Tracking Underwater Target Using Angles-only Measurements

Koteswara Rao.S
Department of Electronics and Communication Engineering
Koneru Lakshmaiah Education Foundation
Vaddeswaram, Guntur, AP, India
skrao@klunivresity.in

Kavitha Lakshmi. M
Department of Computer Science and Engineering
Koneru Lakshmaiah Education Foundation
Vaddeswaram, Guntur, AP, India
kavithalkshm67@gmail.com

Kausar Jahan
Department of Electronics and Communication Engineering
Koneru Lakshmaiah Education Foundation
Vaddeswaram, Guntur, AP, India
kausar465@ieee.org

***Abstract*—This Surveillance plays a critical role in the marine environment. Target is tracked even if measurements of the range are not available, using bearing and elevation measurements. This research intends to track the target and estimate the parameters of target motion and to reduce noise in the estimated parameters using an effective nonlinear filter, Unscented Angles-only Kalman Filter (UAKF). Mathematical modeling is presented in this research, and simulation is done using MATLAB software. The performance of the UAKF algorithm is shown to be efficient in tracking the target and observer maneuver is recommended to get convergence very quickly in underwater surroundings.**

***Keywords*—Underwater 3d target tracking, estimation theory, Unscented Angles-only Kalman filter**

I. Introduction

Passive target tracking is usually followed in underwater to track a target submarine [1,2]. Tracking is a complicated procedure of estimating the state (i.e., location, velocity) of moving targets, as close as possible to the true state by utilizing the measurements obtained from different sensors. It is assumed that observer submarine travels at low speed to eliminate self-noise for target tracking. In this paper, research is towards submarine (observer) tracking a target submarine, utilizing elevation and bearing measurements. The results obtained are compared for each scenario with and without observer maneuver [2].

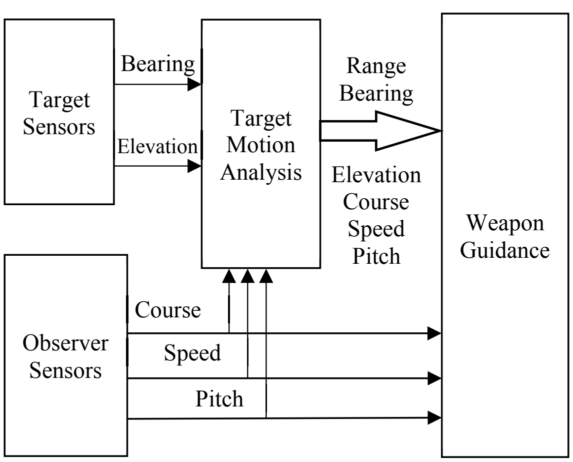

Fig.1. Block diagram for tracking a target in passive mode using bearing and elevation measurements.

It is assumed that only angle measurements are available. So, the procedure is highly nonlinear, and therefore Unscented Angles-only Kalman filter (UAKF), which is a suboptimal nonlinear filter [3-6], is examined for this application. The above process in the form of a block diagram is as shown in Fig.1. The estimated parameters of the target i.e., range, course, bearing, elevation, and speed (R, C, B, E, S) are utilized in the guidance algorithm used forlaunching of weapons on to the target [7-10].

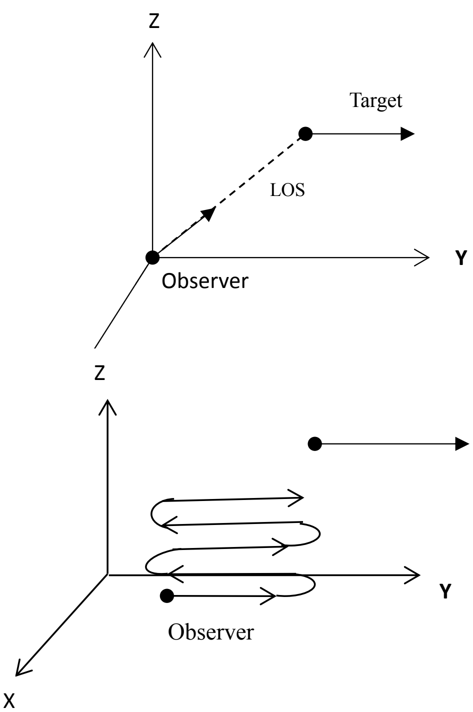

Fig.2 a. Observer without Maneuver

Fig.2 b. Observer S- Maneuver

Fig.2. An observer with maneuver and without maneuver

Fig 2 a. shows observer tracking a target without maneuver. A line joining the observer and target is called the line of sight. Observer submarine tracks the target based on the noise signal generated which is received at the observer and without changing the observer course angle. Fig 2 b shows, the S-maneuver carried out by observer for better observability of target. Observer and target are presumed to be in the same three-dimensional plane. Target and observer are assumed to move with constant speed. Initially, observer travels in the first leg for 2 minutes at 90° course and turns with a turn rate of 0.5° per second towards the 270° course. After 4 minutes of travel, it turns towards 90° of course in the second leg. Similarly, second, third, and fourth legs are repeated except in the third leg, observer course is 270° and in the fourth leg, it is 90° [2].

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Section II deals with the modeling of the state vector, measurements, and UAKF. In section III, the generation of measurements and selected scenario results are discussed. Section IV gives the summary and conclusions on the performance of the algorithm.

II. MATHEMATICAL MODELING

A. System and measurement models

The target state vector $X_S(a)$

$$X_s(a) = [\dot{x}(a) \quad \dot{y}(\dot{a}) \quad \dot{z}(a) \quad Rx(a) \quad Ry(a) \quad Rz(a)] \tag{1}$$

$$X_s(a+1) = \emptyset_s X_s(a) + b(a+1) + \omega\vartheta(a) \tag{2}$$

where Ø= transition matrix

$$\emptyset = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ t & 0 & 0 & 1 & 0 & 0 \\ 0 & t & 0 & 0 & 1 & 0 \\ 0 & 0 & t & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$\omega = \begin{bmatrix} t & 0 & 0 \\ 0 & t & 0 \\ 0 & 0 & t \\ t^2/2 & 0 & 0 \\ 0 & t^2/2 & 0 \\ 0 & 0 & t^2/2 \end{bmatrix} \tag{4}$$

$$b(a+1) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ (-x(a) + x(a+1)) \\ (-y(a) + y(a+1)) \\ (-z(a) + z(a+1)) \end{bmatrix}^T \tag{5}$$

$$\vartheta(a) = \begin{bmatrix} \vartheta_x \\ \vartheta_y \\ \vartheta_z \end{bmatrix} \tag{6}$$

Here, $\vartheta(a)$is plant noise assumed to be white Gaussian. t_s is time interval. The covariance of the plant noise is calculated as follows.

$$E[\omega(a)\vartheta(a)\vartheta^T(a)\omega^T(a)] = Q\delta_{ij} \tag{7}$$

Where Q is

$$Q = \begin{bmatrix} t_s^2 & 0 & t_s^3/2 & 0 & 0 & 0 \\ 0 & t_s^2 & 0 & 0 & t_s^3/2 & 0 \\ 0 & 0 & t_s^2 & 0 & 0 & t_s^3/2 \\ t_s^3/2 & 0 & 0 & t_s^4/4 & 0 & 0 \\ 0 & t_s^3/2 & 0 & 0 & t_s^4/4 & 0 \\ 0 & 0 & t_s^3/2 & 0 & 0 & t_s^4/4 \end{bmatrix} \tag{8}$$

$$\delta_{ij} = \sigma_\vartheta^2 \quad \text{If i=j}$$

$$= 0 \qquad \text{Otherwise}$$

The bearing and elevation measurements, corrupted with noise, are measured with respect to true north.

$$B_m(a+1) = tan^{-1}\left(\frac{(x_t - x_0)}{(y_t - y_0)}\right) + \eta_b(a) \tag{9}$$

$$E_m(a+1) = tan^{-1}\left(\frac{(R_{xy})}{(z_t - z_0)}\right) + \eta_e(a) \tag{10}$$

Where $\qquad R_{xy} = \sqrt{(x_t - x_0)^2 + (y_t - y_0)^2} \qquad (11)$

B. Unscented Transformation Algorithm

Consider a random variable (x) . To calculate the statistical properties of x, Unscented Transformation (UT) is a straight-forward method, when it is moved through a nonlinear transformation. Consider a nonlinear function which is assumed as$y = g(x)$. To calculate the mean and covariance of$y$, a matrix, χ of $2L + 1$ sigma vector is formed. The flow of the algorithm is shown in Fig 3.

$$\chi_0 = \bar{x} \tag{12}$$

$\bar{x}$ is mean of random variable

$$\chi_i = \bar{x} \pm \left(\sqrt{(L+\lambda)P_x}\right)_i i = 1 \ \dots, L. \tag{13}$$

L is the dimension, P_x is the covariance

$$Wt_0^{(m)} = \lambda/(L+\lambda) \tag{14}$$

$Wt_0^{(m)}$is the initial target state vector weight

$$Wt_0^{(c)} = \frac{\lambda}{L+\lambda} + (1 - \alpha^2 + \beta) \tag{15}$$

$Wt_0^{(c)}$ is an initial state covariance matrix weight

$$Wt_i^{(m)} = \frac{Wt_r^{(c)}}{\{2(L+\lambda)\}} i = 1 \ \dots, L \tag{16}$$

$Wt_i^{(m)}$ is the state vector sigma point weight

$Wt_i^{(c)}$ is the state sigma covariance matrix weight

Where $\lambda = \alpha^2(L+D) - L$ and α determines the sigma point around mean $\bar{x}$. D, β are mostly selected as zero and two.

The vectors χ_i are as follows,

$$y_i = g1(\chi_i) i = 1, \dots, 2L \tag{17}$$

The mean and covariance $of \ y_i$ are given by

$$\bar{y} \approx \textstyle\sum_{i=0}^{2L} y_i Wt_i^{(m)} \tag{18}$$

$$P_y \approx \textstyle\sum_{i=0}^{2L} Wt_i^{(c)} \{y_i - \bar{y}_i\}^2$$

UAKF is a simple expansion of the Unscented Transform to the recursive estimation.

The procedure shows the typical UAKF implementation as follows.

C. Unscented Kalman Filter [7-10]

1. By using initial conditions of state vector first compute the sigma points

   $$X(a) = [X_s(a) \quad X_s(a) \pm \sqrt{(L+\lambda)p(a)}] \tag{19}$$

2. Then transform sigma points [10].
3. The following shows predicted state vector and the covariance matrix

   $$X_s(a+1|a) = \textstyle\sum_{i=0}^{2L} We_i^{(c)} [-X_s(a+1|a) + X_s(i, a+1|a)]^2 + Q(a) \tag{20}$$

4. The update state vectors sigma point is

$$X_s(a+1|a) = \begin{bmatrix} X_s(a+1|a) \\ X_s(a+1|a) + \sqrt{(L+\lambda)p(a+1|a)} \\ X_s(a+1|a) - \sqrt{(L+\lambda)p(a+1|a)} \end{bmatrix} \quad (21)$$

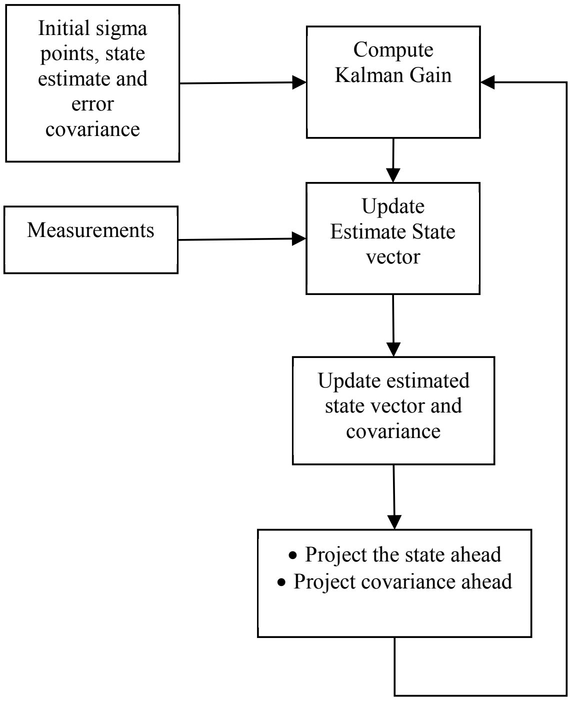

Fig.3. The flow of UAKF algorithm

5. Predicted vector points of the state are transformed via the measurement model. Then measurement prediction is

$$Y_s(a+1|a) = \sum_{i=0}^{2L} Wt_i^{(m)} Y(a+1|a) \quad (22)$$

Where $Y(a+1|a) = h(X_s(a+1))$ (23)

6. The noise measurement is assumed to be additive and independent; cross-covariance is

$$P_{yy} = \sum_{i=0}^{2L} Wt_r^{(c)} [Y(i,a+1|a) - Y_s(a+1|a)]^2 + R(a) \quad (24)$$

$$P_{xy} = \sum_{i=0}^{2L} Wt_i^{(c)} [X(i,a+1|a) - X_s(a+1|a)][Y(i,a+1|a) - Y_s(a+1|a)]^T \quad (25)$$

7. Kalman Gain is (G)

$$\mathrm{G}(a+1) = \mathrm{P}_{xy} P_{yy}^{-1} \quad (26)$$

8. The estimated state vector is

$$X(a+1|a+1) = X(a+1|a) + \mathrm{G}(a+1)(Y(a+1|a+1) - Y(a+1|a)) \quad (27)$$

9. The estimated error covariance is

$$P(a+1|a+1) = P(a+1|a) - \mathrm{G}(a+1) P_{yy} \mathrm{G}(a)^T \quad (28)$$

III. Simulation Results

The target state vector's introductory estimate for implementation of the algorithm is taken as:

$$X_s(0,0) = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 4000 * \sin(E_m) * \cos(B_m) \\ 4000 * \sin(E_m) * cos(B_m) \\ 4000 * \sin(E_m) \end{bmatrix}^T \quad (29)$$

Based on the sonar range of the day, the target's introductory position is calculated, and it is assumed as 4000m. The prediction of velocity components of the target is difficult as only angle measurements are available. So, they are each assumed as 1m/s. The initial state covariance matrix can be represented as a diagonal matrix if the initial state estimate is uniformly distributed and given as:

$$P(0,0) = diagnol\left[6 * (X_s(0,0))^2 / 12\right] \quad (30)$$

TABLE1: Scenarios Chosen to Evaluate The Performance

Sc no	TR (m)	TB (deg)	TC (deg)	TE (deg)	TS (m/s)	TP (deg)	OS (m/s)
1	3000	45	225	45	10	110	7.8
2	3000	0	270	135	12	60.5	12
3	3000	45	270	135	10	45	5
4	3000	135	45	135	12	135	12

TR- Target Range TB- Target Bearing TE- Target Elevation TS-Target Speed TP-Target Pitch TC-Target Course OS-Observer Speed

The experiment is conducted under favorable environmental conditions and hence the angle measurements are presumed to be available continuously. By using MATLAB in the PC (Personal Computer) environment, simulation is carried out. The scenarios that are selected for the performance of the algorithm are as shown in Table 1. For example, scenario1 defines a target moving with an initial bearing of 45°, course and speed of 255° and 10 m/s respectively. The elevation angle is 135°. The measurements of bearing and elevation are corrupted with 0.33°(1sigma) and 0.33°(1sigma) respectively.

TABLE 2. Convergence Time for All Scenarios For UAKF

Sc.no.	UAKF without observer maneuver			UAKF with observer maneuver		
	Range	Course	Speed	Range	Course	Speed
1	23	29	32	25	99	32
2	NC	NC	NC	188	167	191
3	NC	117	NC	293	115	288
4	NC	NC	NC	260	279	241

True values and estimates are available in simulation mode, and therefore the validity of the solution is possible on the basis of certain acceptance criteria. The acceptance criterion is given as:

Course error <= 3°

Speed error <= 5 m/s and

Range error <= 8% of actual range

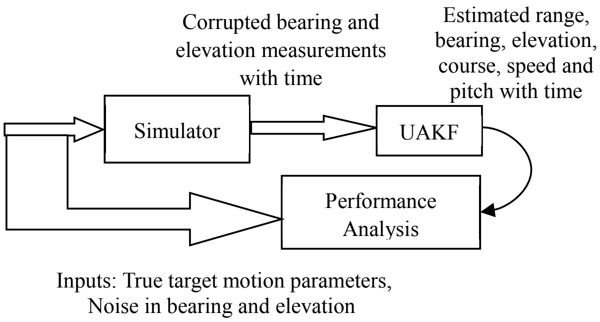

Fig.4. TMA block diagram in simulation mode

Block diagram of target motion analysis in simulation mode is shown in Fig 4. The target motion parameters (TMP) are estimated by corrupted measurements using UAKF. The estimated TMP are compared with that of true values. For scenario 1, Fig 5 presents the observer path without maneuver, tracking the target path. Errors in estimated range, course, and speed are shown in Fig 6 to Fig 8respectively, and numerical results are shown in Table 2. Similarly, Fig 9 shows the target and observer path where the estimated path does not keep on track with the true target path and from Fig 10, 11, 12, it can be observed that error in range, course, and speed is very high and the error is not within the acceptance criteria for scenario 2 respectively. Fig 13 shows the observer and target path with observer following S- maneuver for the same scenario 2. Fig 14, 15, 16 shows errors in range, course, and speed respectively.

In the simulation, for scenario1, it is observed that the range error, course error, and speed error are converged at 23rdsecond, 29thsecond, and 32ndsecond without observer maneuver, whereas, for scenario 2 the solution is not obtained for range, course, and speed. So, for the same scenario 2, observer maneuver is recommended, and the solution is converged at 188thsecond, 167thsecond, and 191stsecond for range, course, and speed respectively. At 191stsecond, the total solution is converged. Similarly, in table 2 the convergence times for other scenarios are shown.

Observer and target movements can be clearly seen from Fig 5, Fig 9, and Fig 13. In Fig 5 true and estimated paths of a target are the same that means without observer maneuver recommendation target is tracked by the observer for scenario 1 and errors are also within the acceptance criteria. Similarly, figure 9 shows that the true target path is not estimated by the observer, and the estimated path error for scenario 2 is also very high. So, for this problem, to track the target, the observer performs S- maneuver for the same scenario 2. Fig 13 shows the estimated and true target path with observer S-maneuver and errors in estimates of target parameters are also within the acceptance criteria and the solution is converged. The convergence times for all scenarios are shown in Table 2.

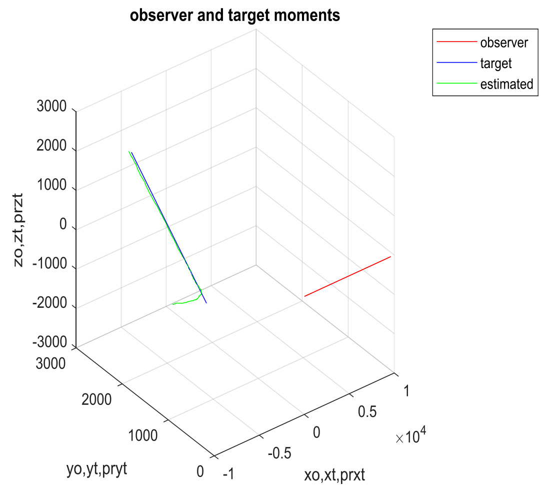

Fig.5. Observer and target path without observer maneuver for scenario 1

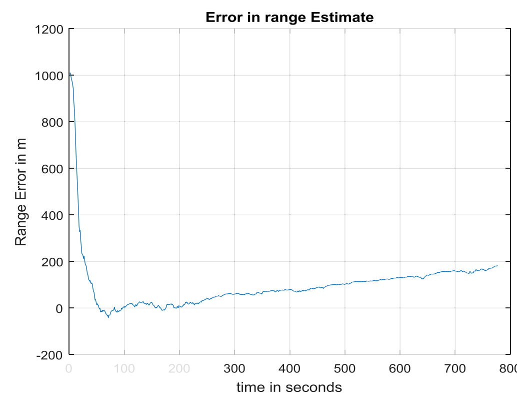

Fig. 6. Error in the estimated range

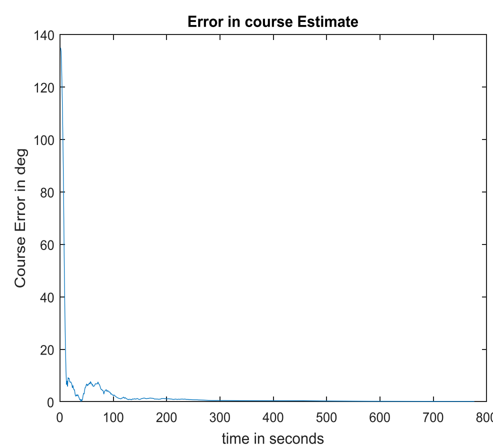

Fig.7. Error in estimated course

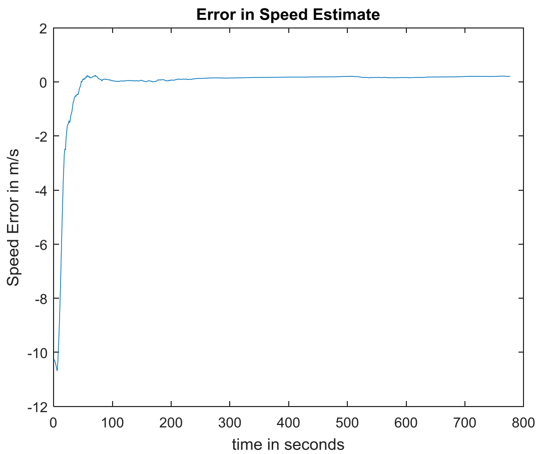

Fig.8. Error in estimated speed

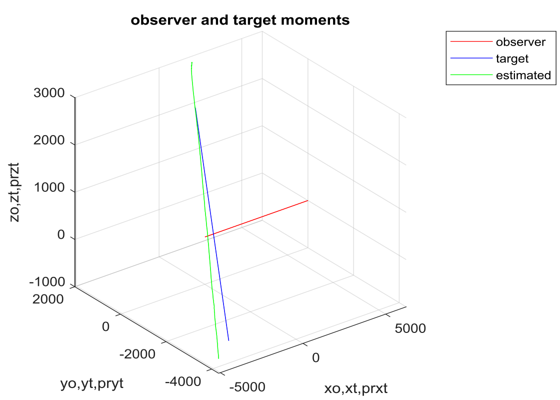

Fig.9. Observer and target path, without observer maneuver for scenario 2

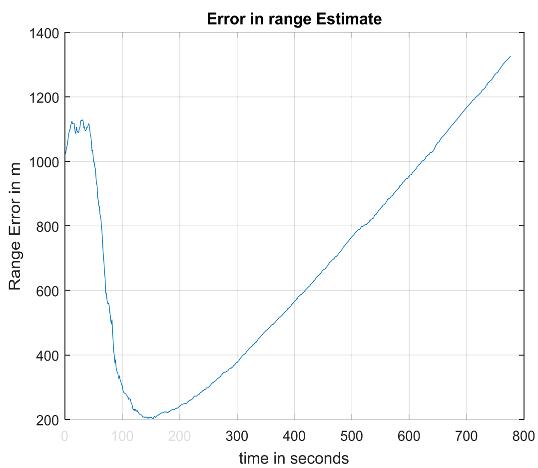

Fig.10.Error in the estimated range

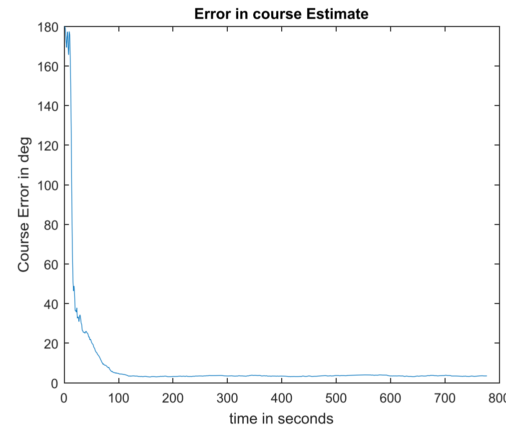

Fig.11.Error in estimated course

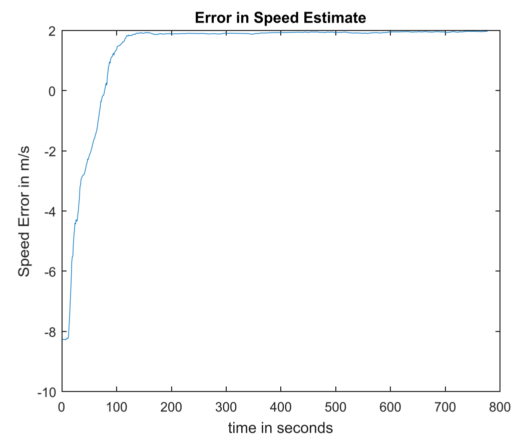

Fig.12. Error in estimated speed

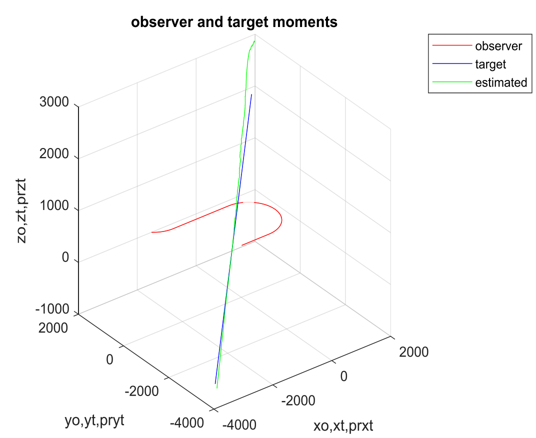

Fig.13.Observer and target path with observer following S-maneuver for scenario 2

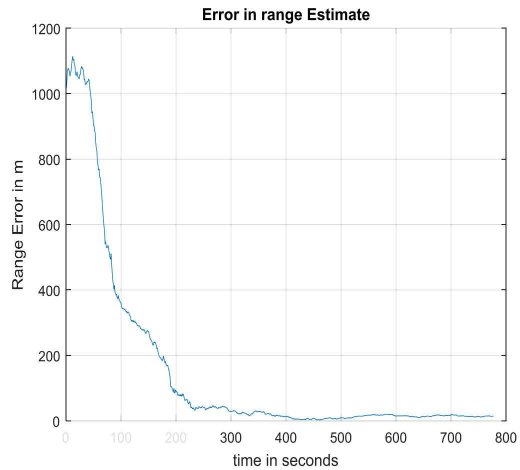

Fig.14.Error in the estimated range

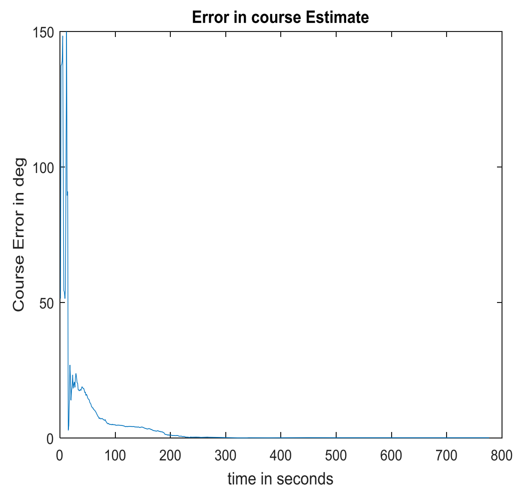

Fig.15.Error in estimated course

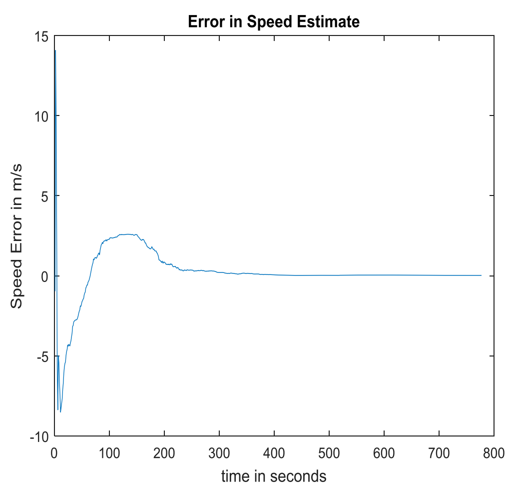

Fig.16.Error in estimated speed

IV. CONCLUSION

With the increasing interest in marine research, tracking undersea target technology has aroused to full attention. Acoustic waves have become the most useful signals for tracking underwater targets, due to the precision and difficulty of the marine environment. In this paper, for better results and less convergence time, observer maneuver is recommended to track the target and UAKF nonlinear filtering algorithm with observer S-maneuver is suitable for passive target tracking and when elevation measurements are also available along with bearing measurements. For better observability of target, observer has to maneuver and get the solution with less convergence of time when compare to without observer maneuver.

REFERENCES

[1] E.A. Wan and R. Van Der Merwe, "The unscented Kalman filter for nonlinear estimation", in 2. Proceedings of Symposiums 2000 on Adaptive System for Signal Processing, Communication, and Control, Canada, Oct. 2000.

[2] Kavitha Lakshmi, S. Koteswara Rao, K. Subrahmanyam, V. Gopi Tilak, "Passive object tracking using MGEKF algorithm" Advances in Intelligent Systems and Computing, Springer Nature Singapore, Vol 701, pp.277-287,2018.

[3] Kausar Jahan, S. Koteswara Rao, "Comparison of MGBEKF and UKF algorithms for bearings-only tracking, international journal of emerging trends in engineering research, Vol 7, No.7, pp-44-47, July 2019.

[4] S. Koteswara Rao, K. Raja Rajeswari, K.S. Lingamurthy, "Unscented Kalman Filter with Application to Bearings-Only 3. Target Tracking", IETE Journal of Research, Vol. 55, No. 2, pp. 63-67, Mar-Apr 2009.

[5] S. Koteswara Rao, V. Sunanda Babu, "Unscented Kalman Filter with Application to Bearings-Only Passive Manoeuvring Target Tracking", IEEE-International Conference on Signal Processing, Communications and Networking, pp. 219-224, Jan'2008.

[6] MeiliangWuz, Andrew W. Smyth, "Application of the unscented Kalman filter for real-time nonlinear structural system 5. identification", Structural Control and Health Monitoring, pp. 971-990, Oct'2006.

[7] Rudolph van der Merwe and Eric A.Wan, "The Square-Root Unscented Kalman Filter for State and Parameter-Estimation", 6. IEEE Trans, pp. 3461-3464, 2001

[8] BrankoRistic, Sanjeev Arulampalam and Neil Gordon, "Beyond the Kalman Filter: Particle Filters for Tracking Applications",7. *Artech House*, 2004.

[9] Dan Simon, "Optimal State Estimation: Kalman, H∞and Nonlinear Approaches", 8. *John Wiley & Sons*, Inc. 2006.

[10] Kausar Jahan, S. Koteswara Rao, "Comparison of MGBEKF and UKF algorithms for bearings-only tracking, international journal of emerging trends in engineering research, Vol 7, No.7, pp-44-47, July 2019.