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Maneuvering Target Tracking using GPS Aided Sonobuoy

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Abstract: In under water environment, Sonobuoy receives target information in the form of acoustic energy and process the data to get range and bearing measurements. Extended Kalman filter is used to process these noise corrupted measurements. This information about target motion parameters is communicated to the airplane by means of an ultra-high frequency link and airplane releases the weapon on to the target. Results obtained in simulation are presented.

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

1. INTRODUCTION

Sonobuoys provide the most effective airborne anti-submarine warfare in the world today [1,2]. Sonobuoy is a floating sensor system used to detect target submarines. It contains a float-bag kind of assembly as upper unit supporting the equipment submerged in water. Sonobuoys are Global positioning system (GPS) integrated such that accurate position of sonobuoy is known. To receive the target information sonobuoys are equipped with acoustic sensors for active target tracking. The data received by the sonobuoy is processed and sent to the aircraft by means of an ultra-high frequency link. Using this information about the target, aircraft releases the weapon on to the target.

Tracking of the target is carried out by Extended Kalman filter (EKF) [3-9]. In this paper, the main contribution is tracking of a maneuvering target, as suggested in [4,5].Target 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 maneuver of the target. Normalized squared innovation process is used to find out whether target is maneuvering or not. To get the finest solution during target maneuver enough amount of process noise is added to the covariance. When the maneuver is completed state noise is lowered back.

Section II contains with mathematical modelling and section III describes implementation of the process. Section IV deals with generation of measurements in simulation environment. Sections V describes simulation and the results obtained.

II. MATHEMATICAL MODELLING

A. *Modeling of State Vector and Measurements [10]*

The $X_s(k)$ be state vector is

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

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

$$X_s(k+1) = \phi(k+1/k)X_s(k) + b(k+1) + \omega(k) \tag{2}$$

where $\omega(k)$ is plant noise and $\phi(k+1/k)$ is

$$\phi(k+1/k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ t & 1 & 1 & 0 \\ 0 & t & 0 & 1 \end{bmatrix} \tag{3}$$

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

$$b(k+1) = [0 \quad 0 \quad -[x_0(k+1) + x_0(k)] - [y_0(k+1) + y_0(k)]]^{T} \tag{4}$$

where $x_0(k)$ and $y_0(k)$ are observer position components. To reduce the mathematical complexity, True North convention is followed. $Z(k)$ is measurement vector

$$Z(k) = \begin{bmatrix} B_m(k) \\ R_m(k) \end{bmatrix} \tag{5}$$

where $B_m(k)$ and $R_m(k)$ are measurements and they are defined as

$$B_m(k) = B(k) + \gamma(k) \tag{6}$$

$$R_m(k) = R(k) + \eta(k) \tag{7}$$

where $B(k)$, true bearing is

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

$R(k)$, true range is

$$R(k) = \sqrt{R_x^2(k) + R_y^2(k)} \tag{9}$$

The measurement and plant noises are uncorrelated. Measurement equation is

$$Z(k) = H(k)X_s(k) + \xi(k) \tag{10}$$

where

$$H(k) = \begin{bmatrix} 0 & 0 & \dfrac{\cos \hat{B}(k)}{\hat{R}(k)} & \dfrac{-\sin \hat{B}(k)}{\hat{R}(k)} \\ 0 & 0 & \sin \hat{B}(k) & \cos \hat{B}(k) \end{bmatrix} \tag{11}$$

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

$$\xi(k) = \begin{bmatrix} \gamma(k) \\ \eta(k) \end{bmatrix} \tag{12}$$

The Extended Kalman filter algorithm is presented in Table 1.

Table 1
Extended Kalman Filter equations

1.	To start with estimation X(0/0), P(0/0) which are initial state vector and its covariance matrix respectively are chosen.	
2.	Predicted state vector $X_s(k+1)$ is	
	$X_s(k+1) = \phi(k+1/k)\, X_s(k) + b(k+1) + \omega(k)$	
3.	The predicted state covariance matrix is	
	$P(k+1/k) = \phi(k+1/k)\, P(k/k)\, \phi^T(k+1/k) + Q(k+1)$	(13)
	where, $Q(k)$ is the covariance of plant noise and it has the value σ_ω^2	
4.	Kalman gain is given as	
	$G(k+1) = P(k+1/k)\, H^T(k+1)\, [r(k+1) + H(k+1)\, P(k+1/k)\, H^T(k+1)]^{-1}$	(14)
	where, $r(k)$ is input measurement covariance matrix.	
5.	The state estimation and its error covariance are	
	$X(k+1/k+1) = X(k+1/k) + G(k+1)\, [Z(k+1) - \hat{Z}(k+1)]$	(15)
	$P(k+1/k+1) = [1 - G(k+1)\, H(k+1)\, P(k+1/k)]$	(16)
6.	For the next iteration	
	$X(k/k) = X(k+1/k+1)$	(17)
	$P(k/k) = P(k+1/k+1)$	(18)

B. Target Maneuver Detection [10, 11]

When target is not maneuvering, the process noise is less. When target maneuvers, the process noise increases. So, in simulation, the covariance matrix is multiplied by fledge factor of 10 during target maneuver period. When target maneuver is completed, the process noise is lowered back after the completion of the target maneuver. The normalized squared innovations

$$\gamma_\varphi(k) = \varphi^T(k)\, s^{-1}(k+1)\, \varphi(k+1) \tag{19}$$

where $\varphi(k+1)$ is

$$\varphi(k+1) = Z(k+1) - h(k+1, X(k+1/k)) \tag{20}$$

Let $S(k)$ is

$$S(k+1) = H(k+1)\, P(k+1/k) H^T(k+1) + \sigma^2 \tag{21}$$

Let

$$d(\xi) = \gamma^T S^{-1} \gamma \geq c \tag{22}$$

where S is diag$\{S(k)\}$

and $$\gamma = \varphi(1) \quad \varphi(2) \quad \ldots\ldots \quad \varphi(k)]^T$$

where c is a constant (threshold) and d is chi-square distributed statistic. This sliding window size is chosen as 5.

III. Implementation of the Process

Initial target state vector, target velocity components are computed using first and second measurement sets of range and bearing measurements as shown in Table 2. The detailed processing of Kalman filter is shown in Figure 1.

A. *Generation of 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.

Table 2
Initialisation of state vector and its covariance matrix

Initial target state vector X(2/2) is given by

$$X(2/2) = [\text{term 1 term 2 } R_m(2) \sin B_m(2)]^T \quad (23)$$

where term 1 and term 2 are defined by

$$\text{term 1} = R_m(2) \sin B_m(2) - R_m(1) \sin B_m(1)/t$$

$$\text{term 2} = R_m(2) \cos B_m(2) - R_m(1) \cos B_m(1)/t \quad (24)$$

Assume that X(2/2) follows uniform distribution. Its covariance matrix is diagonal and given by

$$P_{00}(2/2) = \frac{4 \times \dot{x}^2(2/2)}{12} \quad (25)$$

$$P_{11}(2/2) = \frac{4 \times \dot{y}^2(2/2)}{12} \quad (26)$$

$$P_{22}(2/2) = \frac{4 \times R_x^2(2/2)}{12} \quad (27)$$

$$P_{33}(2/2) = \frac{4 \times R_y^2(2/2)}{12} \quad (28)$$

From the estimated state vector target motion parameters are calculated and given as

$$tcr(k) = \tan^{-1}\left(\frac{\dot{x}(k)}{\dot{y}(k)}\right) \quad (29)$$

$$v_t(k) = \sqrt{\dot{x}(k)^2 + \dot{y}(k)^2} \quad (30)$$

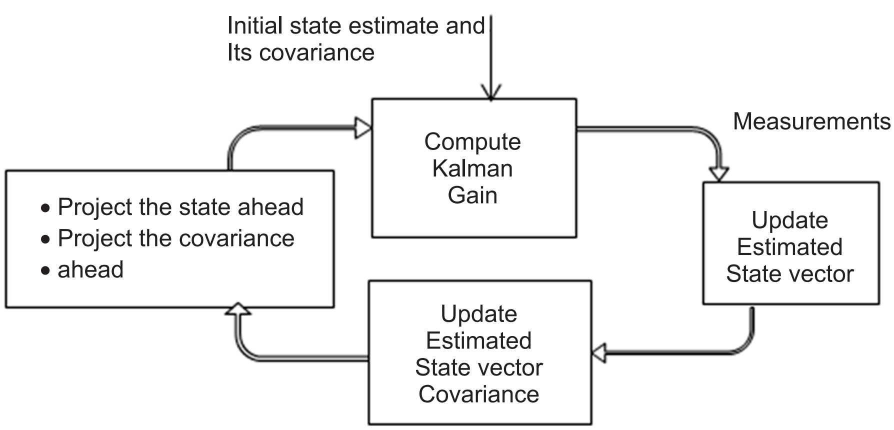

Figure 1: Extended Kalman filter process

It is assumed that the observer is initially at origin and moves at constant velocity v_0. Target moves with uniform velocity v_t and course (*tcr*) with occasional maneuver. Initially observer and target are at distance of R meters. It is assumed that the target and observer are in same plane and the measurements are made in active mode for every t seconds as shown in Figure 2.

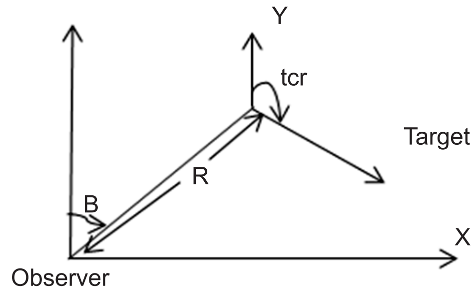

Figure 2: Target and Observer Scenario

Block diagram of target motion analysis in simulation mode is shown in Figure 3. The corrupted measurements are used to estimate target motion parameters (TMP) using EKF. The estimated TMP are compared with that of true values.

2. SIMULATION AND RESULTS

It is assumed that experiment is conducted at favorable environmental conditions. This simulation is carried out on a personal computer using Matlab. The scenario chosen for evaluation of algorithm is shown in Table 3. For example, scenario1 describes a target moving at an initial range of 3000m with course and speeds of 210° and 5 m/s respectively. The initial line of sight is 60°. The bearing and range measurements are corrupted with 0.33°(1σ) and 10 m(1σ) respectively.

The velocity of sound in seawaters is 1500 m/s. As the maximum range of target is chosen as 3000 m, the time taken for the transmitted pulse to reach the target and come back to 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 following acceptance criterion is chosen based on weapon control, this topic is not discussed here) requirement. The solution is converged when error in course estimate <= 3° and error in speed estimate <= 1 m/s.

The estimates and true paths of target are shown in Figure 4 for scenario1. For clarity of the concepts, the errors in estimated course and speed for scenario1 are presented in Figure 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.4. In simulation, it is observed that the estimated course and speed of the target 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).

Now it is assumed that the turn rate of the target is 3° and the maneuver starts at 300th sample. Target next course is 240°. So it takes 10 samples to maneuver 30° and the maneuver is completed at 310th sample. The scenario2 chosen for evaluation of algorithm for maneuvering target is shown in Table 5 and the convergence time (seconds) for the scenario2 is given in Table.6. The estimated and true paths of maneuvering target are shown in Figure 7. The errors in estimated course and speed for are presented in Figure 8 and 9. It is observed that the estimated course and speed of the target after maneuver are converged at 418th sample and 312th sample respectively for scenario 2. So, the total solution is obtained at 418th sample (that is 1672s).

From the results obtained, it is clear that EKF can be recommended for tracking submarine using sonobuoy.

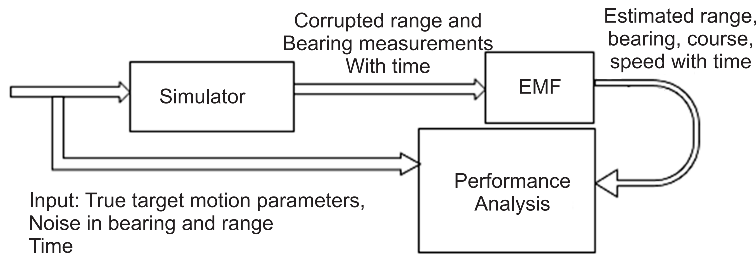

Figure 3: Block diagram for TMA in simulation mode

Table 3
Scenario chosen for non-maneuvering target

Scenario	*Target range (m)*	*Target bearing (deg)*	*Target course (deg)*	*Target speed (m/s)*	*Range corrupted with (1σ)(m)*	*Bearing corrupted with (1σ)(deg)*	*Observer speed (m/s)*
1	3000	60	210	5	10	0.33	0.5

Table 4
Convergence time (samples) for non- maneuvering target

Scenario	*Course*	*Speed*	*Total convergence*
1	12	13	13

Table 5
Scenario chosen for maneuvering target

Scenario	*Target range (m)*	*Target bearing (deg)*	*Target course (deg)*	*Target next course at 300th sample onwards (deg)*	*Target speed (m/s)*	*Range corrupted with (1σ)(m)*	*Bearing corrupted with (1σ)(deg)*	*Observer speed (m/s)*
2	3000	60	210	240	5	10	0.33	0.5

Table 6
Convergence time (samples) for maneuvering target

Scenario	*Course*	*Speed*	*Total convergence*
2	418	312	418

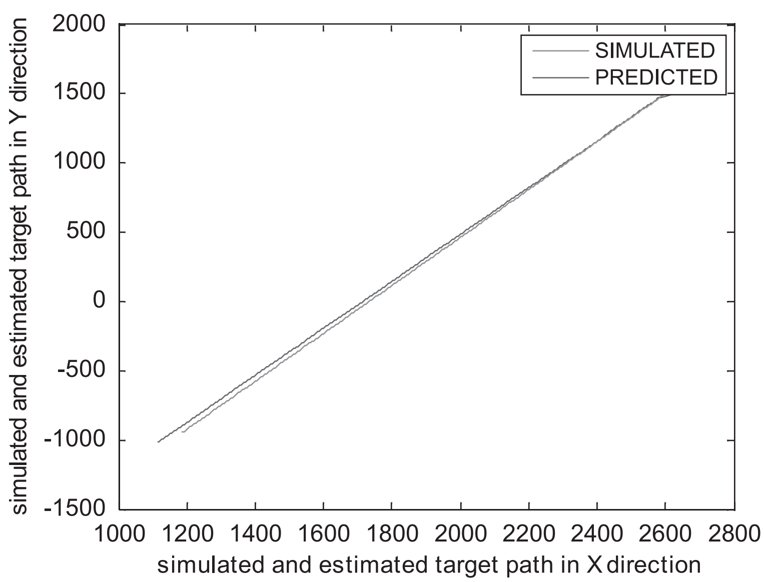

Figure 4: Simulated and estimated target paths

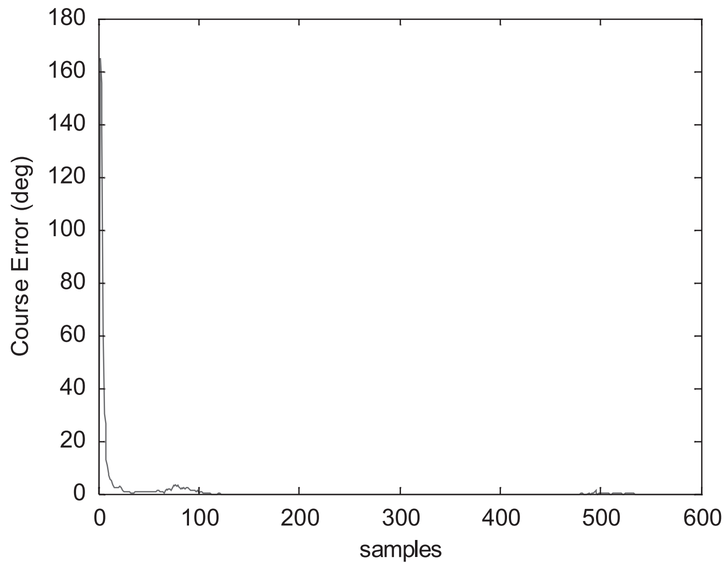

Figure 5: Error in course estimate

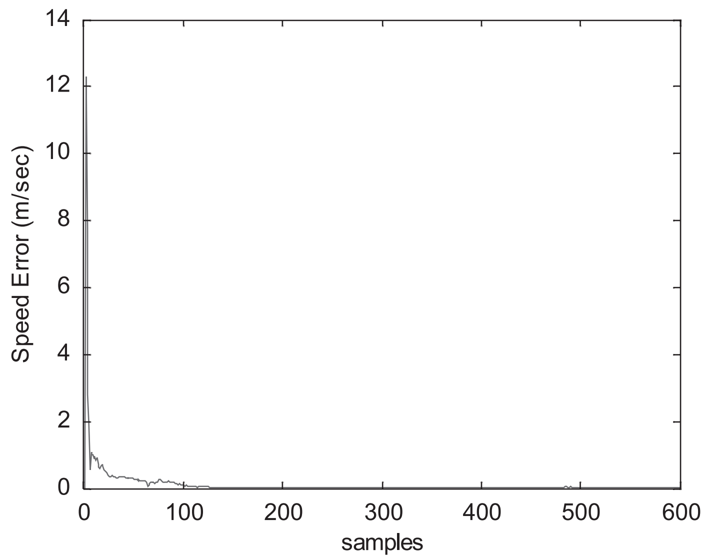

Figure 6: Error in speed estimate

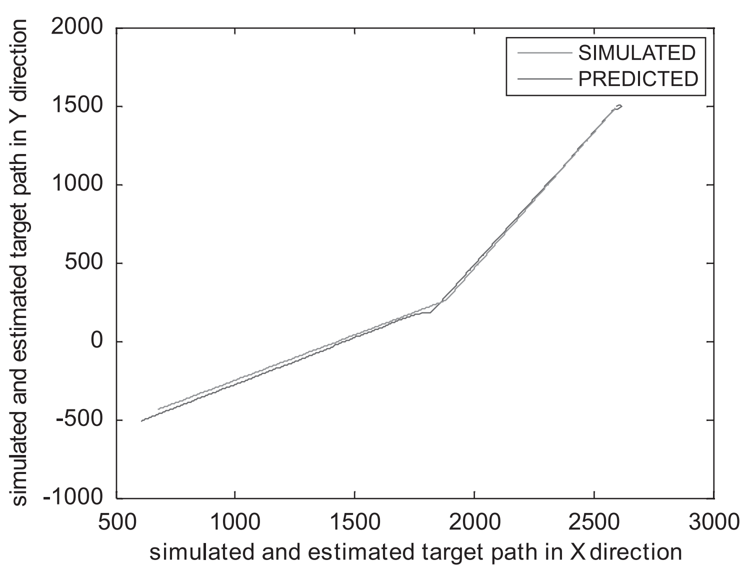

Figure 7: Simulated and estimated target paths

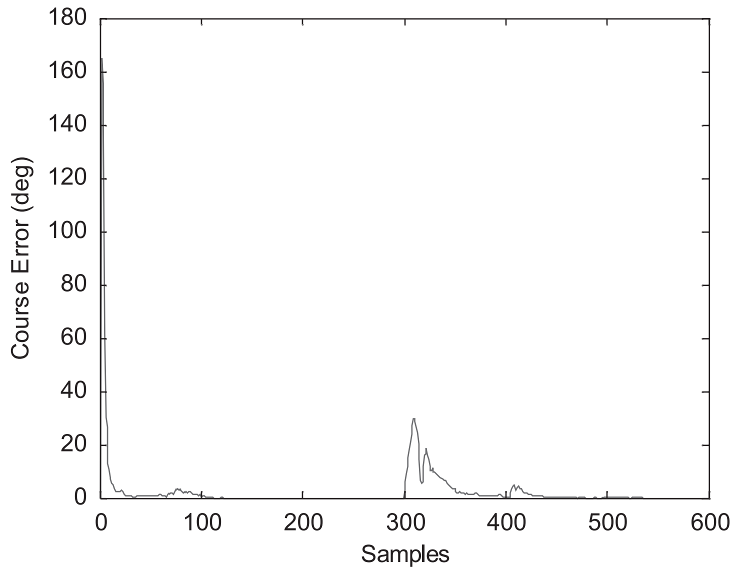

Figure 8: Error in course estimate

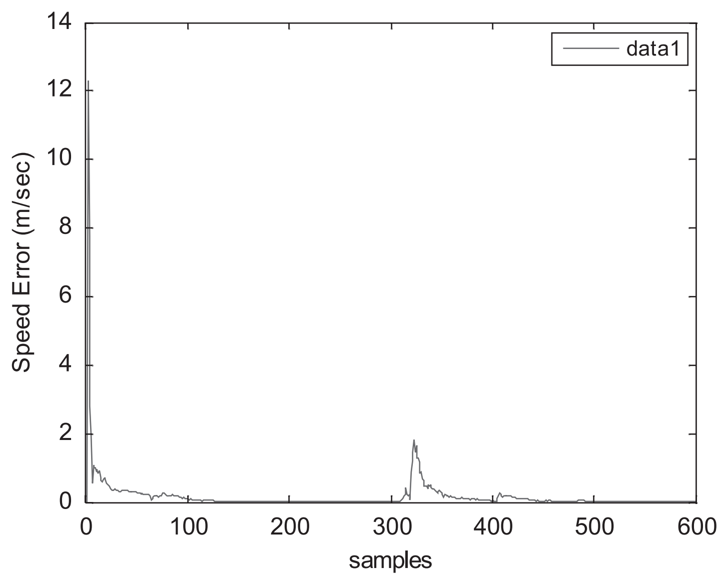

Figure 9: Error in speed estimate

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