International Journal of Pure and Applied Mathematics
Volume 117 No. 21 2017, 301-309
ISSN: 1311-8080 (printed version); ISSN: 1314-3395 (on-line version)
url: http://www.ijpam.eu
Special Issue
ijpam.eu

Active Sonar Target Tracking Using Extended Kalman Filter

[1]J.Venkateswara Rao,[2]U.Dinesh,[3]S.Koteswara Rao,
[4]B.Omkar LakshmiJagan
[1,2]Department of Electronics and Communication Engineering
KoneruLakshmaiah Education Foundation,
Vaddeswaram, Guntur, Andhra Pradesh, India-522502
venkateshjonnalagadda1@gmail.com, dineshuppala7@gmail.com
[3]Department of Electronics and Communication Engineering
KoneruLakshmaiah Education Foundation,
Vaddeswaram, Guntur, Andhra Pradesh, India-522502
skrao@kluniversity.in
[4]Department of Electrical and Electronics Engineering
KoneruLakshmaiah Education Foundation,
Vaddeswaram, Guntur, Andhra Pradesh, India-522502
omkarjagan@gmail.com

Abstract

In underwater, object data is received by active sonar. The activesonar produces object range and bearing measurements. Extended Kalman filter (EKF) is used to reduce the noise incorrupted measurements for generation of object motion parameters(OMP). OMP is communicated to the aircraft through a link namely ultra-high frequency link for further processing. Results obtained in the simulation are presented.

Key Words: Global positioning system, active sonar, object motion analysis, statistical signal processing.

1. Introduction

In anunderwaterobject, tracking is a very challengingtask. Activesonarisequipped with acoustic sensor to get the estimated path of the object. In this research paper, object tracking is done by implementing the Extended Kalman Filter (EKF) algorithm.

Active sonarprovides the most effective airborne warfare in the world today [1,2]. It is used to detect object with help of floating sensor system. It contains a float-bag kind of assembly as the upper unit supporting the equipment submerged in water. Activesonars are integrated withGlobal positioning system (GPS) to determine the accurate position of object path. Data received by the active sonar are processed and sent to the aircraft by means of an ultra-high frequency link for further processing.

Tracking of the object is carried out by Extended Kalman filter (EKF) [3-5]. In this paper, the vital contribution is tracking of a maneuvering object, as suggested in [6]. Object maneuver cannot be predicted simply by observing bearing residual plot. So, zero mean chi-square distributed random sequence residuals in sliding window is used for finding the maneuver of the object. Normalized squared innovation process is used to identify whether an object is maneuvering or not. To get the best result during object maneuver sufficient amount of process noise is added to the covariance. When the maneuver is finished state noise is lowered back.The featured processingof Kalmanfilter.

It is assumed that observer is at the origin and stand still. The object moves with uniform speed (V_t)and course (TCR). Initially, the observer and object are assumed at be a distance R meters. An imaginary line joining object and observer positions is called a line of sight (LOS) and it makes an angle (bearing) with respect to True North/Y-axis as shown in Fig.1 [7-9].It is assumed that object and observer are in the same plane. The measurements are made in active mode for every t seconds.

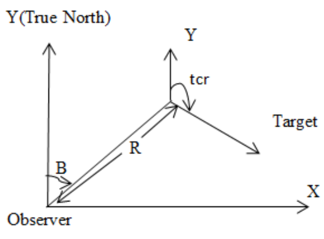

Fig.1: Object and Observer Scenario

Block diagram of TMA in simulation mode is shown in Fig.1.The object motion parameters (OMP) are estimated by the corrupted measurements using EKF. The estimated TMP is compared with that of true values and the performance analysis of the algorithm is carried out against a number of scenarios [10-12].

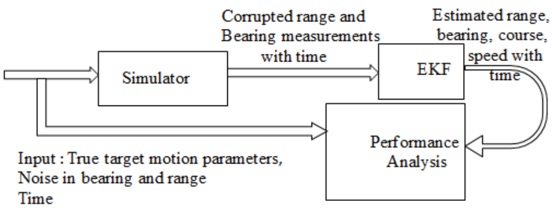

Fig.2: Block Diagram of TMA in Simulation Mode

Section 2 contains in mathematical modelling. Sections.Simulation and the results for the given scenarios in section 3.

2. Mathematical Modelling

A. Modeling of state vector and measurements

The $X_o(i)$ bestate vector is

$$X_o(i) = [\dot{x}(i)\dot{y}(i)R_x(i)R_y(i)]^T \quad (1)$$

Where$\dot{x}(i)$ and $\dot{y}$ (i) areobject velocitiesand $R_x(i)$ and $R_y(i)$ areobjectrangecomponents in x and y directions respectively.The State equations

$$X_o(i+1) = \varnothing(i+1/i)X_o(i) + b(i+1) + \omega(i) \quad (2)$$

Where$\omega(i)$ is plant noiseand $\varnothing(i+1/i)$ is

$$\varnothing(i+1/i) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ t & 1 & 1 & 0 \\ 0 & t & 0 & 1 \end{bmatrix} \quad (3)$$

Here t is measurement interval. b(i+1), deterministic matrix is

$$b(i+1) = [0 \;\; 0 \; -[x_0(i+1) + x_0(i)] - [y_0(i+1) + y_0(i)]^T \quad (4)$$

where $x_0(i)$and $y_0(i)$are observer position components. To reduce the mathematicalcomplexity, TrueNorth convention is followed. Z(i) is measurement vector

$$Z(i) = \begin{bmatrix} B_m(i) \\ R_m(i) \end{bmatrix} \quad (5)$$

Where$B_m(i)$ and$R_m(i)$ are measurements and they are defined as

$$B_m(i) = B(i) + \gamma(i) \quad (6)$$

$$R_m(i) = R(i) + \eta(i) \quad (7)$$

WhereB(i) , true bearings

$$B(i) = \tan^{-1}\left(\frac{R_x(i)}{R_y(i)}\right) \quad (8)$$

R(i), trueranges

$$R(i) = \sqrt{R_x^2(i) + R_y^2(i)} \quad (9)$$

The measurement and plant noises are uncorrelated measurement equation is

$$Z(i) = H(i)X_o(i) + \xi(i) \quad (10)$$

where $H(i) = \begin{bmatrix} 0 & 0 & \frac{\cos\hat{B}(i)}{\hat{R}(i)} & \frac{-\sin\hat{B}(i)}{\hat{R}(i)} \\ 0 & 0 & \sin\hat{B}(i) & \cos\hat{B}(i) \end{bmatrix}$ (11)

$\hat{B}(i)$ and $\hat{R}(i)$denotes estimated values. And

$$\xi(i) = \begin{bmatrix} \gamma(i) \\ \eta(i) \end{bmatrix} \quad (12)$$

The Extended Kalman filter algorithm is presented in Table1.

Table 1: Extended Kalman Filter Equations

1.To start with estimationX(0/0), P(0/0) which are initial state and covariance matrix respectively.
2.Predicted state vector$X_o(i+1)$ is
$X_o(i+1) = Ø(i+1/i)X_o(i) + b(i+1) + \omega(i)$
3.The predicted state covariance matrix is
$P(i+1/i) = Ø(i+1/i)P(i/i)Ø^T(i+1/i) + Q(i+1)$(13)
Wherecovariance of plant noise is represented as Q(i) and it has the value σ_ω^2
4. Gain is given as
$G(i+1) = P(i+1/(i)H$^T $(i+1)$ 〖$[r(i+1) + H(i+1)P(i+1/(i)H$^T $(i+1)])$〗 ^(-1))(14)
where input measurement covariance matrix is r(i).
5.The estimated state and its covariance error are
$X(i+1/(i+1) = X(i+1/(i) + G(i+1)[Z(i+1) - Z\check{}(i+1)]))$(15)
$P(i+1/i+1) = [1 - G(i+1)H(i+1)P(i+1/i)$(16)
6.For the next iteration
$X(i/i) = X(i+1/i+1)$(17)
$P(i/i) = P(i+1/i+1)$(18)

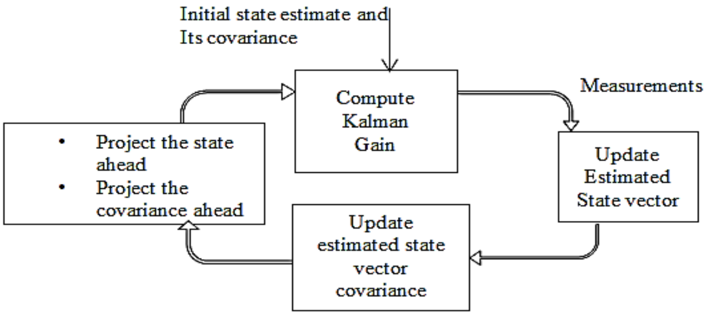

Fig. 3: ExtendedKalman Filter Process

3. Simulation and Results

It is assumed that the experiment is conducted at favorable environmental conditions. This simulation is carried out on a personal computer using Matlab.

The scenario chosen for evaluation of the algorithm is shown in Table 2. For example, scenario1 describes an object moving at an initial range of 4000m with course and speeds of 2100and 5m/s respectively. The initial line of sight is 600. Bearing and range measurements are corrupted with 0.330(1σ) and 10m(1 σ) respectively.

The velocity of sound in seawaters is 1500m/s. As the maximum range of an object is chosen as 4000m, the time taken for the transmitted pulse to reach the object and come back to the observer is (6000/1500) 4seconds. Hence measurements are taken at 4 s interval. In simulation mode, estimated and actual values are available and hence the validity of the solution based on certain acceptance criterion is possible. The solution is converged when course estimate error is<= $3^0$and speed estimate error is <= 1m/s. The estimates and true paths of the object are shown in Fig.4.a, for scenario1.For clarity of the concepts, the errors in the estimated course and speed for scenario1are presented in Fig.5.aand 6.a The solution is converged when the course and speed are converged. The convergence time (seconds) for the scenario is given in Table.3. In simulation, it is observed that the estimated speed,course of the object are converged at 12th sample and 13th sample respectively for the chosen scenario. So, the total solution is obtained at 13thsample (that is52s).

Table 2: ScenarioChosen forNon-maneuvering Object

Scenario	Object range(m)	Object bearing(deg)	Object course(deg)	Object speed(m/s)	Range corrupted with(1σ)(m)	Bearing corrupted with (1σ)(deg)	Observer speed(m/s)
2	4000	135	290	8.5	10	0.33	0.2

Table 3: Convergence Time (samples) for Non-maneuvering Object

Scenario	Course	Speed	Total convergence
1	11	8	11

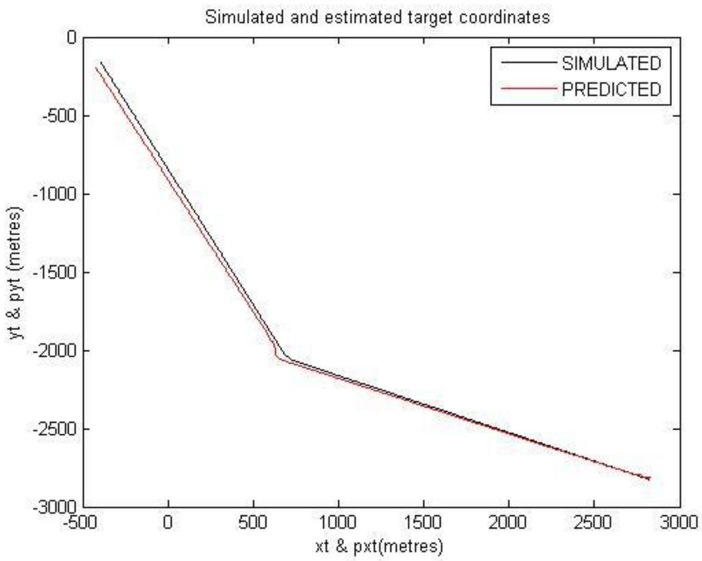

Fig.4: Simulated and Estimated Target Coordinates

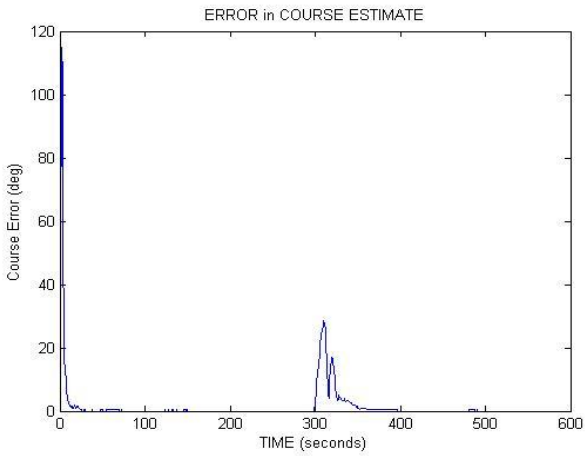

Fig. 5: Course Estimate Error

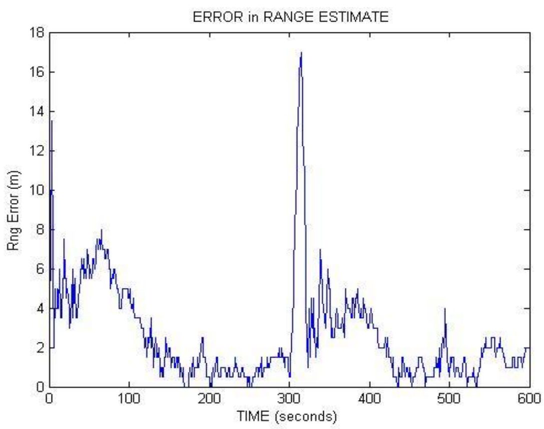

Fig. 6: Range Estimate Error

4. Conclusion

The implementation of Extended Kalman Filter (EKF) algorithm is explained in this paper. EKF algorithm is used to estimate object motion parameters by using active sonar. Simulation results are carried out. Based on the results, EKF is recommended to track underwater objects by using active sonar .

References

[1] Edwin E. Westerfield, Dennis J Duven, Larry L. Warnke, Development of a global positioning system/active sonar system for determining Ballastic missile impact points, john Hopkins APL Technical digest 5(4)(1984), 335-340.

[2] Gregory J. Baker, Bonin Y.R.M., GPS equipped active sonar, http://www.sokkia.com.tw/NOVATEL/Documents/Waypoint/Reports/active sonar.pdf

[3] Blackman S., Popolli R., Design and analysis of modern tracking systems, Norwood, MA, Artech House (1999).

[4] Barshalom Y., Fortman T.E., Tracking and Data association, Academic Press, Inc., San Diego, USA (1991).

[5] Bar-shalmon Y., Lee X.R., Estimation and tracking principles, Techniques and Software, Artech House, Boston, London (1993).

[6] KoteswaraRao S., Algorithm for detection of maneuvering targets in bearings only passive target tracking, IEE proc.-sonar Navig 146(3) (1999), 141-146.

[7] Gordon N., Ristic B., Arulampalam S., Beyond the kalman filter: Particle filters for tracking applications, Artech House, London (2004).

[8] KoteswaraRao S., Modified gain extended Kalman filter with application to bearings only passive maneuvering target tracking, IEE proc. Radar Sonar navig. 152(4) (2005), 239-244.

[9] Liu Y., Li X.R., Measure of Nonlinearity for Estimation, IEEE Trans. Signal Processing63(9) (2015), 2377-2388.

[10] Omkar Lakshmi Jagan B., KoteswaraRao S., Kavitha Lakshmi M., Passive Target Tracking Using ESM Measurements in EW Environment, Journal of Advanced Research in Dynamical and Control Systems 10(3) (2017), 37-43.

[11] Omkar Lakshmi Jagan B., KoteswaraRao S., Kavitha Lakshmi M., Concert Assessment of Unscented and Cubature Kalman Filters for Target Tracking, Journal of Advanced Research in Dynamical and Control Systems 10(4) (2017), 48-56.

[12] KausarJahan, Koteswara Rao S., MGBEKF and UKF Application to Bearings-Only Tracking, International Journal of Pure and Applied Mathematics 116(24) (2017), 369-379.