Int. J. Electron. Commun. (AEÜ) 69 (2015) 281–289

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

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

Bearings-only maneuvering target tracking based on truncated quadrature Kalman filtering

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ARTICLE INFO

Article history:
Received 20 May 2014
Accepted 19 September 2014

Keywords:
Maneuvering target tracking
Truncated quadrature Kalman filtering
Least square method

ABSTRACT

In this paper, a novel bearings-only maneuvering target tracking algorithm based on truncated quadrature Kalman filtering (TQKF) is proposed. In the proposed method, when the target maneuvers, in order to reduce the effect on performance duo to the increasing variance of the prior distribution, a modified prior distribution based on the current measurement is proposed. In the update step, the first two moments of the modified prior distribution is approximately estimated based on the least square estimation method and Gauss–Hermite quadrature rule, and the posterior distribution is jointly updated by using the prior distribution and the modified prior distribution. Moreover, in order to adaptively choose the estimated results obtained by the prior PDF and the truncated prior PDF, a fuzzy logic approach in which a Gaussian membership function is employed is proposed to determine the weight α. Finally, the experiment results show that the proposed algorithm results in more accurate tracking than the existing one, namely, the unscented Kalman filter (UKF), the quadrature Kalman filter (QKF), interact multiple model extended Kalman filter (IMMEKF) and multiple model Rao–Blackwellized particle filter (MMRBPF).

1. Introduction

Bearing-only maneuvering target tracking by multiple passive sensors is a problem of considerable importance in a variety of fields including radar, sonar and oceanography. Source localization and tracking has therefore received considerable attention in the literature, and has resulted in many different estimation schemes [1,2]. In many applications the tracking problem is further complicated because the motion and/or location of the sensors is uncertain [2]. The bearings-only tracking (BOT) problem is unobservable without sensor maneuvers for a passive sensor, the azimuth and elevation measurements do not allow an instantaneous range determination. To solve this problem, two solutions have been considered. First, if the passive sensor platform is allowed to move freely [3], it is possible to recover range observability by selecting an appropriate path for the platform. The problem of a passive tracking using a single sensor of uncertain location is discussed in [4]. However, in some applications, the sensor platforms have very slow mobility compared with the target dynamics, so this solution is not feasible. A possible solution is to use several passive sensors and fuse their information in some way to estimate the range [5,6]. In this paper we are focused on the problem of bearings-only maneuvering target tracking by multiple passive sensors.

For the bearings-only maneuvering target tracking, many algorithms have been presented in the literature, including the probabilistic multi-hypothesis tracking (PMHT) algorithm [7], Markov Chain Monte Carlo (MCMC) methods [8], and particle filtering [9,10]. A promising approach is the interacting multiple model (IMM) algorithm, originally developed by Blom [11], which is based on a hybrid system description of the maneuver scenarios, the occurrence of target maneuvers is explicitly included in the kinematics equations through regime jumps. In the presence of clutter, the integration of the IMM and PDAF is an efficient solution to the uncertainty of measurement origins. Li et al. [12] proposed a multiple model Rao–Blackwellized particle filter (MMRBPF) based algorithm for maneuvering target tracking in a cluttered environment. Rao-Blackwellization allows the algorithm to be partitioned into target tracking and model selection sub-problems, where the target tracking can be solved by the probabilistic data association filter, and the model selection by sequential importance sampling. The main shortcoming of their method is its heavy computational load.

Another difficulty with BOT is that it is a nonlinear problem. The usual approach for recursive estimation is to employ an extended Kalman filter (EKF) [13]. Because the LOS is an incomplete position observation, it cannot be converted into Cartesian coordinates to allow for linear filtering. In recursive bearings-only tracking, the use

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http://dx.doi.org/10.1016/j.aeue.2014.09.013
1434-8411/

of the Cartesian coordinate EKF exhibits erratic estimation results and unstable behavior [13], even without the detrimental effects caused by the presence of false detections or clutter. To alleviate this problem, Julier and Uhlmann proposed the unscented Kalman filter (UKF) [14], which can captures the posterior mean and covariance accurately to the 2nd order for any nonlinearity by recursively propagating a set of carefully selected sigma points, with errors only introduced in the 3rd and higher orders. However, in certain conditions, e.g., if the measurements are sufficiently precise, the UKF approximates the posterior poorly. The mathematical proof that explains why the UKF does not work well for informative measurements is given in [15]. In order to improve the performance of the UKF for informative measurements, García-Fernández et al. [16] proposed the truncated unscented Kalman filtering (TUKF), which approximated the PDF of the measurement noise by a truncated one and approximated Kalman filter equations applied to a mixture of the prior and a truncated version of the prior. When the measurement is informative, the performance of the TUKF is better than that of any other conventional Kalman-filter-type algorithms. The disadvantage is that the TUKF requires the measurement function of the current state to be bijective so that it cannot be widely used as a general Kalman filtering algorithm. However, the TUKF can be generalized to be able to deal with certain kinds of non-bijective measurements functions. In [17], García-Fernández proposed the mixture truncated unscented Kalman filtering (MTUKF) as a generalization of the TUKF when the likelihood has a support made up of several regions.

In this paper, we develop a truncated quadrature Kalman filtering (TQKF) for bearings-only maneuvering target tracking. The main contribution of the TQKF includes two parts:

(1) In the TQKF, unlike the unscented Kalman filtering (UKF) and quadrature Kalman filtering (QKF) [18], a modified prior distribution based on the current measurement is defined, which can effectively reduce the variance of the prior distribution when the target maneuvers, and improve the approximate accuracy of the prior distribution. So the TQKF can be used to track the maneuvering target.
(2) A novel bearings-only maneuvering target tracking algorithm based on TQKF is developed. In the TUKF, in order to approximate the first two moments of the modified prior pdf, the measurement function is required to be bijective. In the passive tracking environment, the measurement function is highly nonlinearity which cannot meet the requirement of TUKF. Therefore, in the proposed method, the first two moments of the modified prior distribution is approximately estimated by using the least square estimation method and Gauss–Hermite quadrature rule. Finally, the posterior distribution is jointly updated by using the prior distribution and the modified prior distribution.

The rest of the paper is organized as follows. In Section 2, the problem formulation is presented. In Section 3, the proposed maneuvering target tracking algorithm is presented, including the basic theory and the truncated quadrature Kalman filtering. The experiment results are provided in Section 4. Finally, some conclusions are given in Section 5.

2. Problem formulation

Consider the nonlinear discrete time dynamic system:

$$x_k = f(x_{k-1}) + w_{k-1} \tag{1}$$

$$z_k = h(x_k) + v_k \tag{2}$$

where $x_k \in \Re^{n_x}$ is the system state vector at time k, $z_k \in \Re^{n_z}$ is the measurement vector at time k. $f(\cdot)$ and $h(\cdot)$ represent some known nonlinear functions respectively. $w_{k-1} \in \Re^{n_w}$ denotes the process noise, $v_k \in \Re^{n_v}$ denotes the measurement noise.

With a single passive sensor, when the sensor is allowed to move freely, it is possible to recover range observability by selecting an appropriate path. For a stationary multiple passive sensor system, to avoid observability problem, the range must be acquired through multiple passive sensors. This paper considers multiple passive sensors. The observation equation is defined as

$$Z_k = H(x_k) + V_k \tag{3}$$

where

$$Z_k = [z_k^{1T} \quad z_k^{2T} \ldots z_k^{nT}]^T = [(\theta_1, \beta_1)^T (\theta_2, \beta_2)^T \ldots (\theta_n, \beta_n)^T]T \tag{4}$$

$$H(X_k) = [h_1(x_k)^T \quad h_2(x_k)^T \ldots h_n(x_k)^T]^T \tag{5}$$

$$V_k = [v_k^{1T}\, v_k^{2T} \ldots v_k^{nT}]^T \tag{6}$$

where θ_i denotes the azimuth originated from sensor i, β_i denotes the elevation originated from sensor i, $h_i(x_k)$ is the nonlinear measurement equation of sensor i, and V_k denotes the measurement noise vector. We assume that the angle errors $v_k^i (i = 1, 2, \ldots, n)$ are mutually independent and the measurement noise V_k has a diagonal covariance R_k:

$$R_k = E(V_k V_k^T) = \mathrm{diag}[\sigma_{\theta_1}^2 \sigma_{\beta_1}^2, \ldots, \sigma_{\theta_n}^2 \sigma_{\beta_n}^2] \tag{7}$$

where $(\sigma_{\theta_i}^2 (i = 1, 2, \ldots n))$ is the azimuth error variance of the sensor i, and $\sigma_{\beta_i}^2 (i = 1, 2, \ldots n)$ is the elevation error variance of sensor i.

3. Proposed maneuvering target tracking method

3.1. Basic theory

We assume the state vector as $x_k = [a_k^T, b_k^T]^T$, where $a_k \in R^{n_a}$, $b_k \in R^{n_b}$, and $n_x = n_a + n_b$, so the measurement equation can be written as

$$z_k = h(a_k) + v_k \tag{8}$$

where $h(\cdot)$ is the nonlinear function of a_k. The derivation of the TUKF must subject to two basic hypotheses: (1) the measurement function $h(\cdot)$ is a bijective, continuous function; (2) the PDF of the additive noise has a bounded, connected support

(9)$p_\eta(v_k) = 0, \quad \eta \notin I_n \subset R^{n_z}$.where I_η is an n_z-dimensional connected region. According to hypotheses 2, the measurement likelihood function given the state can be written as

$$p(z_k | x_k) = p(z_k | a_k) = p_\eta(z_k - h(a_k))\chi_{I_\eta}(z_k - h(a_k)) \tag{10}$$

where $\chi_{I_\eta}(\cdot)$ is the indicator function on the subset I_η.

According to hypotheses 1, (11) can be written as

$$p(z_k | x_k) = p_v(z_k - h(a_k))\chi_{I_{x(z)}}(x_k) \tag{11}$$

where

$$I_x(z_k) = \{x_k | x_k = [(h^{-1}(z_k - v_k))^T, b_k^T]^T, v_k \in I_v, \\ b_k \in R^{n_b}\} = I_a(z_k) \times R^{n_b} \tag{12}$$

Applying Bayes' rule and (12), the posterior PDF of x_k is

$$p(x_k | z_k) \propto p(z_k | x_k) \cdot p_0(x_k) = p_v(z_k - h(a_k))\chi_{I_{x(z)}}(x_k) p_0(x_k) \\ \propto p(z_k | x_k) \cdot p_1(x_k; z_k) \tag{13}$$