. And the other is the online estimation methods, such as the Kalman-filter-based bias estimation algorithm [4,5], and neural-network-based bias estimation algorithm [6], etc. All of these algorithms supposed the association relationships between targets and measurements are completely known. Although the association relationships can be obtained via some classical association methods such as nearest neighbor (NN) [7], joint probabilistic data association (JPDA) [8], and multiple hypothesis tracking (MHT) [9], etc., the association results would become rather bad in the targets or clutter dense scene, especially before registration.

The random finite sets (RFS) theory [10] has been proposed to tackle the multi-target tracking problems. MAHLER developed the probability hypothesis density (PHD) filter [11], which is the first order moment approximation to full multi-target filter in RFS framework. The Gaussian mixture probability hypothesis density (GM-PHD) filter [12], proposed by VO, is a main approach to implement the PHD recursion for linear Gaussian model, in which the weights, means and covariance matrices of Gaussian component are propagated by the Kalman filter. The nonlinear Kalman filter (e.g. Extended Kalman filter or Unscented Kalman filter) can

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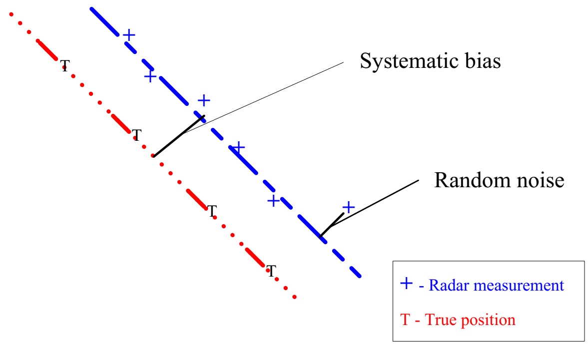

Fig. 1. Sensor measurement errors.

be directly used in the nonlinear dynamics model and measurement model [13]. LIAN and LI proposed the bias estimation algorithm using probability hypothesis density filter for the first time [14,15], but the measurements of the target must be obtained by at least two distributed radars, hence, the multi-sensor approximation form of PHD filter is used, which is valid only for relatively large number of targets [15].

The automatic dependent surveillance broadcasting (ADS-B), which has been widely equipped in civil aviation, collects position, speed and other information from airborne equipments such as global position system (GPS). Then the airborne ADS-B transmitter broadcasts the reports via air-ground data link (e.g. very high frequency Data Link, VDL). ADS-B land receiver could locate the targets using the reports. The ADS-B always provides surveillance data with much higher accuracy of location than radar, so the ADS-B surveillance data could be used as the high-accuracy reference source. BESADA proposed an off-line method for estimation of systematic bias using ADS-B in air traffic control [16]. HE considers a time delay between ADS-B reports and radar measurements in the systematic bias estimation of single radar [17]. But they supposed the association relationships are priori known, and do not take multi-target scene into account.

In this paper, we propose a novel method of estimating systematic bias of radar. Two major contributions in the proposed method are

- The novel dynamics model and measurement model of systematic bias are developed by using ADS-B as the reference source.
- Our method is capable of estimating the systematic bias of radar in multi-target tracking scene without priori information of association by introducing the novel dynamics model and measurement model of systematic bias into the PHD filter.

Numerical results are provided to verify the effectiveness and improved performance of the PHD filter for systematic bias estimation of radar aided by ADS-B.

The rest of this paper is organized as follows. In Section 2, the novel dynamics model and measurement model of systematic bias are developed. The GM-PHD recursion for systematic bias estimation of radar is proposed in Section 3. Numerical results are presented in Section 4, and conclusions are drawn in Section 5.

2. Dynamics model and measurement model of systematic bias

Radar measurements contain the range ($\tilde{r}_k^{(i)}$), azimuth ($\tilde{\theta}_k^{(i)}$) and elevation ($\tilde{\varphi}_k^{(i)}$). They can be modeled as

$$\begin{cases} \tilde{r}_k^{(i)} = r_k^{(i)} + \Delta r + nr_k^{(i)} \\ \tilde{\theta}_k^{(i)} = \theta_k^{(i)} + \Delta\theta + n\theta_k^{(i)} \\ \tilde{\varphi}_k^{(i)} = \varphi_k^{(i)} + \Delta\varphi + n\varphi_k^{(i)} \end{cases}, \tag{1}$$

where $\left(r_k^{(i)}, \theta_k^{(i)}, \varphi_k^{(i)}\right)$ presents the true position of the target in the polar coordinate, Δr, $\Delta\theta$ and $\Delta\varphi$ are the systematic biases of range, azimuth and elevation, respectively. $nr_k^{(i)}$, $n\theta_k^{(i)}$ and $n\varphi_k^{(i)}$ are measurement noises.

ADS-B report is presented in geographic coordinate, e.g. the target position is presented as latitude, longitude and height above the sea level. While radar measurement is presented in radar-centered local polar coordinate, and the target position is measured by range, azimuth and elevation. Thus a coordinate transformation is needed to produce a unified coordinate system for dynamics and measurement model. In this paper, the radar-centered Cartesian coordinate is used as the unified coordinate system.

At time step$k$, ADS-B report $(L_{k,ADS-B}^{(i)}, \lambda_{k,ADS-B}^{(i)}, H_{k,ADS-B}^{(i)})$ of target i is generated by the airborne GPS navigation system, where $L_{k,ADS-B}^{(i)}$, $\lambda_{k,ADS-B}^{(i)}$, and $H_{k,ADS-B}^{(i)}$ denote latitude, longitude and height above the sea level, respectively. It can be transformed to ECEF (Earth-centered Earth-fixed) coordinate using the following:

$$\begin{cases} Ex_{k,ADS-B}^{(i)} = (C + H_{k,ADS-B}^{(i)}) \cos L_{k,ADS-B}^{(i)} \cos \lambda_{k,ADS-B}^{(i)} \\ Ey_{k,ADS-B}^{(i)} = (C + H_{k,ADS-B}^{(i)}) \cos L_{k,ADS-B}^{(i)} \sin \lambda_{k,ADS-B}^{(i)} \\ Ez_{k,ADS-B}^{(i)} = \left[C(1-e^2) + H_{k,ADS-B}^{(i)}\right] \sin L_{k,ADS-B}^{(i)} \end{cases}, \tag{2}$$

where$C = \frac{E_q}{(1 - e^2 \sin^2 L_{k,ADS-B}^{(i)})^{\frac{1}{2}}}$, e denotes the eccentricity of the earth, and E_q denotes the equatorial radius [17].

Suppose that the radar station in the geographic coordinate is $(L_{RS}, \lambda_{RS}, H_{RS})$, and its ECEF coordinate $(Ex_{RS}, Ey_{RS}, Ez_{RS})$ can be obtained using Eq. (2).

The ADS-B report of target i in ECEF coordinate $\left(Ex_{k,ADS-B}^{(i)}, Ey_{k,ADS-B}^{(i)}, Ez_{k,ADS-B}^{(i)}\right)$ can be transformed to the radar-centered Cartesian coordinate $(Cx_{k,ADS-B}^{(i)}, Cy_{k,ADS-B}^{(i)}, Cz_{k,ADS-B}^{(i)})$ as follows:

$$\begin{bmatrix} Cx_{k,ADS-B}^{(i)} \\ Cy_{k,ADS-B}^{(i)} \\ Cz_{k,ADS-B}^{(i)} \end{bmatrix} = \begin{bmatrix} Ex_{k,ADS-B}^{(i)} - Ex_{RS} \\ Ey_{k,ADS-B}^{(i)} - Ey_{RS} \\ Ez_{k,ADS-B}^{(i)} - Ez_{RS} \end{bmatrix} + \mathbf{T}_{RS} \begin{bmatrix} Ex_{k,ADS-B}^{(i)} \\ Ey_{k,ADS-B}^{(i)} \\ Ez_{k,ADS-B}^{(i)} \end{bmatrix}, \tag{3}$$

where $(Ex_{RS}, Ey_{RS}, Ez_{RS})$ is the ECEF coordinate of radar