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Advanced statistically robust estimation algorithm for underwater vehicle localization and ranging for sonar applications

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Abstract

Objectives: Range and bearing measurements of underwater vehicle is obtained by helicopter which uses dunking sonar. Considering range and bearing measurements the target position is identified and target motion parameters are available to guide the weapon on the target vehicle.
Methods/Statistical analysis: Target motion parameters are finally found by using Extended Kalman filter. Present weapon parameters are initial turning angle, straight run distance and many other which are obtained using the known parameters like speed, course of the helicopter and the target motion parameters.
Findings: Results of Monte Carlo simulation are shown which gives the better performances of the algorithm for typical scenarios using Matlab.
Application/Improvements: The proposed algorithm can be used for undersea sonar based applications.
Keywords: Estimation, stochastic, bearing, line of sight, Kalman filter, sonar, weapon

1. Introduction

In two dimensional scenario, Target Motion Analysis (TMA) is generally used in underwater environment. Dunking sonar is positioned into the sea from a helicopter in hovering mode to find out the path of the target submarine in sea water. The sonar in active mode finds out target bearing and range measurements. These are passed on to the helicopter signal processing system through a cable. Target and observer both are moving in a straight but in their respective directions. Observer estimates the target motion parameters like range, bearing and speed of the target to process the measurements [1-4].

Dunking sonar system consists of simulator which is an active mode target motion analysis system. The weapon to be induced on the target, and the sonar, both are placed in the helicopter. Helicopter is in hovering mode, sonar is sent to the sea to get the target position. Since the sonar cannot be able to give the depth of the target from the surface it is assumed that the sonar and target are on the same plane. Due to noisy environment of the SONAR data from different sensors like range bearing elevation are also noisy. These noisy measurements often results in nonlinear states and measurements. If the measurements and states are linear, kalman filter is used for prediction and estimation of states. Kalman filter for estimation and prediction is mainly used between1959-1961. Kalman filter is defined as filtering technique used for linear quadratic estimations combined with the series of noisy measurements, whereas Sonar environment is noisy and nonlinear in particular[5-7]. Linearized Kalman filter transforms polar measurements into Cartesian co-ordinates whereas the extended Kalman filter works directly on polar coordinates. Using the sonar signal processing system in helicopter measurements, Recent study by S.T. pork and L.E. Lee on above stated versions of kalman filter tells that both performs well. This paper deals with EKF all through the paper [3-6]. So a filtering technique for nonlinear system was adapted which is a nonlinear system having linear approximation called Extended Kalman Filter (EKF).

2. Mathematical modeling

X_s (k) is state vector of the target

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

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$\dot{x}(k)$ and $\dot{y}(k)$ are target velocity components and $R_x(k)$ and $R_y(k)$ are range components.

$X_s(k+1) = \Phi(k+1/k)X_s(k) + b(k+1) + \omega(k)$ (2)

Where $\omega(k)$ is the plant noise having zero mean b(k+1) is deterministic vector and $\Phi(k+1/k)$ is the transient matrix.

Transient matrix is given by

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

Sample time elapse between the measurements is t.

Deterministic matrix is given by

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

True north convention is followed by all angles to reduce mathematical complexity, x_0 and y_0 are components of ownship position respectively. Z (k) is measurement vector and it is given by

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

Where $B_m(k)$ is the bearing measurements and R_m is the range measurement.

They are defined as

$B_m(k) = B(k) + \gamma(k)$ (6)

$R_m(k) = R(k) + \eta(k)$ (7)

Actual bearing is B (k) and actual range is R (k)

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

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

The noises η (k) and γ (k) are induced which are uncorrelated and Gaussian.

By using above equations, measurement equation is given by

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

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

Assume the plant and measurement noise are uncorrelated to each other. The predicted covariance is given by

$P(k+1/k) = \emptyset(k+1/k)P(k/k)\emptyset^T(k+1/k) + Q(k+1)$ (12)

Where, Q is the covariance of plant noise

Kalman gain is given as

$G(k+1) = P(k+1/k)H^T(k+1)[r(K+1) + H(k+1)P(k+1/k)H^T(k+1)]^{-1}$ (13)

Where, r(k+1) is said to be input covariance matrix of error covariance.

Thus the state estimation and its error in covariance are given as

$X(k+1/k+1) = X(k+1/k) + G(k+1)[Z(k+1) - \hat{Z}(k+1)]$ (14)

$P(k+1/k+1) = [1 - G(k+1)H(k+1)P(k\,1/k)$ (15)

3. Simulator

Simulator accepts the inputs given and simulates the observer and target position. It generates range and bearing for each second and induces Gaussian noise in each measurement of range and bearing. Target parameters are range, course, bearing, elevation and the observer parameters are course and speed which are given as inputs to the simulator. Sigma_b and sigma_r are errors assumed in bearing and range respectively is also given as inputs. Initially observer is considered to be at origin and the angles are measured with respect to true north.

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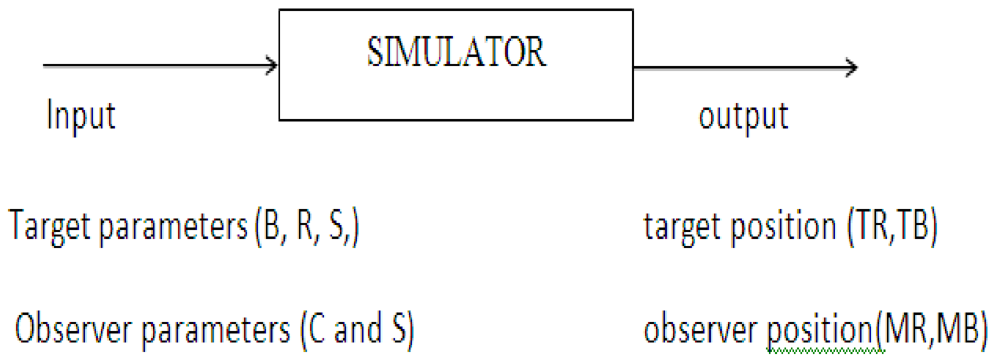
Figure 1. 2D simulator with inputs and outputs

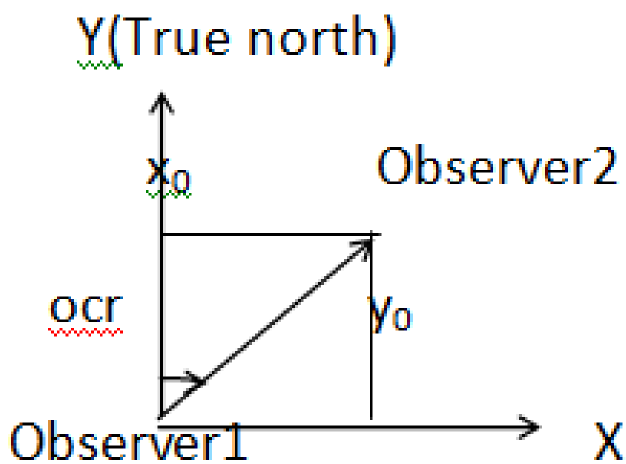


Where B is bearing R is range S is speed (B,S,R) are the target parameters. C is course related to observer. MR, MB is measured range and bearings and TB,TR are true bearing and ranges.

3.1. Observer position

Observer position is initially taken as origin and is shown as

Figure 2. Observer position in motion



O1 and O2 are the observer initial and next position after a time t_s moving with a velocity v_0. (x_0,y_0) are observer initial coordinates and ocr is the angle made with north.

$$\sin(ocr) = \frac{x_0}{v_0}$$

$$\cos(ocr) = \frac{y_0}{v_0}$$

Change in observer position for each second is found and added to its previous position.

$$dx_0 = v_0 * \sin(ocr) * t_s$$

$$dy_0 = v_0 * \cos(ocr) * t_s$$

dx_0 and dy_0 are changes in observer position after a time interval t_s. New position of the observer becomes

$$x_0 = dx_0 + x_0$$

$$y_0 = dy_0 + y_0$$

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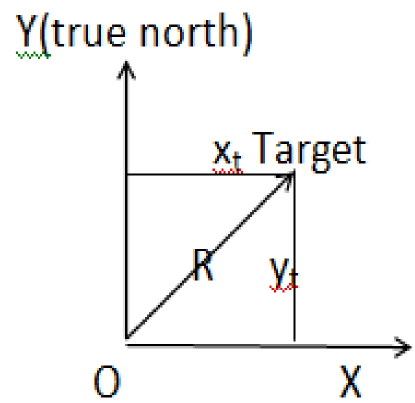
3.2. Initial target position

Figure 3. Initial observer and target position



From the input bearing and range measurements initial target position is known using following equations

$x_t = range * \sin(bearing) = R * \sin(B)$

$y_t = range * \cos(bearing) = R * \cos(B)$

Where (x_t, y_t) is the position of target with respect to origin.

When the target moves with a velocity v_t, dxt and dyt are the changes of target position in x and y direction for time t_s seconds. Target course is given by tcr.

Figure 4. Target position in motion

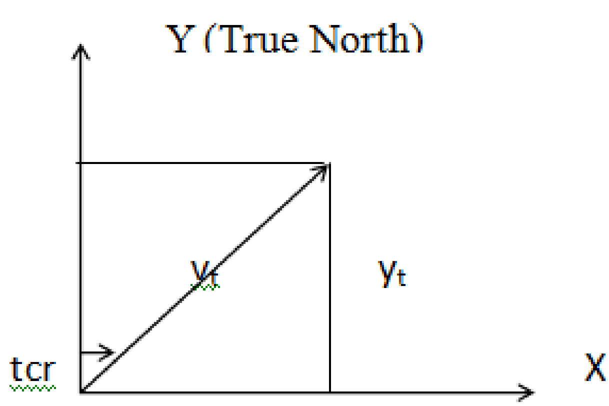


Figure 5. Simulated and estimated range

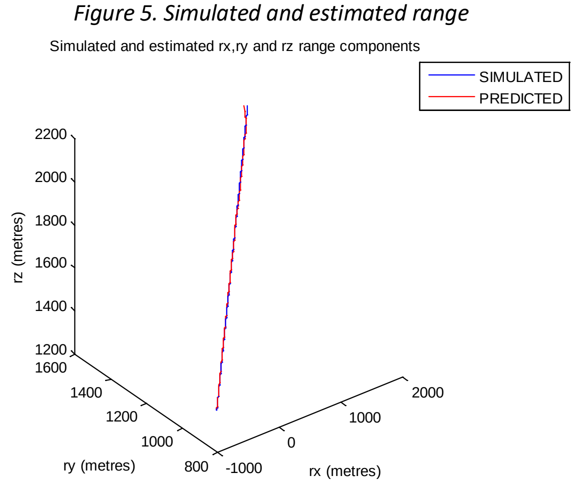


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Figure 6. Simulated and estimated target

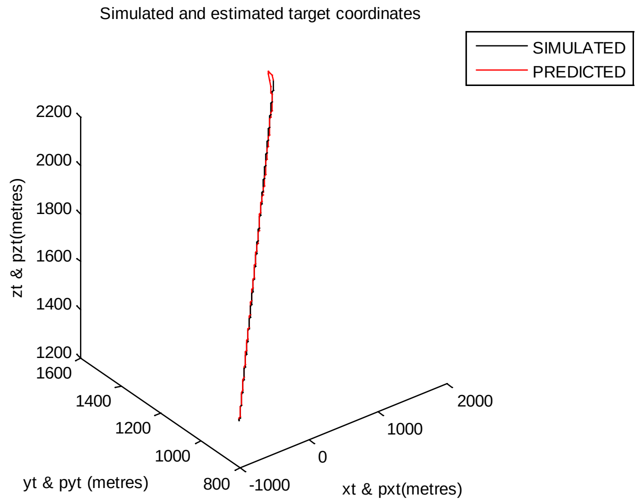

Figure 7. Simulated and estimated target velocity

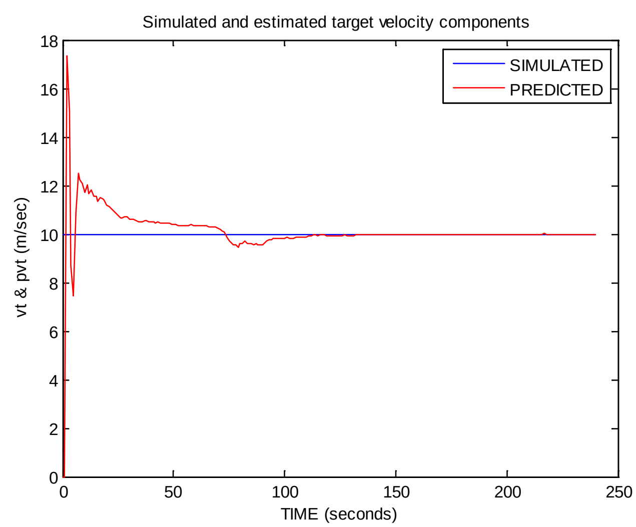

Figure 8. Simulated and estimated target course

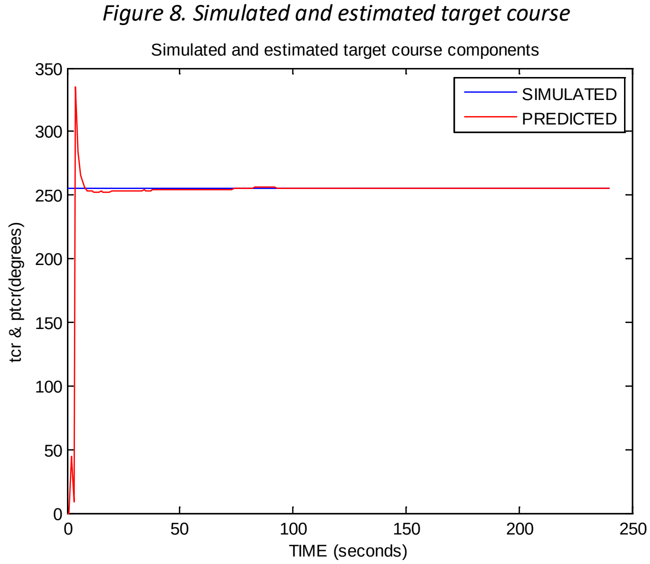

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Figure 9. Simulated and estimated target elevation

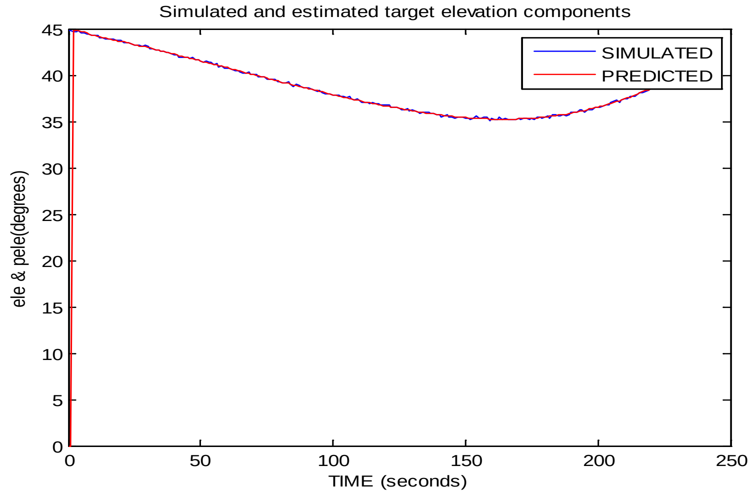

Figure 10. Error in range estimate

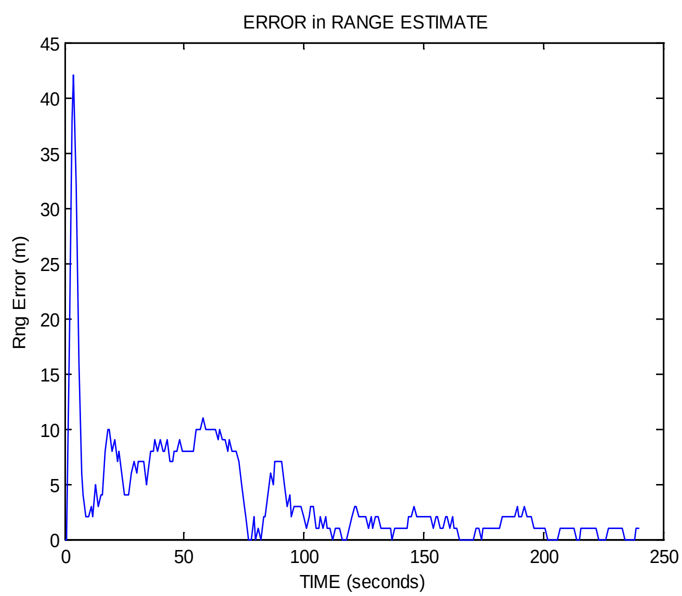

Figure 11. Error in bearing estimate

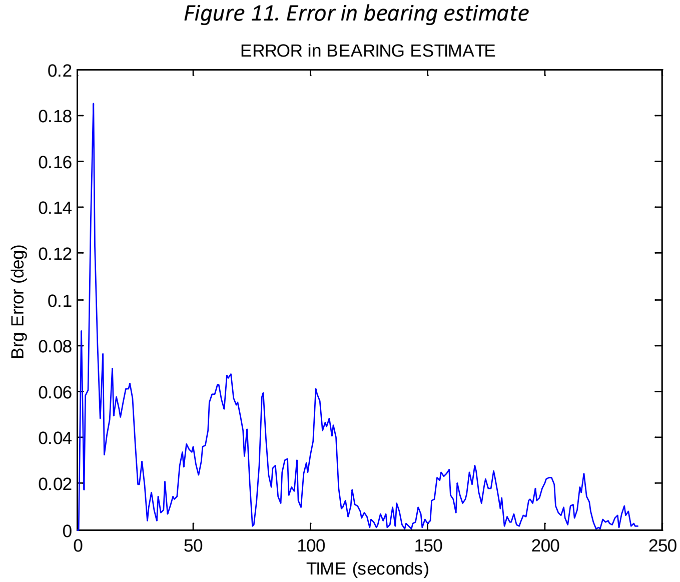

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Figure 12. Time versus speed error

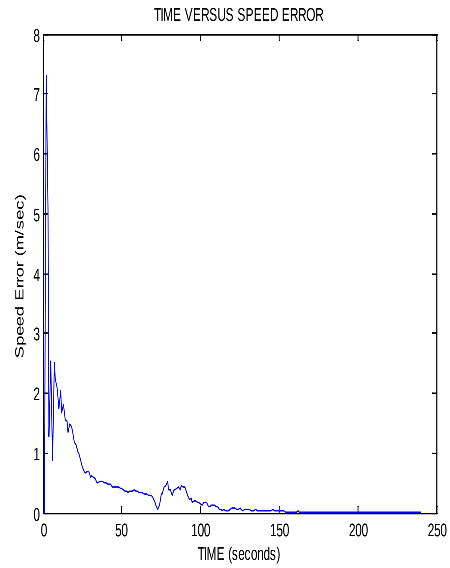

Figure 13. Error in course estimate

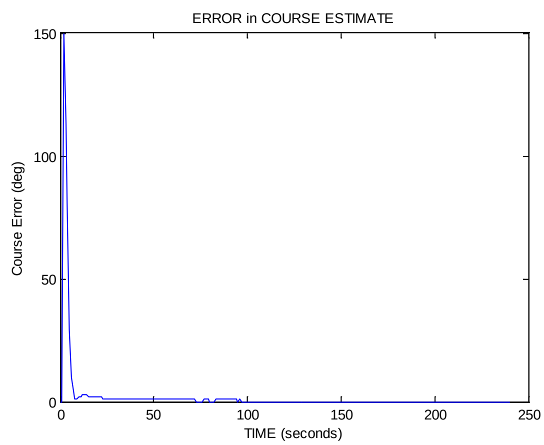

Figure 14. Simulated target co ordinates

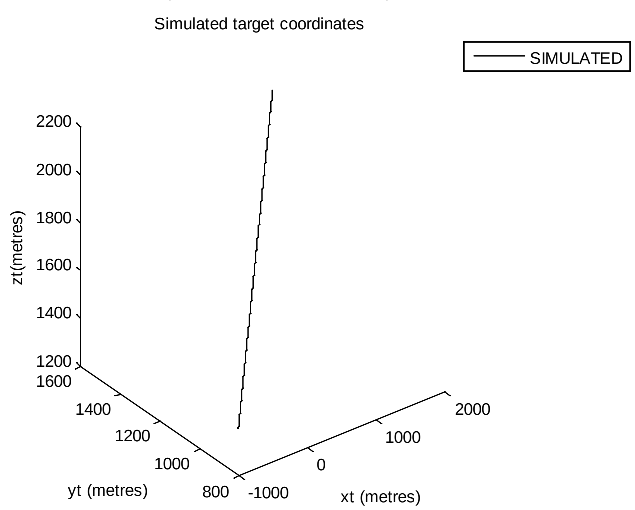

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Figure 15. Error in elevation estimate

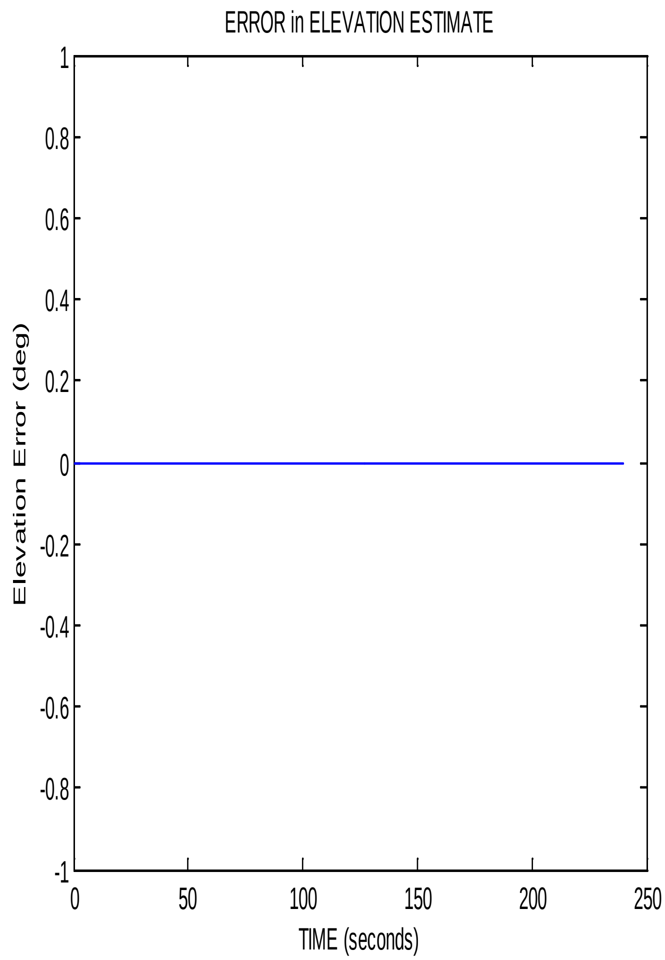

Figure 16. Simulated observer coordinates

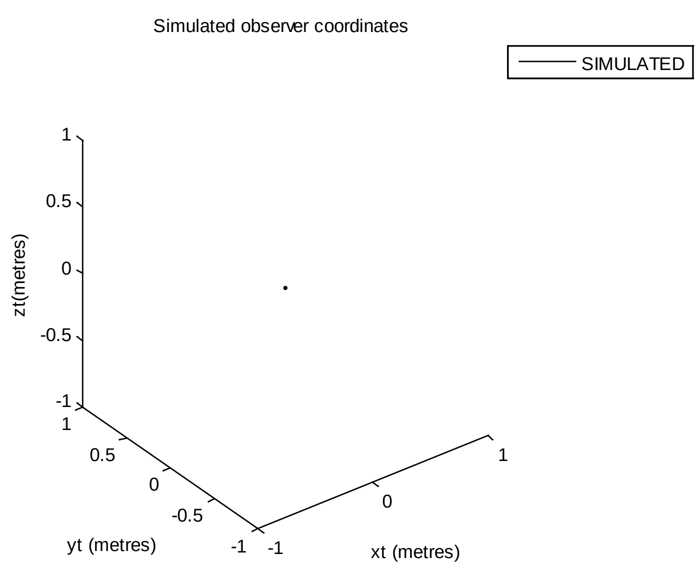

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Figure 17. Simulated and estimated range

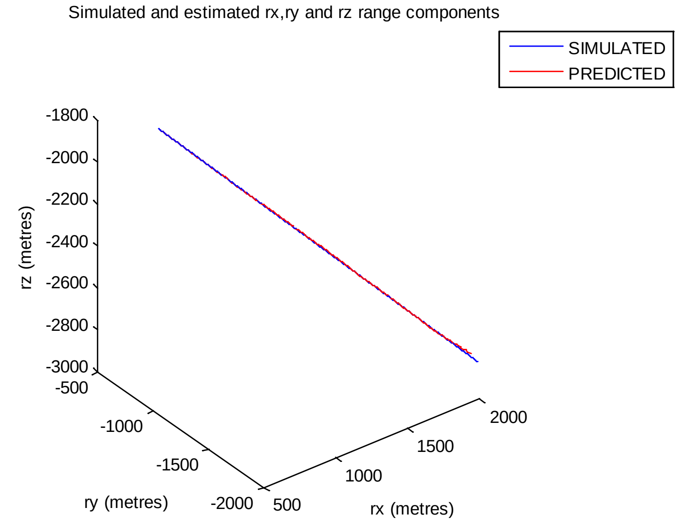

Figure 18. Simulated and estimated target

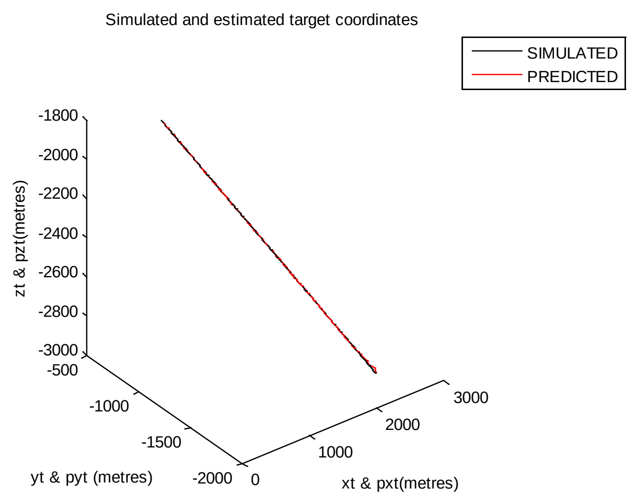

Figure 19. Simulated and estimated target velocity

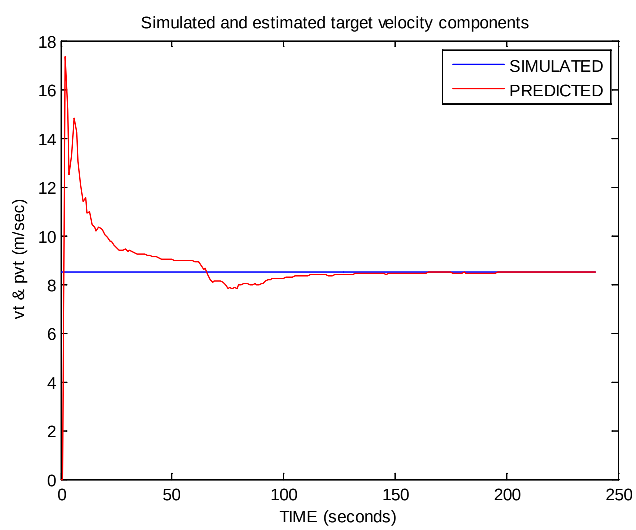

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Figure 20. Simulated and estimated target course

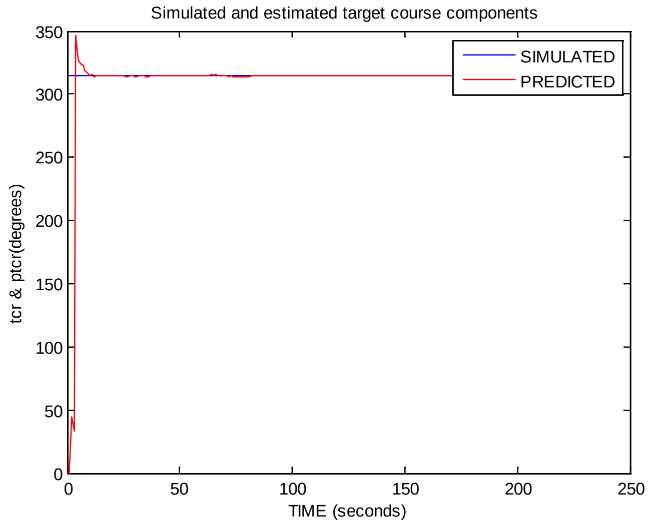

Figure 21. Simulated and estimated target elevation

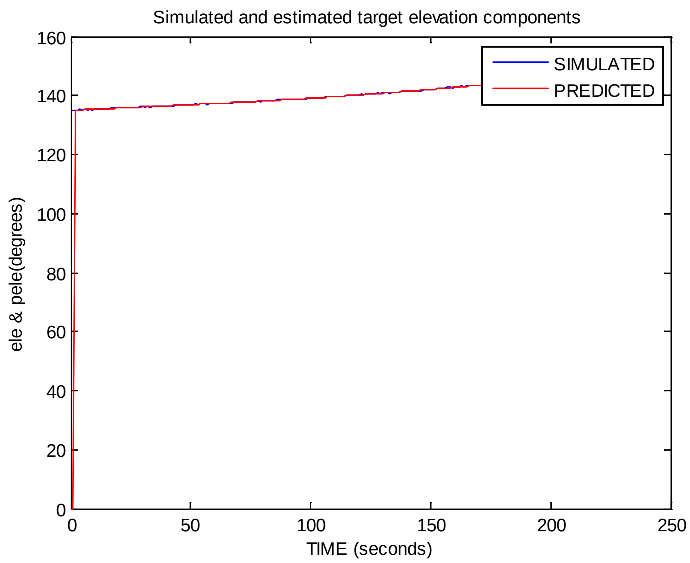

Figure 22. Error in range estimate

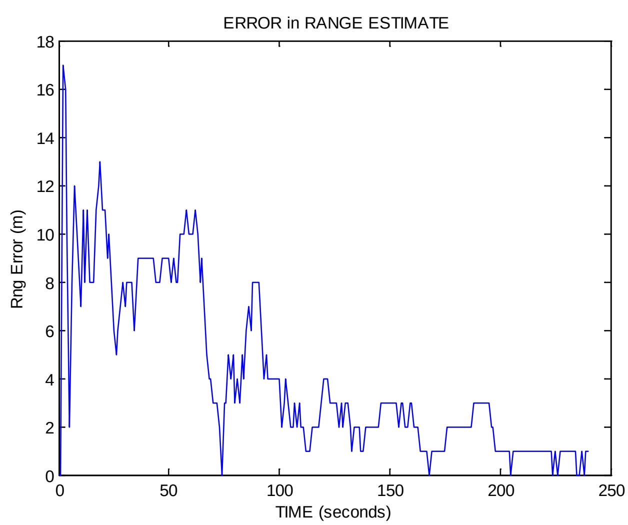

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Figure 23. Error in bearing estimate

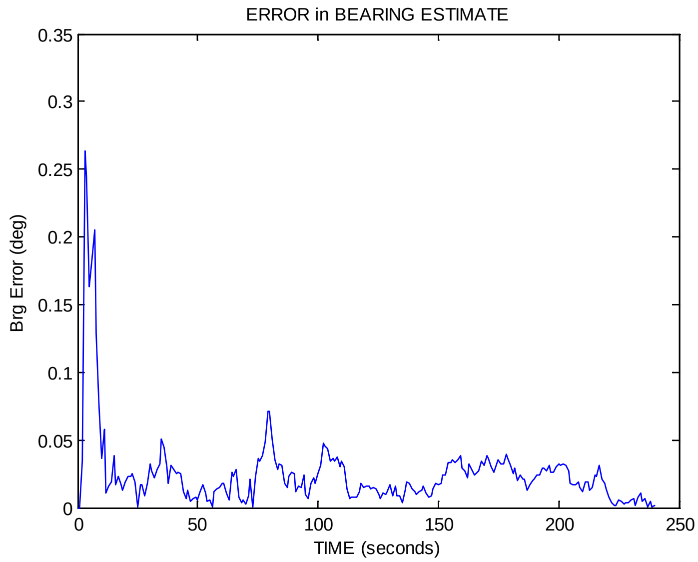

Figure 24. Time versus speed error

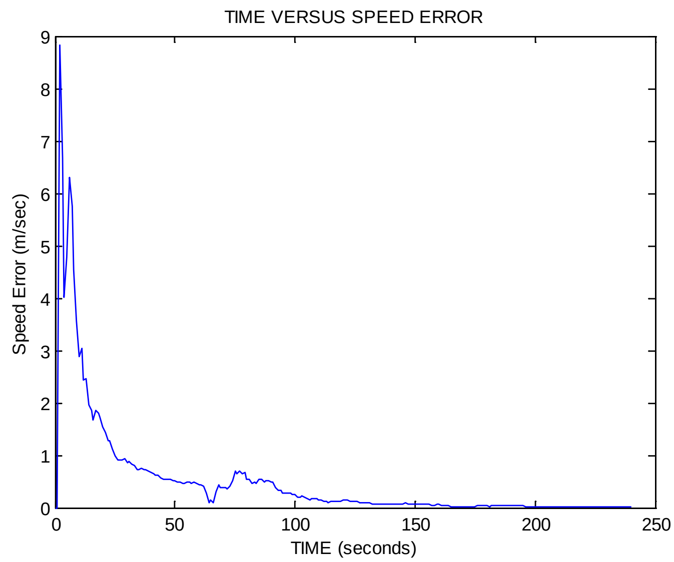

Figure 25. Error in course estimate

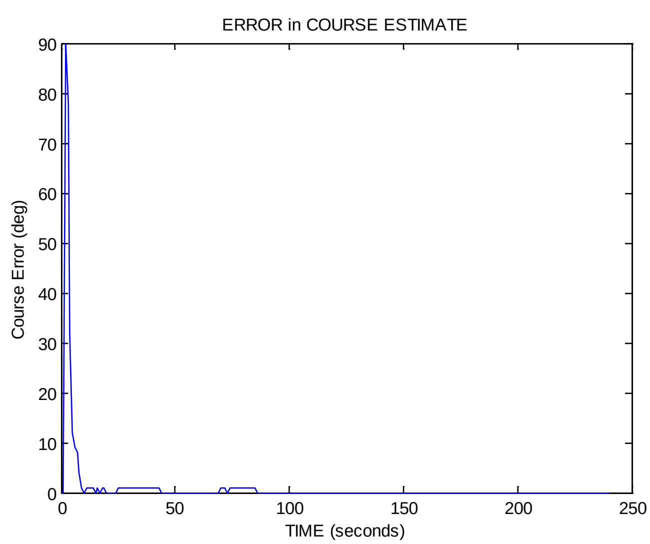

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Figure 26. Error in elevation estimate

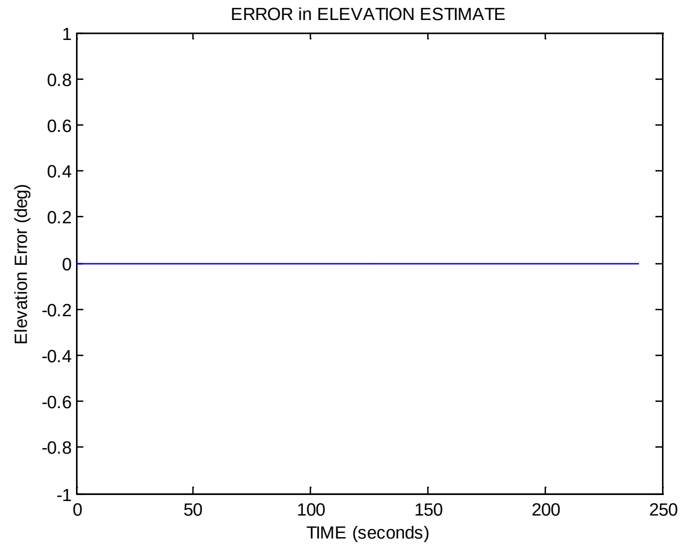


Figure 27. Simulated target coordinates

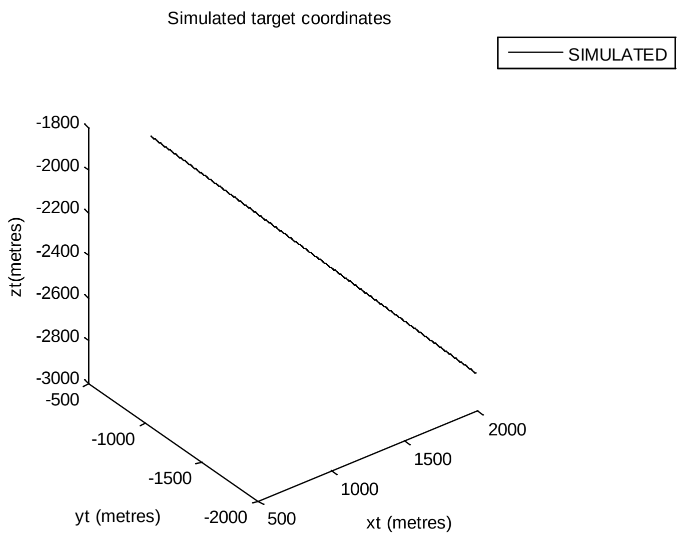
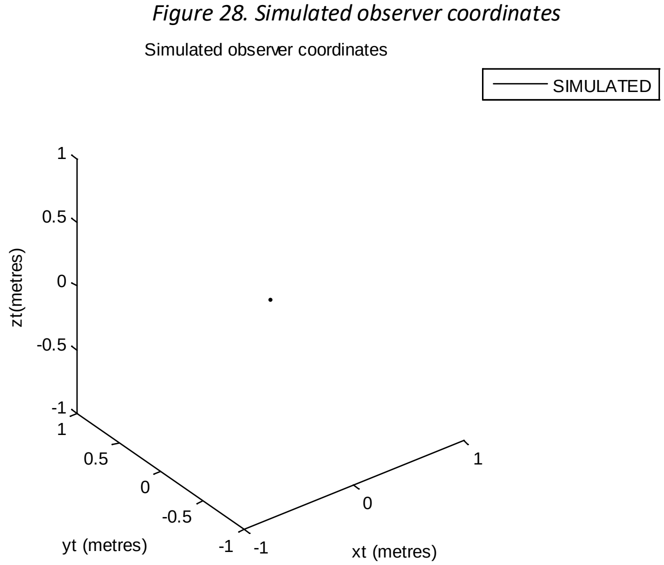


Figure 28. Simulated observer coordinates



$$dx_t = v_t * \sin(tcr) * t_s$$

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$dy_t = v_t * \cos(tcr) * t_s$

Now the new target position after time $t_s$is given as

$x_t = dx_t + x_t$

$y_t = dy_t + y_t$

Zero Mean Gaussian noise is nowadded to range and bearing measurements and the standard deviations are sigma_r and sigma_b.

True bearing $= tan^{-1} \frac{x_t - x_0}{y_t - y_0}$

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

Now the measured range and bearings are given by

Measured range= true range+sigma_r

Measured bearing= true bearing + sigma_b

4. Implementation of the algorithm

The target velocity components are computed with the use of first and second measurement sets of range and bearing and the Kalman filter starts its computation from the second measurement itself.

Target state vector has its initial estimate which is X(2/2)

X(2/2) $= [term1 \;\; term2 \;\; R_m(2)sinB_m(2)]^T$ (16)

Term1 and term2 are defined by

$term1 = R_m(2)sinB_m(2) - R_m(1)sinB_m(1)/\mathrm{t}$

$term2 = R_m(2)cosB_m(2) - R_m(1)cosB_m(1)/\mathrm{t}$ (17)

Uniform distribution of initial estimate X(2/2) is assumed. Now the initial covariance diagonal matrix elements is given by

$P_{00}(2/2) = \frac{4*\dot{x}^2(2/2)}{12}$ (18)

$P_{11}(2/2) = \frac{4*\dot{y}^2(2/2)}{12}$ (19)

$P_{22}(2/2) = \frac{4*{R_x}^2(2/2)}{12}$ (20)

$P_{33}(2/2) = \frac{4*{R_y}^2(2/2)}{12}$ (21)

From the estimated state vector target motion parameters are calculated viz .,range, course, bearing and speed of the target.

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

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

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

$B(k) = \sqrt{\dot{x}(k)^2 + \dot{y}(k)^2}$ (22)

5. Simulation and results

Table 1. Input Scenarios for Observer and Target

Scenario	Target range	Target bearing	Target Course	Target speed	Observer course	Observer speed
1	3000	45	255	10	NA	0
2	4000	135	315	8.5	NA	0

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The velocity of sound in sea water is 1500m/s. As the maximum range of target is 3000m (Table 1), the time taken for the transmitted pulse to reach and come back to observer is (6000/1500) 4seconds. Let the maximum noise (3σ) in the range and bearing measurements be 1^0 and 20m respectively. The scenarios are shown in Table 1 and depicted in the figures. Figures 1 to 16 represent scenario 1 and Figures 17 to 28 shows simulation of scenario 2. Table 2 presents the output scenario for the corresponding input scenarios.

Sigma_b = 0.33
Sigma_r= 7
X_0 = 0
Y_0 = 0
(X_0,Y_0) are the initial position of observer.

Table 2. Outputs scenario for the corresponding Input scenarios

Scenario	Resultant Bearing	Predicted bearing	Resultant range	Predicted range	Resultant course	Predicted course	speed	Predicted speed
1	323	323	1.729201e+003	1730	255	255	10	10
2	315	315	2.098661e+003	2099.7	315	315	8.5	9

6. Conclusion

The studied scenarios show that the algorithm is good for target tracking from a hovering helicopter through which sonar is sent to track the target. Hence it is also used in underwater applications. Extended Kalman filter is used in this algorithm to estimate range and bearing measurements of underwater targets. It is observed from taken scenarios that the errors are small and can be settled down easily.

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