Optik 127 (2016) 2840–2847

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Integrated Unscented Kalman filter for underwater passive target tracking with towed array measurements

D.V.A.N.Ravi Kumar[a,*], S.Koteswara Rao[b], K.Padma Raju[c]

[a] GVPCEW, JNT University, Kakinada, India
[b] KL University, Vijayawada, India
[c] JNT University, Kakinada, India

ARTICLE INFO

Article history:
Received 13 June 2015
Accepted 23 November 2015

Keywords:
Extended Kalman filter
Unscented Kalman filter
Towed array
Least squares estimator
Integrated Unscented Kalman filter

ABSTRACT

Under water moving target is usually tracked using the Traditional non-linear estimators such as Extended Kalman filter (EKF) and Unscented Kalman filter (UKF) with the help of noisy measurements given by a SONAR operating in passive mode. Here in this paper an Integration Technique based approach which works on the principle "Collective Opinion is better than individual" is proposed to improve the performance of the existing algorithms. In this novel method multiple UKFs accept measurements from towed array and the estimates of these different UKFs are integrated using least squares estimator, and hence the algorithm is named as Integrated Unscented Kalman filter (IUKF). Monte Carlo simulation in MATLAB R2009a is carried out to compare the performance of the proposed IUKF with the existing traditional nonlinear estimators EKF and UKF for two different scenarios to show the superiority of the proposed method.

1. Introduction

Tracking is a sophisticated process of estimating the state (i.e. position and velocity) of a moving target as close to the true state as possible using the available noisy measurements. This is essential in the war environment for two main reasons, One to escape ourself from being attached, and second to demolish the enemy. The noise corrupted measurements can be received from SONAR in active or passive mode. Active mode involves a process of intentional release of signal, Reception of echo and getting an idea of Range and Azimuth of the target while passive mode SONAR is restricted only to listen and hence it gives only Azimuth measurements of the target. The drawback associated with active SONAR is, the concept of releasing the signal at enemy can cause us to be detected prior to the enemy being detected. This setback is not associated with passive SONAR due to the absence of signal transmission. The advantage of using active measurements over passive measurements is that, the tracking with former can be done easily due to the availability of range measurement along with the bearing measurement which is not the case with the later. The pros and cons are associated with both the measurements. So an intensive research is going on in the field of Target Tracking using both types of measurements with an edge of passive over active tracking.

The Traditional Kalman Filter (KF) Eqs. (5.17), (5.18) and (5.19) of [1] can be used to track an underwater Moving Target with active SONAR measurements where the state and measurement equations are linear with the simple assumption that the measurement Gaussian noise mean is zero even after conversion of measurements from polar to Cartesian systems as shown in [7]. The improved performance is achieved by applying (KF) after proper calculation of actual mean and covariance of the measurement noise in Cartesian system and subtracting this mean from the measurements to make the mean of measurement noise zero. The resulted (KF) with debiasing is applied for active tracking in [7].

Tracking a target with passive measurements cannot be done by traditional (KF) due to the incapability of (KF) to deal with nonlinear measurement equation associated with passive measurements. A nonlinear version of (KF) named as extended kalman filter (EKF) does this job by approximating the non-linear measurement equation to a linear one with the help of Taylor Series Expansion. Application of (EKF) in modified polar coordinates to BOT is available in [5]. The performance of Bearings-only Tracking (BOT) using passive measurements with EKF is brought to a newlevel by introducing a modified gain function in a covariance matrix of state vector which prevents the occasional divergence and estimator instability. The resulted estimator is called as Modified Gain Bearings-Only extended Kalman filter (MGBEKF) [6].

* Corresponding author. Tel.: +91 8985482118.
E-mail address: ravikumardwarapu@gvpcew.ac.in (D.V.A.N.Ravi Kumar).

http://dx.doi.org/10.1016/j.ijleo.2015.11.217

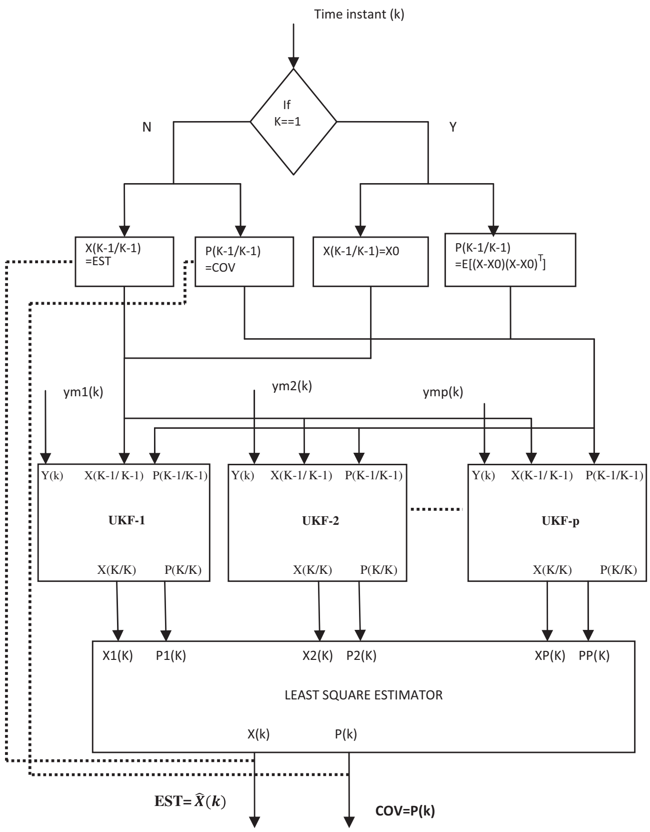

Fig. 1. Block diagram of IUKF.

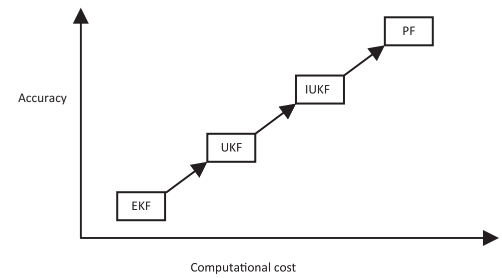

Fig. 2. Comparision of the Nonlinear Estimators.

The BOT with passive measurements life made easier with the introduction of Unscented Kalman filter (UKF) by Julier and Uhlmann [4] which uses an unscented Transformation of mean and co-variance over a non-linear measurement transfer function with the help of sigma points. The application of UKF to BOT is shown in [8]. The superiority of UKF over EKF for BOT using towed array measurements is shown in [3].

The recent work going on in the area of BOT is the usage of Particle Filter (PF) and its derivatives [1,2]. The appreciation of PF is first due to its capability to deal with highly nonlinear measurement equation associated with passive tracking, and second to deal with non-Gaussian measurement noise. The drawback of PF is that, atleast 1000 particles are needed which in turn requires sophisticated processors and a lot of computational time.

Here in this paper a novel method based on integration technique named as Integrated Unscented Kalman filter (IUKF) is introduced. This works on the principle of "Collective Opinion of state is better than individual one" So multiple UKFs give opinion about the state of the target and uncertainty levels in their opinion after receiving measurements from towed array. From these multiple opinions,a final estimate of the state will be made by the Least Square Estimator(LSE). The block diagram of IUKF is shown in Fig. 1. This approach has an advantage of low estimation errors over the traditional nonlinear estimators EKF, UKF and at the same time the computational time is much lesser than PF as shown in Fig. 2. So this Integration Based Estimator can serve the purpose of BOT in optimal sense.

Section 2 deals with the mathematical modeling of tracking (State & measurement models), Proposed Integration Technique and different metrics to compare the performance of IUKF with traditional non-linear estimators. Section 3 explains the Simulation, analysis and results of 2 scenarios (a prototype scenario, and a wartime scenario) and finally the paper is concluded with Section 4.

2. Mathematical modeling

2.1. State model of a moving target

Let $x(k)$, $y(k)$ be the position components of the target with respect to origin in x and y directions respectively at time instant k. $\dot{x}(k)$, $\dot{y}(k)$ be the velocity components in x and y directions respectively at time instant k.

Then the state vector at time instant k can be written as

$$X(k) = \left[x(k) \quad y(k) \quad \dot{x}(k) \quad \dot{y}(k)\right]^T \tag{1}$$

The target dynamics can be modeled as linear, discretized wiener velocity model

$$\begin{bmatrix} x(k+1) \\ y(k+1) \\ \dot{x}(k+1) \\ \dot{y}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(k) \\ y(k) \\ \dot{x}(k) \\ \dot{y}(k) \end{bmatrix} + Q(k) \tag{2}$$

where ΔT is the time interval between the states, $Q(k)$ is the Gaussian process noise with a mean zero and a co-variance as given in Eq. (13) of [3] is as follows

$$E\left[Q(k)Q(k)^T\right] = \begin{bmatrix} \frac{\Delta T^3}{3} & 0 & \frac{\Delta T^2}{2} & 0 \\ 0 & \frac{\Delta T^3}{3} & 0 & \frac{\Delta T^2}{2} \\ \frac{\Delta T^2}{2} & 0 & \Delta T & 0 \\ 0 & \frac{\Delta T^2}{2} & 0 & \Delta T \end{bmatrix} q$$

where q is the spectral density of the acceleration errors

Eq. (2) can now be expressed as

$$X(k+1) = FX(k) + Q(k) \tag{3}$$

With state transition matrix

$$F = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

2.2. Measurement model of towed array

let S1 and S2 be two stationary sensors located on the towed array at (S1(1), S1(2)), (S2(1), S2(2)) with respect to origin and ($x(k)$, $y(k)$) be the coordinates of the position of target with respect to