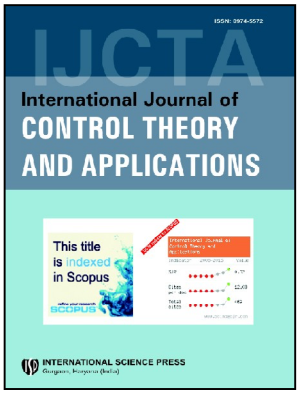

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Target Tracking Inautonomous Underwater Vehicle

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Abstract: The main objective of this research work is to inspect the path of the underwater target in active mode using Autonomous Underwater Vehicle (AUV). Range, bearing and elevation measurements of AUV are used to find out the target path using estimated course and speed. Unscented Kalman Filter (UKF) in AUV is discussed to track the target adaptively using normalized squared innovation process. Once the target is accessible to the weapon, AUV releases the weapon on to the target. As per the acceptance criterion, the target path with course error less than 3^0 and speed error less than 1m/s is calculated using UKF and the results are satisfactory.

Keywords: Target tracking, Stochastic processing, Statistical signal processing, Autonomous Underwater Vehicle (AUV)

1. INTRODUCTION

Autonomous under vehicle (AUV) is the safest underwater warfare system existing in the world today. AUV is a robot like system floating on the surface of sea mainly used in target tracking. It sends acoustic waves to track the target parameters like range, bearing and elevation. AUV processes the data to estimate target motion parameters. When the target is within reach, the weapon is released from AUV on to the target [1-3]. Target motion parameters particularly at long ranges are nonlinear. So, unscented Kalman filter (UKF) is considered based on rapidly convergent and unbiased filter problems in extended Kalman filter and modified gain extended Kalman filter.

In this paper, the main contribution is tracking of a maneuvering target. Target maneuver cannot be visualized easily by observing bearing residual plot. So, normalized squared innovation processis to detect the target maneuver by using sliding window format. The target is said to be maneuvered, when the innovations exceed the threshold. To get the fine solution during target maneuver more process noise is inputted to the covariance. When the maneuver is completed state noise is lowered back.

Section 2 deals with mathematical modeling and section 3 describes generalized simulator. Section 4 deals about the simulation results and then section 5 is conclusion.

2. MATHEMATICAL MODELLING

Let the state vectorwith $\dot{x}(k),\ \dot{y}(k),\ \dot{z}(k)$ (targetvelocities) and $R_x(k)\ R_y(k)\ R_z(k)$ (target ranges) in x and y directions. The state equation becomes[4]

$$X_s(k+1) = \text{Ø}X_s(k) + b(k+1) + \Gamma w(k) \tag{1}$$

Ø is given by

$$\phi = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ t & 0 & 0 & 1 & 0 & 0 \\ 0 & t & 0 & 0 & 1 & 0 \\ 0 & 0 & t & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

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

To reduce the mathematical complexity, true north convention is followed by all angles.

$Z(k)$ is the measurement matrix containing. $R_m(k)\ B_m(k)$ and $E_m(k)$ (measured Range Bearing and Elevation) and these are given by

$$R_m(k) = R(k) + \xi_R(k) \tag{3}$$

$$B_m(k) = B(k) + \xi_B(k) \tag{4}$$

$$E_m(k) = E(k) + \xi_E(k) \tag{5}$$

where, $R(k)\ B(k)$ and $E(k)$ are true range, true bearing and true elevation.Measurement vector is

$$Z(k) = H(k)\, X_S(k) + \xi(k) \tag{6}$$

where, H(k) is

$$\begin{bmatrix} 0 & 0 & 0 & \sin(E)\sin(B) & \sin(E)\cos(B) & \cos(E) \\ 0 & 0 & 0 & \dfrac{\cos(B)}{R_{xy}} & \dfrac{-\sin(B)}{R_{xy}} & 0 \\ 0 & 0 & 0 & \dfrac{\cos(E)\sin(B)}{R} & \dfrac{\cos(E)\cos(B)}{R} & \dfrac{-\sin(E)}{R} \end{bmatrix} \tag{7}$$

and

$$\xi(k) = [\xi_R\ \xi_B\ \xi_E]^T \tag{8}$$

The unscented Kalman filter is a combination of classical filter and an unscented transformation, which is made in order to transmit transformation in the model through a non-linear process. UKF gives adequately precise solution.

An easy method is adapted for a random variable to evaluate the statistical properties, that endures a non-linear transformation is called an unscented transformation. Suppose a random variable x, having an expected value x, covariance P_x and dimension L, imparting through y = g(x). 2L+1 sigma vectors are usedto compute statistics of y.

UKF implementation is as follows[5-9].

Table 1
UKF algorithm

1. Sigma state vectors are presented as

$$X(k) = \left[X_s(k) \quad \sqrt{(n+\lambda)p(k)} + X_s(k) \quad -\sqrt{(n+\lambda)p(k)} + X_s(k) \right] \tag{9}$$

2. The same are modified using equation (1),
3. The state vector is predicted as

$$X_s(k+1|k) = \sum_{i=0}^{2n} W_i^{(m)} X_s(i,k+1|k) \tag{10}$$

4. The predicted covariance matrix is

$$P(k+1|k) = \sum_{i=0}^{2n} W_i^{(c)} \left[X_s(i,k+1|k) - X_s(k+1|k) \right] \left[X_s(i,k+1|k) - X_s(k+1|k) \right]^T + S(k) \tag{11}$$

5. The updated state vector is

$$X(k+1|k) = \left[X_s(k+1|k) \quad X_s(k+1|k) + \sqrt{(n+\lambda)p(k+1|k)} \quad X_s(k+1|k) - \sqrt{(n+\lambda)p(k+1|k)} \right] \tag{12}$$

6. Then measurement predicted as

$$y(k+1|k) = \sum_{i=0}^{2n} W_i^{(m)} Y(k+1|k) \tag{13}$$

7. Covariance of innovation is

$$P_{yy} = R(k) + \sum_{i=0}^{2n} W_i^{(c)} \left[Y(i,k+1|k) - y(k+1|k) \right] \left[Y(i,k+1|k) - y(k+1|k) \right]^T \tag{14}$$

8. cross covariance is

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(c)} \left[X(i,k+1|k) - X(k+1|k) \right] \left[Y(i,k+1|k) - y(k+1|k) \right]^T \tag{15}$$

9. Kalman gain is

$$G(k+1) = inv(P_{xy} P_{yy}) \tag{16}$$

10. The state is estimated as

$$X(k+1|k+1) = G(k+1)(y(k+1|k+1) - y(k+1|k) + X(k+1|k) \tag{17}$$

11. Its covariance is

$$P(k+1|k+1) = -G(k+1) P_{yy} G(k+1)^T + P(k+1|k) \tag{18}$$

2.1. 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. Oncetarget maneuver is fulfilled, the process noise is lowered back after the completion of the target maneuver. The normalized squared innovations is

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

where $\varphi(k+1)$ is

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

Let S(k)

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

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

where S is diag{S(k)}

and $$[\varphi(1) \quad \varphi(2) \; \ldots \ldots \; \varphi(k)]^T$$

where c is a constant (threshold) and d is chi-square distributed statistic. This sliding window size is chosen as5.

Initial target state vector, target velocity components are computed using first and second measurement sets of range bearing and elevation measurements. The detailed processing of Kalman filter is shown in Figure 1[5-8].

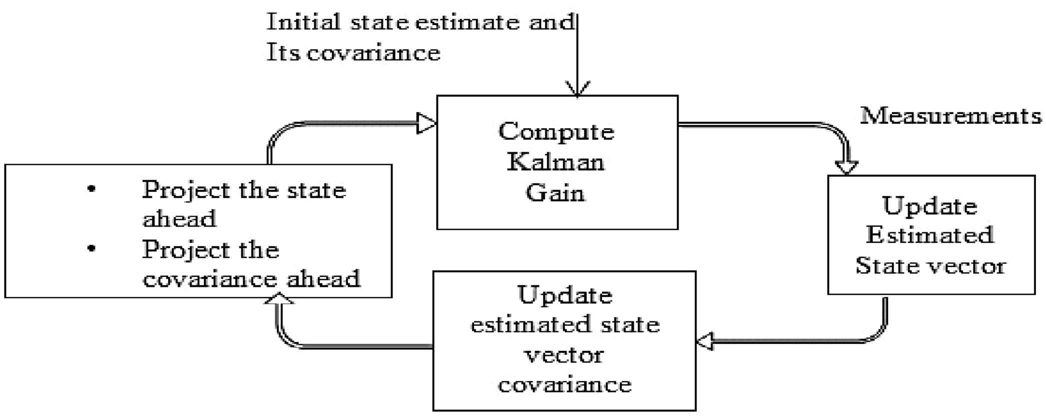

Figure 1: Unscented Kalman filter process

3. GENERALIZED SIMULATOR

Let initial position of the target be (x_t, y_t, z_t) and the target moves with velocity v_t. After time t seconds,observer position changes and the change in the observer position is given by

$$dx_0 = v_0 * \sin(ocr) * \sin(oph) * t \tag{23}$$

$$dy_0 = v_0 * \cos(ocr) * \sin(oph) * t \tag{24}$$

$$dz_0 = v_0 * \cos(oph) * t$$

where ocr and oph are observer course and pitch respectively. Now the new observer position becomes

$$x_0 = x_0 + dx_0 \tag{25}$$

$$y_0 = y_0 + dy_0 \tag{26}$$

$$z_0 = z_0 + dz_0 \tag{27}$$

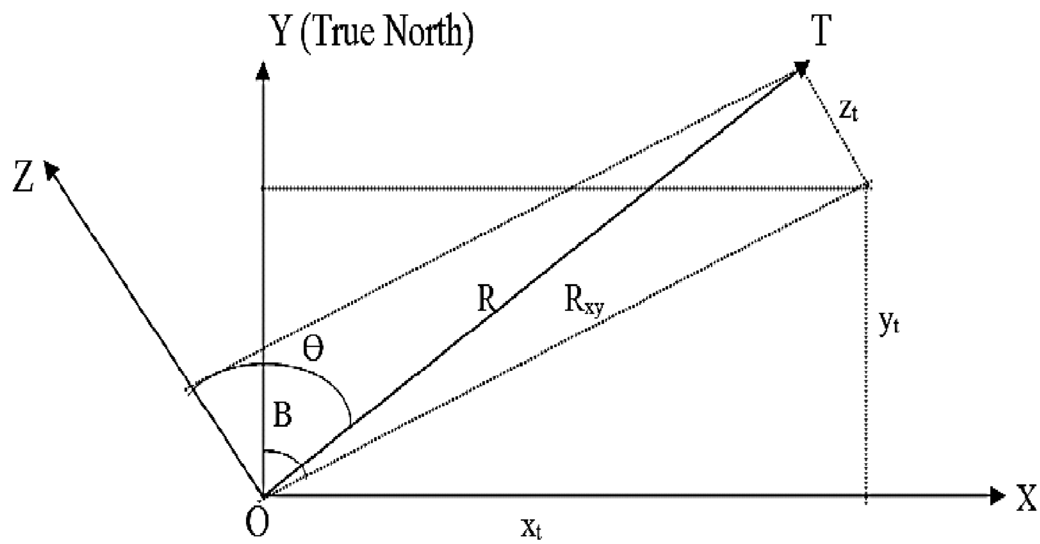

Figure 2: Target and observer positions

From Figure 2.

$$x_t = R_{xy} * \sin(B) \tag{28}$$

$$y_t = R_{xy} * \cos(B) \tag{29}$$

$$\sin(\theta) = R_{xy}/R \tag{30}$$

Substituting equations (28) in (29) and (30)

$$x_t = R * \sin(\theta) * \sin(B) \tag{31}$$

$$\text{yt} = \text{R} * \sin(\theta) * \cos(B) \tag{32}$$

$$z_t = R * \cos(\theta) \tag{33}$$

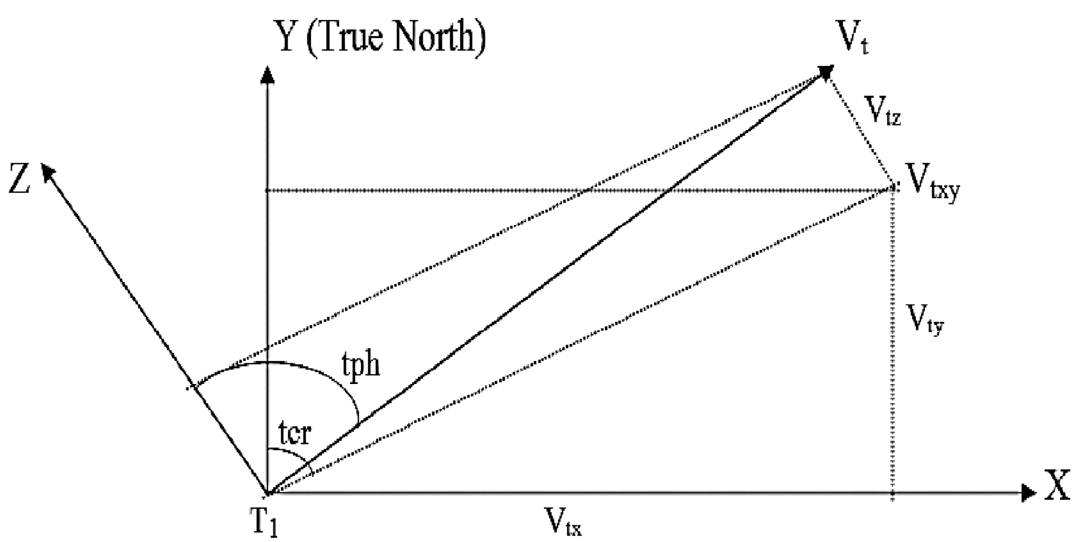

Figure 3: Target and observer velocities

When the target is in motion with velocity v_t, change in target position after t seconds, from Figure 3.

$$dx_t = v_t * \sin(tcr) * \sin(tph) * t \quad (34)$$

$$dy_t = v_t * \sin(tcr) * \sin(tph) * t \quad (35)$$

$$dz_t = v_t * \cos(tph) * t \quad (36)$$

where tcr and tph are target course and pitch respectively.

Now the new target position is

$$x_t = x_t + dx_t \quad (37)$$

$$y_t = y_t + dy_t \quad (38)$$

$$z_t = z_t + dz_t \quad (39)$$

Tareget true bearing, range and elevation are

$$true\,bearning = \tan^{-1}\left(\frac{x_t - x_o}{y_t - y_o}\right) \quad (40)$$

$$true\,range = \sqrt{(x_t - x_o)^2 + (y_t - y_0)^2 + (z_t - z_0)^2} \quad (41)$$

$$true\,elevation = \tan^{-1}\left(\frac{R_{xy}}{z_t - z_o}\right) \quad (42)$$

Block diagram of target motion analysis in simulation mode is shown in Figure 4. The target motion parameters (TMP) are estimated by corrupted measurements using EKF. The estimated TMP are compared with that of true values.

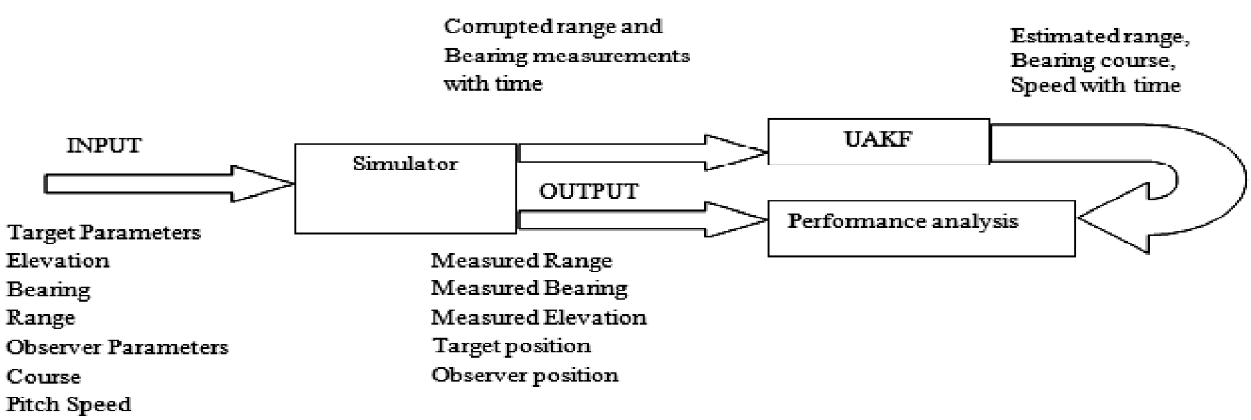

Figure 4: Block diagram of TMA in simulation mode

4. SIMULATION RESULTS

It is assumed that the experiment is conducted in favorable conditions. This simulation is carried out on a personal computer using Matlab. The scenario chosen for evaluation of algorithm is presented in Table 2. For example, scenario 1 describes a target moving at an initial range of 3000m with bearing and elevations of 45^0. Its initial course is 255^0moving with a speed of 10m/s. The range, bearing and elevation measurements are corrupted with 10m(1ó), 0.33^0(1ó) and 0.33^0(1ó) respectively.

In simulation mode, estimated and actual values are available and hence the validity of the solution is 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 <= 3^0, error in speed estimate <= 1m/s and error in elevation estimate <= 1^0.

The estimates and true paths of target are shown in Figure 5 for scenario1. For clarity of the concepts, the errors in estimated speed, course and elevation for scenario1 are presented in Figure 6, 7 and 8 respectively. The solution is converged when course, speed and elevation are converged.Convergence time for scenario 1 is shown in Table.3. In simulation, it is observed that the estimated target parameters are converged at 28th sample for course , 26th samplefor speed and 3rd samplefor elevation respectively for scenario1.So, for scenario 1, the total solution is obtained at 28 samples.

Now it is assumed that the turn rate of the target is 3^0 and the maneuver starts at 300th sample. Target next course is 290^0. So it takes 12 samples to maneuver 35^0 and the maneuver is completed at 312th sample. The scenario 2 chosen for evaluation of algorithm for maneuvering target is shown in Table.4and the convergence time (seconds) for the scenario2 is given in Table.5.The estimates and true paths of maneuvering target are shown in Figure 9. For clarity of the concepts, theestimated speed error, course error and elevation errorare presented in Figure 10, 11 and 12 respectively. It is observed that the estimated course, speed and elevation of the target after maneuvers are converged at 348th, 313th and 313th sample respectively for scenario 2. So, the total solution is obtained at 348th sample.

Table 2
Input scenario chosen for non-maneuvering target

Scenario	*Target range (m)*	*Target bearing (deg)*	*Target Course (deg)*	*Target speed (m/s)*	*Target Elevation (deg)*	*Noise in bearing (1σ)(deg)*	*Noise in Range (1σ)(m)*	*Noise in bearing measurements (1 σ)(deg)*
1	3000	45	255	10	45	0.33	10m	0.33

Table 3
Convergence time in samples for non-maneuvering targets

Scenario1	*Course*	*Speed*	*Elevation*	*Total solution*
1	28	25	3	28

Table 4
Input scenarios chosen for maneuvering targets

Scenario	*Target range (m)*	*Target bearing (deg)*	*Target Course (deg)*	*Target next course (deg)*	*Target speed (m/s)*	*Target Elevation (deg)*	*Noise in bearing (1σ)(deg)*	*Noise in Range (1σ)(m)*	*Noise in bearing measurements (1 σ)(deg)*
1	3000	45	255	290	10	45	0.33	10m	0.33

Table 5
Convergence time in samples for maneuvering targets

Scenario1	*Course*	*Speed*	*Elevation*	*Total solution*
1	348	313	313	348

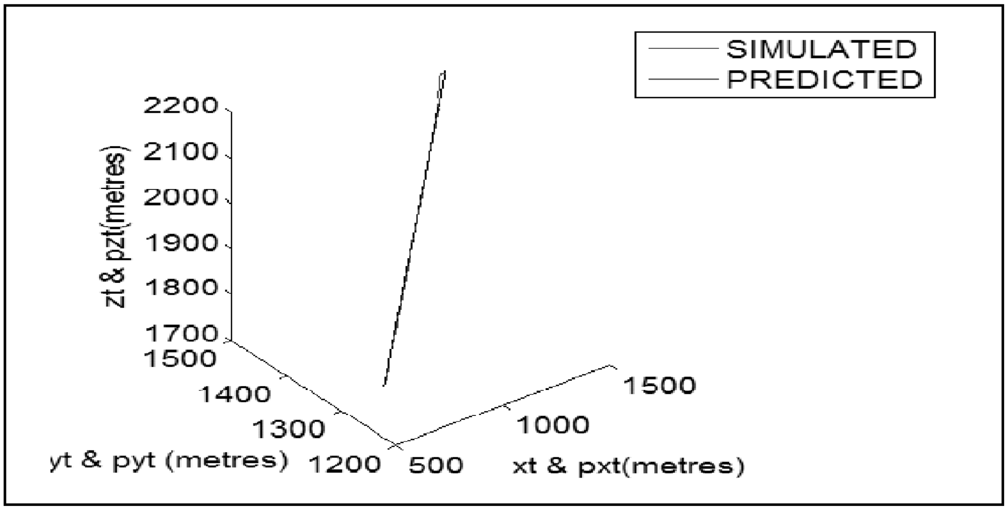

Figure 5: Simulated and estimated target paths

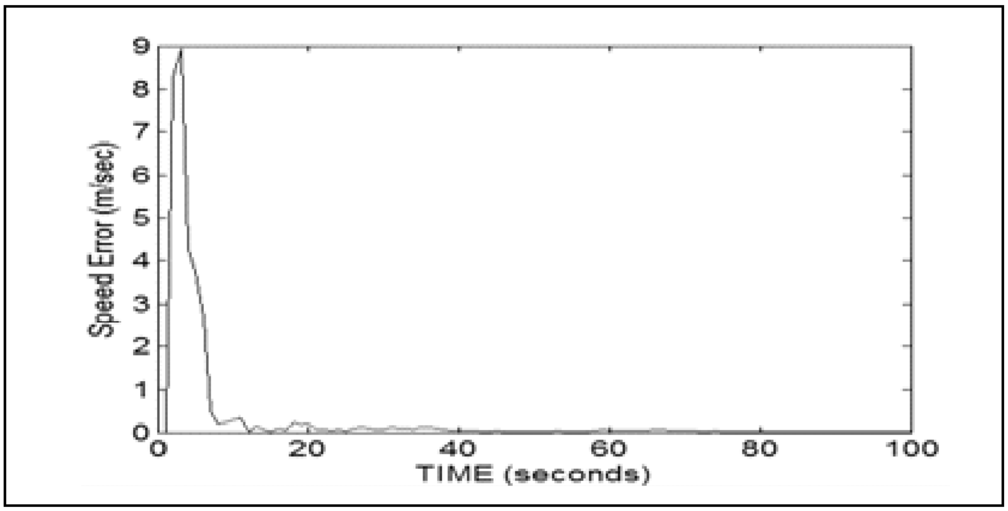

Figure 6: Error in speed estimate

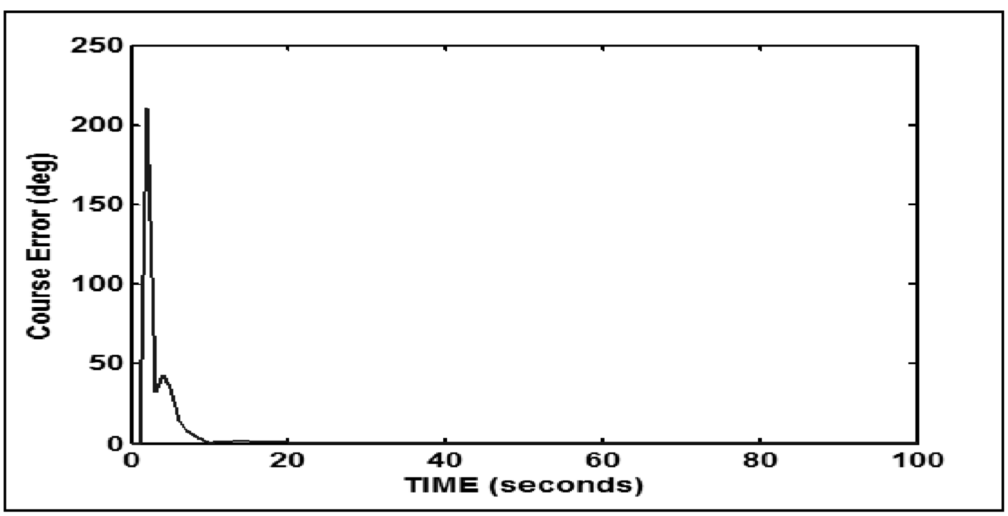

Figure 7: Error in course estimate

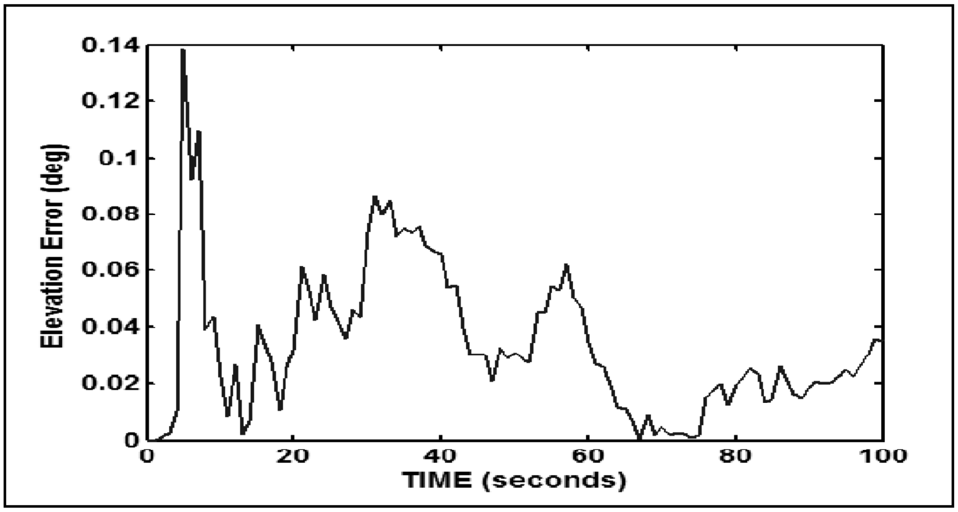

Figure 8: Error in elevation estimate

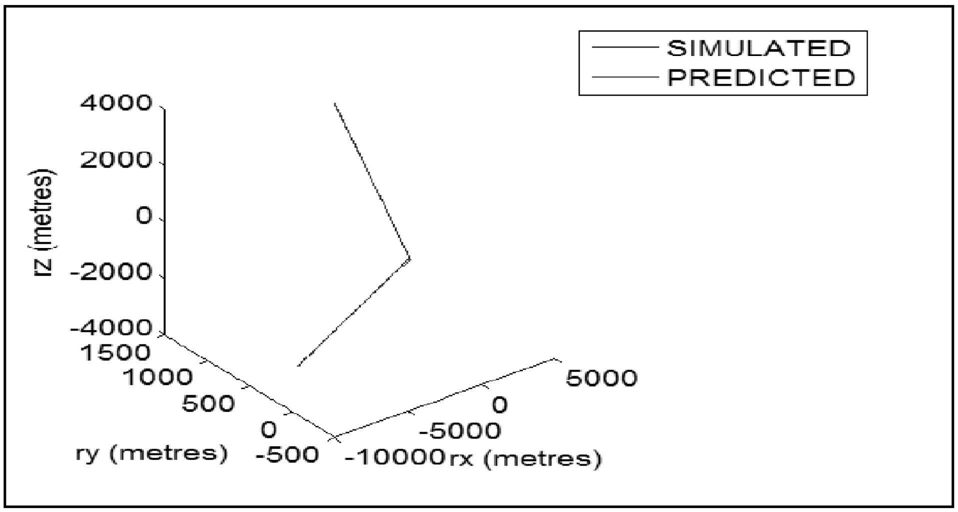

Figure 9: Simulated and estimated target paths

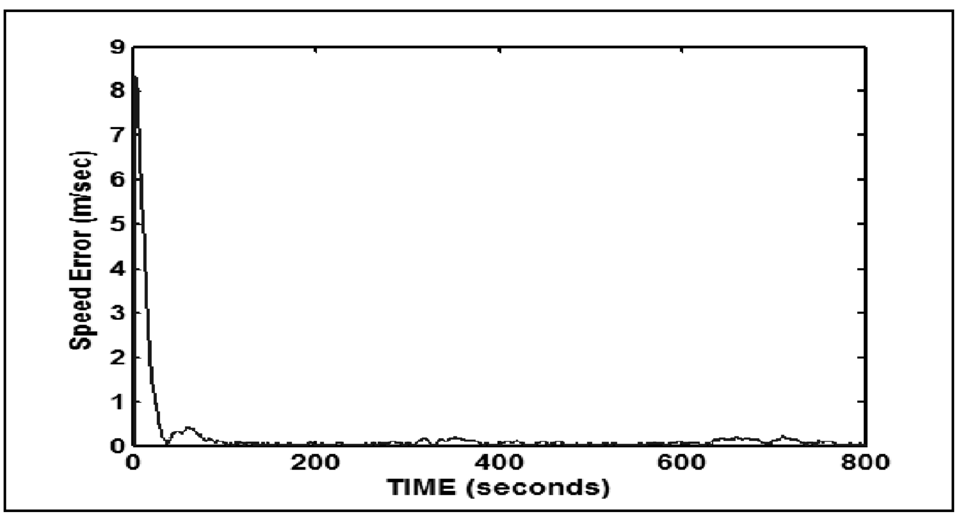

Figure 10: Error in speed estimate

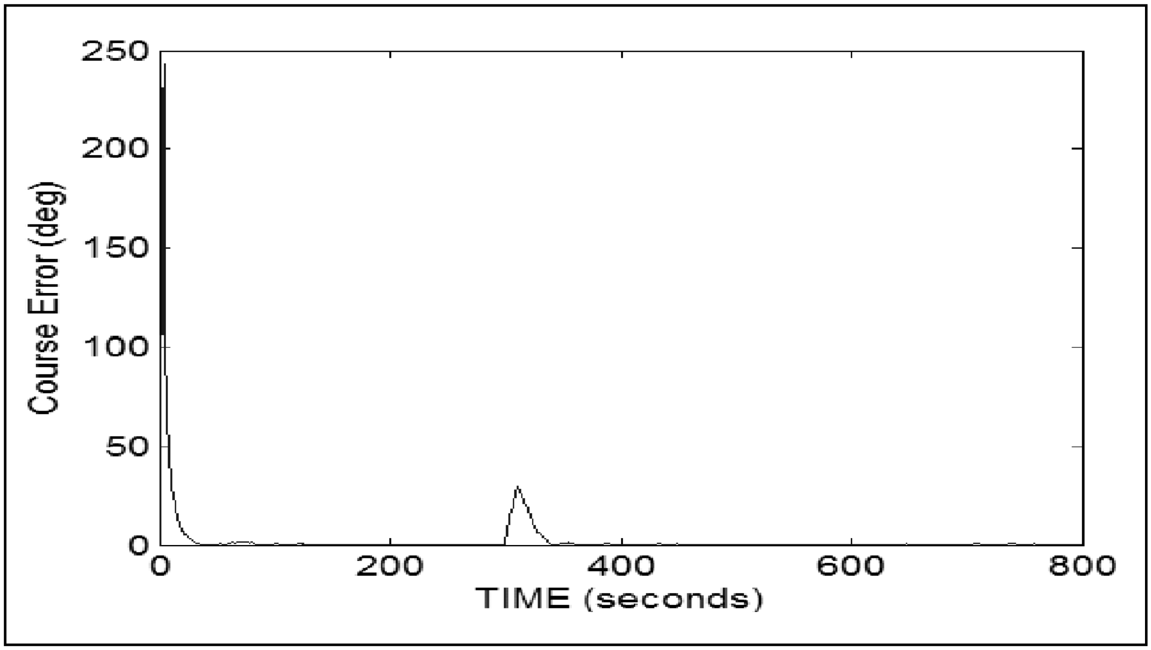

Figure 11: Error in course estimate

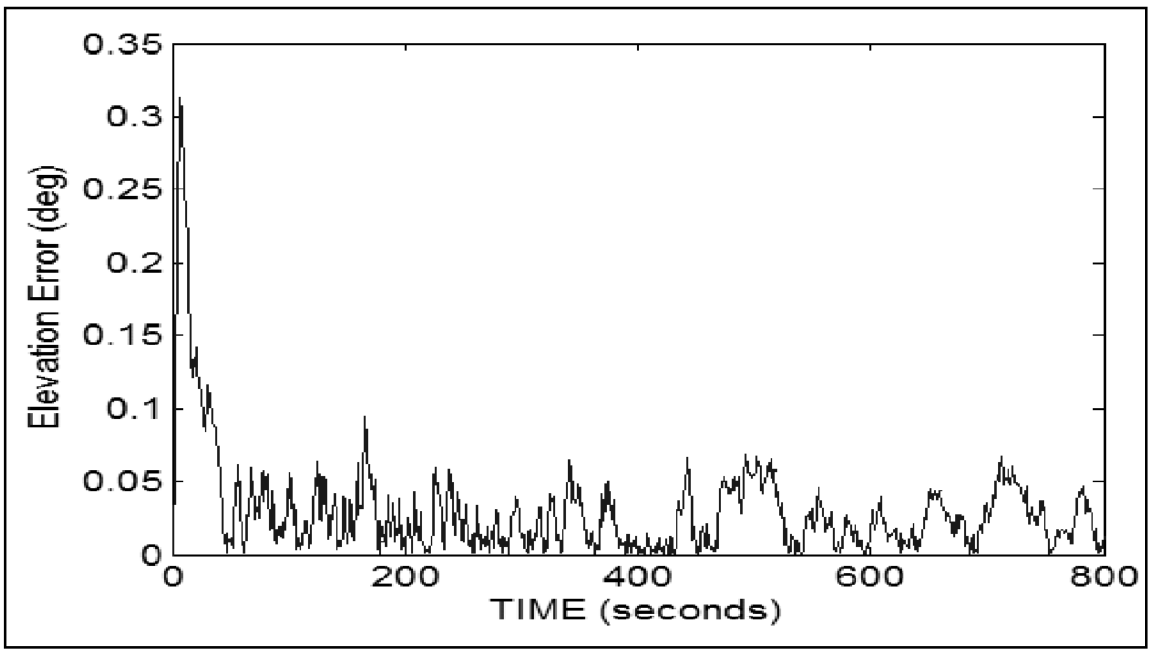

Figure 12: Error in course estimate

5. CONCLUSION

Based on the results obtained in simulation, Unscented Kalman filter is recommended to estimate target course, speed in active target tracking from AUV systems.

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