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Review Article

IMPLEMENTATION OF UKF FOR TRACKING AN UNDERWATER TARGET USING DUNKING SONAR

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Abstract
In underwater, dunking sonar generates underwater target range and bearing measurements and the same information is communicated to a helicopter for further processing. The noise corrupted measurements are processed to estimate target motion parameters using online Unscented Kalman Filter. These estimates are useful to find out the track of the target, once the target direction is known then the weapon will release on to the target. Simulation results using Matlab are shown in this paper.

Keywords Dunking sonar, target motion analysis, Unscented Kalman filter

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INTRODUCTION

Target motion analysis (TMA), in two-dimensional scenario is mostly used in underwater atmosphere [1]. Dunking sonar is positioned in the sea from a helicopter in hovering mode to find out the path of the target submarine in sea waters. The sonar in active mode finds out target bearing and range measurements. These are communicated to the helicopter signal processing system through a cable. It is to assume that the target moves with uniform velocity and the observer is stand still. Observer estimates the target range, bearing, course and speed using the noise corrupted bearing and range measurements [2-3]. Unscented Kalman filter is used to smooth the measurements and to estimate course and speed the target. Using the estimated parameters, weapon pre-set parameters are calculated in helicopter fire control system to release weapon on the target. Now a days, signal processing technology is developing in vast areas in all engineering fields [4-10].

Mathematical modelling of target state vector, measurements and Kalman filter in brief are described in section2. Section 3 deals with implementation of the algorithm and generation of target motion measurements in simulation environment. In section 4 results obtained in simulation are described.

MATHEMATICAL MODELLING

Modelling of State Vector and Measurements

Let $X_S(\kappa)$ be state vector, given as:

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

Here $\dot{x}(\kappa)$ and $\dot{y}(\kappa)$ are target velocity and $R_x(\kappa)$ and $R_y(\kappa)$ are range components. The State equation of the target is:

$$X_s(\kappa+1) = \emptyset(\kappa+1/\kappa)X_s(\kappa) + b(\kappa+1) + \omega(\kappa) \quad (2)$$

Here $\omega(\kappa)$ is plant noise and transient matrix $\emptyset(\kappa+1/\kappa)$ is given as:

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

Here t is measurement interval and $b(\kappa+1)$ is deterministic matrix:

$$b(\kappa+1) = \begin{bmatrix} 0 \\ 0 \\ -(x_0(\kappa+1) - x_0(\kappa)) \\ -(y_0(\kappa+1) - y_0(\kappa)) \end{bmatrix}^T \quad (4)$$

Here $x_0(\kappa)$ and $y_0(\kappa)$ are observer position components. Measurement matrix $Z(\kappa)$ is given as:

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

Here $B_m(\kappa)$ and $R_m(\kappa)$ are measurements and they are defined as:

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

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

Where bearing and range is given as $B(\kappa)$ and $R(\kappa)$:

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

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

$\eta(\kappa)$ and $\gamma(\kappa)$ are the noises which are uncorrelated. The equation of measurement is:

$$Z(\kappa) = H(\kappa)X_s(\kappa) + \xi(\kappa) \quad (10)$$

$$\text{Here, } H(\kappa) = \begin{bmatrix} 0 & 0 & \frac{\cos\hat{B}(\kappa)}{\hat{R}(\kappa)} & \frac{-\sin\hat{B}(\kappa)}{\hat{R}(\kappa)} \\ 0 & 0 & \sin\hat{B}(\kappa) & \cos\hat{B}(\kappa) \end{bmatrix} \quad (11)$$

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

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

The Unscented Transform [2-6] algorithm is presented in Table1.

Table:1 Unscented Transform (UT) equations

In UKF, the mixing up of the initial states as well as noise variables are delineated as the state random variables. The sigma point selection method of UT is implemented to the delineated state random variables to calculate the corresponding matrix of sigma points [7-10]. Assume x as a variable having random characteristics and is propagating through a function $y = O(x)$ that is of nonlinear process. Let $\bar{x}$ be the mean of x and P_x be its covariance. The values of y are computed by contemplating a

matrix χ consisting of sigma vectors χ_i where i has a highest value of $2L_1 + 1$ (here L_1 is the matrix dimension of x). Each χ_i vector is given with consequent weight W_i. The χ matrix is developed by utilising the subsequent equations:

$$\chi_0 = \bar{x}$$

$$\chi_i = \bar{x} + \left(\sqrt{(L_1 + \lambda) + P_x}\right)_i \; i = 1,2, \dots \dots, L_1$$

$$\chi_i = \bar{x} - \left(\sqrt{(L_1 + \lambda) + P_x}\right)_{i-L_1} \; i = L_1 + 1, \dots \dots, 2L_1$$

$$W_0^{(m)} = \lambda/(L_1 + \lambda) \qquad (13)$$

$$W_0^{(c)} = \lambda \,/\, ((L_1 + \lambda) + (1 - \vartheta^2 + \xi))$$

$$W_i^{(m)} = W_i^{(c)} = 1/\big(2(L_1 + \lambda)\big) \; i = 1,2, \dots, 2L_1$$

where $\lambda = \vartheta^2(L_1 + \alpha) - L_1$ is a scaling factor. ϑ is assigned to a minor definite value that defines the distribution of sigma points over the mean. α is a scaling factor (generally set to zero) and ξ includes prior information of the spread of x ($\xi = 2$ is best possible for Gaussian process).

$\left(\sqrt{(L_1 + \lambda) + P_x}\right)_i$ represents the i^{th} row of the matrix square root. $W_0^{(m)}$,$W_0^{(c)}$, $W^{(m)}$ and $W^{(c)}$ represents the weights of initialized object state vector, state covariance matrix, state sigma point vector and state sigma point covariance matrix respectively. The nonlinear function used for propagating these sigma vectors is represented as

$$y_i = O(\chi_i) i = 1,2, \dots ., 2L_1 \qquad (14)$$

The mean and covariance of weighted posterior sigma points are used to estimate the mean and covariance of x [10].

Implementation of the Process

Initial of the target state vector, target velocity components are computed using first and second measurement sets of range and bearing measurements as shown in Table2.

Generation of target motion measurements in simulation environment

A simulator is developed to generate target range and bearing measurements. This simulator accepts the inputs given and simulates the observer and target positions. It generates range and bearing measurements at each second and corrupts with white Gaussian noise [8, 9].

Table:2 Unscented Kalman Filter Algorithm

The UKF implementation steps are as follows:

(a) Let n be the dimension of object state vector. $(2n + 1)$ state vectors are calculated from the initial points using sigma points:

$$X(\kappa) = \begin{bmatrix} X_s(\kappa) \\ X_s(\kappa) + \sqrt{(n + \lambda) + P(\kappa)} \\ X_s(\kappa) - \sqrt{(n + \lambda) + P(\kappa)} \end{bmatrix}^T \qquad (15)$$

(b) Based on the process model in (2), transform the sigma points.

(c) The predicted state estimate at time $(\kappa + 1)$ with κ measurements is given as:

$$X_s(\kappa + 1) = \sum_{i=0}^{2n} W_i^{(m)} X_s\big(i, (\kappa + 1)\big) \qquad (16)$$

(d) The predicted covariance matrix, assuming additive and independent process noise, is taken as:

$$P(\kappa + 1) = \sum_{i=0}^{2n} W_i^{(c)} \big[X_s\big(i, (\kappa + 1)\big) - X_s(\kappa + 1)\big]\big[X_s\big(i, (\kappa + 1)\big) - X_s(\kappa + 1)\big]^T + Q(\kappa) \qquad (17)$$

(e) The sigma points are updated using the predicted mean and predicted covariance as follows:

$$X(\kappa + 1) = \begin{bmatrix} X_s(\kappa + 1) \\ X_s(\kappa + 1) + \sqrt{(n + \lambda) + P(\kappa + 1)} \\ X_s(\kappa + 1) - \sqrt{(n + \lambda) + P(\kappa + 1)} \end{bmatrix}^T \qquad (18)$$

(f) Based on the measurement model given in (16), transform the predicted sigma points.

(g) The predicted measurement matrix is:

$$\hat{z}(\kappa + 1) = \sum_{i=0}^{2n} W_i^{(m)} Y(\kappa + 1) \qquad (19)$$

where $Y(\kappa + 1) = h(X_s(\kappa + 1))$ (20)

(h) The innovation covariance matrix is calculated as:

$$P_{yy} = \sum_{i=0}^{2n} W_i^{(c)} \big[Y\big(i, (\kappa + 1)\big) - \hat{z}(\kappa + 1)\big]\big[Y\big(i, (\kappa + 1)\big) - \hat{z}(\kappa + 1)\big]^T + \sigma_B^2(\kappa) \qquad (21)$$

(i) The cross-covariance matrix is calculated as:

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(c)} \big[X_s\big(i, (\kappa + 1)\big) - X_s(\kappa + 1)\big]\big[X_s\big(i, (\kappa + 1)\big) - X_s(\kappa + 1)\big]^T \qquad (22)$$

Kalman gain is calculated as:

$$G(\kappa + 1) = P_{xy} P_{yy}^{-1} \qquad (23)$$

(j) The estimated state is calculated as:

$$X(\kappa+1) = X(\kappa+1) + G(\kappa+1)\big(\hat{z}(\kappa+1) - \hat{z}(\kappa+1)\big) \quad (24)$$

where $z(\kappa+1)$is measurement vector matrix.

(k) The inaccuracy in estimated covariance matrix is:

$$P(\kappa+1) = P(\kappa+1) - G(\kappa+1)P_{yy}G^T(\kappa+1) \quad (25)$$

Here observer is presumed to be standstill at starting point. The movement of the target is uniform in conjunction to speed (v_t) and course (tcr). Initially the observer and target are assumed at be a distance R meters. Line joining observer and target is known as line of sight (LOS) and it makes an angle (bearing) with respect to North/Y-axis as shown in Fig.1. The measurements are made in active mode for every t seconds

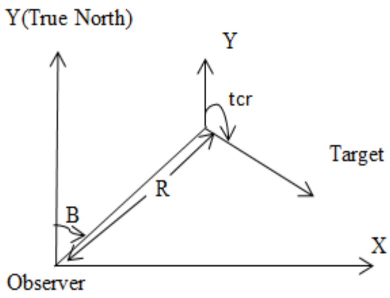

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Fig. 1 Target and Observer Scenario

The target position (x_t, y_t) with respect to origin is given by:

$x_t = R\ \sin(B)$ (26)

$y_t = R\cos(B)$ (27)

After t seconds

$dx_t = v_t\ \sin(tcr)\ t$ (28)

$dy_t = v_t\ \cos(tcr)\ t$ (29)

Now the new target position after time t is given as:

$x_t = dx_t + x_t$ (30)

$y_t = dy_t + y_t$ (31)

True bearing and range are calculated as follows

True bearing $= tan^{-1}(x_t - x_0)/(y_t - y_0)$ (32)

$true\ range = \sqrt{(x_t - x_0)^2 + (y_t - y_0)^2}$ (33)

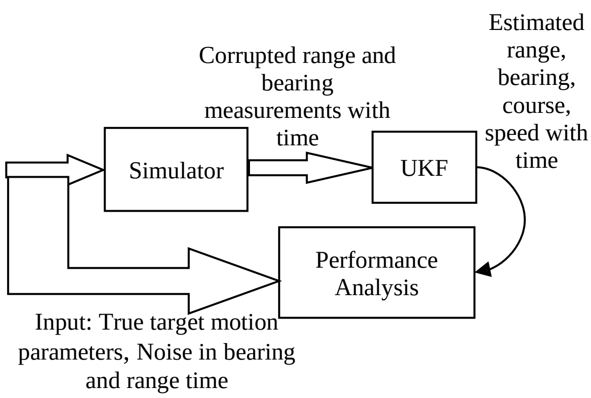

Fig. 2 Building blocks illustration of TMA in simulation

Figure 2 gives the block diagram of process followed for obtaining TMA in simulation mode. The corrupted observations are used to approximate target motion parameters (TMP) using UKF. The estimated TMP [10] are contrasted with that of actual values and the performance analysis of the algorithm is carried out against a number of scenarios.

IMPLEMENTATION AND OUTCOMES

It is presumed that research is steered at favourable environmental conditions where the measurements are available continuously. Simulation is done in a MATLAB environment. The scenarios preferred for valuation of algorithm are presented in Table III. For instance, scenario1 illustrates a target moving at an opening range of 3000m with course and speeds of 255° and 10m/s respectively. The opening line of sight angle is 45°. The azimuth bearing and range observations are distorted with a standard deviation in noise of 0.33° (1σ) and 7m (1 σ) respectively.

Table:3 Input Scenarios Chosen for the Algorithm

Parameters	Scenarios	
	1	**2**
Target's initial range (m)	3000	4000
Target's initial bearing (deg)	45	135
Target's initial Course (deg)	255	315
Target's initial speed (m/s)	10	8.5

The velocity of sound in seawaters is 1500m/s. As the maximum range of target is chosen as 3000m, the time taken by the transmitted signal to reach the target and return to observer is (6000/1500) 4 seconds. Hence measurements are taken at 4 s interval. In simulation mode, real values are obtainable and estimated values are found out and checked for validity of the result based on tolerance criteria. The tolerance measure is chosen as follows: inaccuracy in range <= 8% of true range, inaccuracy in course estimate <= 3° and inaccuracy in speed estimate <= 1m/s.

The estimations and real trajectories of target are shown in Fig.3 and Fig.4 for scenarios 1 and 2 respectively. For transparency of the concepts, the inaccuracies in speed and course estimate for scenario1and 2 shown in Fig.5 (a), 5 (b) and 6 (a) and 6 (b) respectively. The solution is said to be converged once the range, course and speed inaccuracies satisfy the tolerance criteria. The solution convergence time for given scenarios of Table III are given in Table IV. It is noted that the target course and speed estimate for scenario 1 are converged at 8th and 25th sample. Hence, for scenario 1, the total result is achieved at 25 samples (that is 100s) similarly for scenario 2, the approximated solution course and speed have converged at 10th and 22nd sample respectively. So, the convergence time for scenario 2 is obtained at 22nd sample (that is 88 s).

Table:4 Convergence time of solution obtained

Scenario	Course	Speed	Total solution
1	8	25	25
2	10	22	22

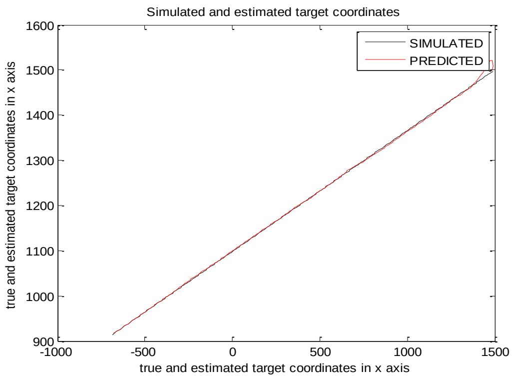

Fig. 3 Simulated and predicted target paths for scenario 1

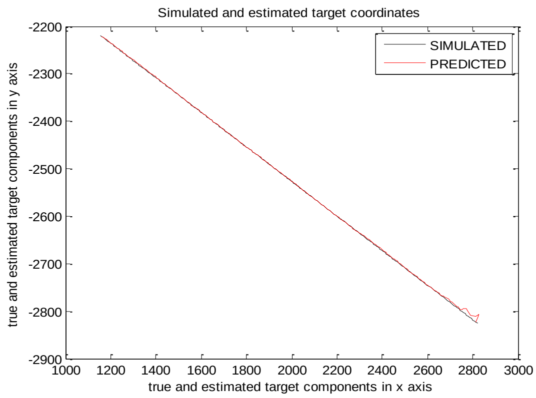

Fig. 4 Simulated and predicted target paths for scenario 2

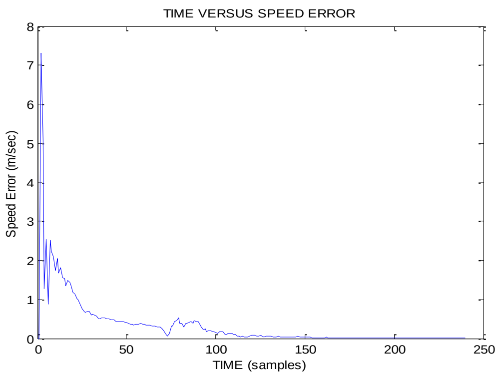

Fig. 5 (a) Inaccuracy in speed

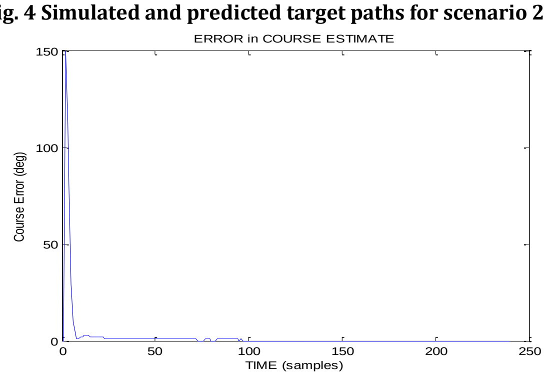

Fig.5(b).Inaccuracy in course estimate
Fig.5.Inaccuracies in estimates in scenario 1

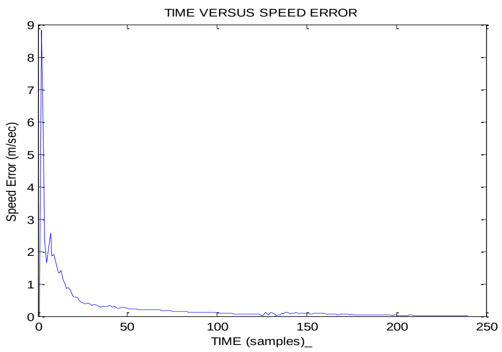

Fig.6(a).Inaccuracy in speed estimate

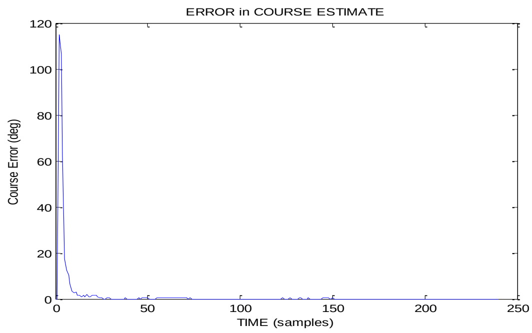

Fig.6(b).Inaccuracy in course estimate

Fig.6.Inaccuracies in estimate in scenario 2

CONCLUSION

Unscented Kalman filter is employed to approximate target path, direction and speed using dunking sonar system. Simulation is conducted in Matlab environment and outcomes are shown. Based on the results, UKF is recommended to track underwater targets using dunking sonar system.

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