Abstract: In underwater, object information is received by sonobuoy. The sonobuoy generates object range and bearing measurements. Extended Kalman filter is utilized to process the noise corrupted 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.

Keywords: Global positioning system, sonobuoy, object motion analysis, stochastic processing, statistical processing

1. Introduction

In an underwater object, tracking is a very challenging task. Sonobuoys are equipped 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.

Sonobuoys provide 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. Sonobuoys are integrated with Global positioning system (GPS) to determine the accurate position of object path. Data received by the sonobuoy 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 main contribution is tracking of a maneuvering object, as suggested in [6]. Object maneuver cannot be visualized easily by observing bearing residual plot. So, zero mean chi-square distributed random sequence residuals in sliding window is used for detecting the maneuver of the object. Normalized squared innovation process is used to find out whether an object is maneuvering or not. To get the finest solution during object maneuver sufficient amount of process noise is added to the covariance. When the maneuver is completed state noise is lowered back. The detailed processing of Kalman filter is shown in Fig.1.

Figure 1. Extended Kalman filter process

It is assumed that observer is at the origin and stand still. The object moves with uniform speed (Vt) 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.2 [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.

Figure 2. Object and Observer scenario
Block diagram of TMA in simulation mode is shown in Fig.3. The corrupted measurements are used to estimate object motion parameters (TMP) 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].

![Block diagram of TMA in simulation mode.](image)

Figure 3. Block diagram of TMA in simulation mode.

Section II contains in mathematical modelling. Sections III describes the simulation and the results obtained for the given scenarios.

2. Mathematical Modelling

A. Modeling of state vector and measurements

The $X_o(i)$ be state vector

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

(1)

Where $\dot{x}(i)$ and $\dot{y}(i)$ are object velocities and $R_x(i)$ and $R_y(i)$ are object range components in x and y directions respectively. The State equation is

$$X_o(i+1) = \mathcal{F}(i)X_o(i) + \mathcal{B}(i) + \omega(i)$$

(2)

Where $\omega(i)$ is plant noise and $\mathcal{F}(i+1)$ is

$$\mathcal{F}(i+1) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ t & 1 & 1 & 0 \\ 0 & t & 0 & 1 \end{bmatrix}$$

(3)

Here $t$ is measurement interval. $\mathcal{B}(i+1)$, deterministic matrix is

$$\mathcal{B}(i+1) = [0 \ 0 \ -x_0(i+1)+x_0(i) \ -y_0(i+1)+y_0(i)]^T$$

(4)

where $x_0(i)$ and $y_0(i)$ are observer position components.

To reduce the mathematical complexity, True North convention is followed. $Z(i)$ is measurement vector

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

(5)

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

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

(6)

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

(7)

Where $B(i)$, true bearing is

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

(8)

$R(i)$, true range is

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

(9)

The measurement and plant noises are uncorrelated. Measurement equation is

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

(10)

where

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

(11)

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

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

(12)

The Extended Kalman filter algorithm is presented in Table 1.
Table.1. Extended Kalman Filter equations

1. To start with estimation $x(0)$, $P(0)$ which are initial state vector and its covariance matrix respectively are chosen.

2. The predicted state vector $x_{k+1}$ is

$$x_{k+1} = A x_k + B u_k + w_k$$

3. The predicted state covariance matrix is

$$P_{k+1|k} = A P_{k|k} A^T + Q_k$$

4. Kalman gain is given as

$$K_{k+1} = P_{k+1|k} H^T (H P_{k+1|k} H^T + R)^{-1}$$

5. The state estimation and its error covariance are

$$\hat{x}_{k+1} = x_{k+1} + K_{k+1} (y_k - H x_{k+1})$$

$$P_{k+1} = P_{k+1|k} - K_{k+1} H P_{k+1|k}$$

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, scenario 1 describes an object moving at an initial range of 3000m with course and speeds of 2100 and 5 m/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 3000m, the time taken for the transmitted pulse to reach the object and come back to the observer is (6000/1500) 4 seconds. 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 error in course estimate <= 0.30 and error in speed estimate & It =< 1m/s. The estimates and true paths of the object are shown in Fig.4 for scenario 1. For clarity of the concepts, the errors in the estimated course and speed for scenario 1 are presented in Fig.5 and 6. 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 course and speed of the object are converged at 12th sample and 13th sample respectively for the chosen scenario. So, the total solution is obtained at 13th sample (that is 52s).

4. Conclusion

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

References


