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Undersea Maneuvering Target Tracking Using Novel Estimation Algorithm

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ABSTRACT

In underwater scenario, algorithms that assume constant velocity model are suitable for tracking non maneuvering targets but fail if target is maneuvering. The Interacting Multiple Model algorithm is a widely accepted state estimation scheme for solving maneuvering target tracking problems. This paper presents the IMM method of tracking under water maneuvering targets using active sonar measurements. UKF is used throughout the process and the simulation results for two scenarios are presented.

I. INTRODUCTION

In this paper, our objective is to achieve underwater maneuvering target tracking using active sonar range and bearing measurements. In the underwater scenario, the sonars fitted on to ships and submarines seek target localization by pumping acoustic energy into the water. The energy virtually illuminates the target and the noisy target range and bearing measurements are available. The noisy range and bearing measurements are smoothed and further used to estimate course and speed of the target. The ownship course and speed are assumed to be available without noise. (This assumption is made to present the concepts with clarity).

The generic case of target tracking can be broadly classified into two distinct classes-tracking a maneuvering target and tracking a non-maneuvering or constant velocity target. Needless to say, the challenges posed by maneuvering target tracking are much greater as compared to the non-maneuvering case. Tracking a non-maneuvering target has been historically a well discussed problem and has been mainly solved by using the Unscented Kalman Filter (UKF), its variants or more recently, the Particle Filters, based on sequential Monte Carlo methods. However, when faced with a maneuvering target, the problem becomes insurmountable due to model inadequacies. The key to successful target tracking lies in the effective extraction of useful information about the target's state from observations and a good model of the target will facilitate this information extraction process to a great extent, as rightly emphasized in [1]. UKF is proven to be one of the best algorithms for tracking a non maneuvering target. But when the target model being used by the UKF is that of a constant velocity one, due to the mismatch of the target motion model, it fails to get convergence.

A. Multiple Model Introductions

Hence for tracking a maneuvering target, the need is felt to use a multiple model approach. The multiple model approach gets around the difficulty due to model uncertainty in different legs of target run by using more than one target motion models. The basic idea is to assume a set of models as possible candidates of the true target motion model in effect at that time; run a bank of elementary filters, each based on a unique model in the set and generate the overall estimates by the process of combining the results of all the elementary filters. This combined approach to target motion parameter estimation for maneuvering targets is thus, definitely a better approach than using single UKF or its variants.

In current literature, three generations of Multiple Model algorithms have been discussed in [2]. With multiple model concepts as common, output processing, cooperation strategies and model set adaptation respectively form the benchmarks of these three generations. The first generation MM method or "the Autonomous MM algorithm" was initiated by Magill [3]and promoted by May beck [4]. The second generation, Blom's "Interacting Multiple Model", has been practically evaluated in tracking scenarios and demonstrated by Bar-Shalom. The third generation, characterized by its variable structure, is still relatively new and unproven in practical applications. For its well known applicability to field problems like Air Traffic Control (ATC), the IMM approach is chosen to design the algorithm.

B. Unscented Kalman Filter

Although the traditional Kalman filter is optimal when the model is linear, unfortunately for many of the state estimation problems like the above mentioned scenario, non-linearity in models exist thereby limiting the practical usefulness of the Kalman Filter and the EKF. Hence, the feasibility of a novel transformation, known as unscented transformation, which is designed to propagate information in the form of mean vector and covariance matrix through a non-linear process, is explored for underwater applications. The unscented transformation coupled with certain parts of the classic Kalman filter, provides a more accurate method than the EKF for nonlinear state estimation [6]. It is more accurate, easier to implement and uses the same order of calculations. The IMM-UKF is thus, the best combination possible to tackle the problem presented. The IMM [9-16] model set used in the algorithm presented contains three UKFs catering to the constant velocity model and the coordinated turn model. The constant velocity UKF is primarily responsible for tracking the target in its non-maneuvering phase, the coordinated right turn UKF tracks it in the right

maneuvering phase and the coordinated left turn UKF [13-16] tracks it in the left maneuvering phase.
Section-II contains mathematical modeling of measurements, target and own ship path. It also contains a brief introduction of UKF [15] and IMM algorithms. Detailed simulation is carried out and the results are presented in section-III. Finally the paper is concluded in section-IV.

II. MATHEMATICAL MODELLING

The Target-Observer scenario depicting the motion of target and observer is shown in Fig 1. The imaginary line joining target and observer is called Line Of Sight (LOS). The angle made by LOS with Y-Axis is called bearing (B). Length of LOS is called Range (R) of the target.

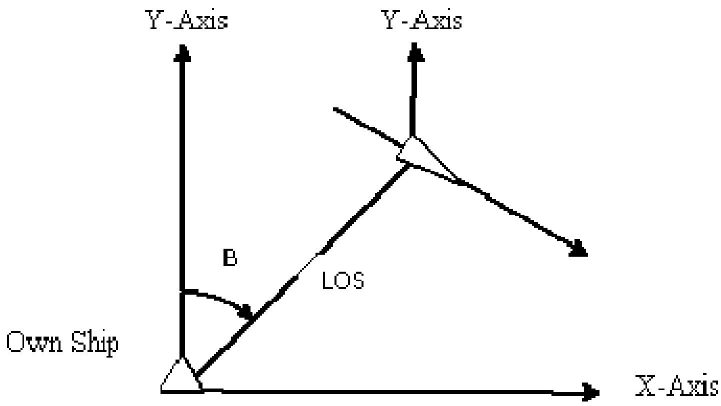

Figure 1: Target and Ownship encounter.

A. State and Measurement Equations

Let the target state vector be X(k), where

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

Where $\dot{x}(k)$ and $\dot{y}(k)$ are target velocity components and, $R_x(k) = R^* \sin(B)$ and $R_y(k) = R^* \cos(B)$ are range components along x and y axes respectively. The target state dynamic equation is given by

$$X(k+1) = \emptyset(k+1/k)X(k) + \beta(k+1) + \Gamma\,\omega(k) \tag{2}$$

Where $\emptyset$ and β are transition matrix and deterministic vector respectively.

$$\beta(k+1) = [0 \quad 0 \quad -(x_0(k+1) - x_0(k)) \quad -(y_0(k+1) - y_0(k))] \tag{3}$$

Where x_0 and y_0 are observer position components. The plant noise $\omega(k) = \begin{bmatrix}\omega_x \\ \omega_y\end{bmatrix}$ is assumed to be zero mean white Gaussian with $E[\omega(k)\omega'(j)] = Q\delta_{kj}$ in this paper all angles are assumed to be with respect to. y-axis. This convention is to reduce mathematical complexity and for easy implementation. The bearing measurement β_m and range measurement R_m is modelled as

$$\beta(k+1) = \tan^{-1}\left(\frac{R_x(k+1)}{R_y(k+1)}\right) + \varsigma(k) \tag{4}$$

$$R_m(k+1) = \sqrt{R_x(k+1)^2 + R_y(k+1)^2} + \xi(k) \tag{5}$$

where $\varsigma(k)$ and $\xi(k)$ are the errors in the bearing and range measurements respectively while these errors are assumed to be zero mean Gaussian with variances σ_B^2 and σ_R^2 respectively. The measurement and plant noises are assumed to be uncorrelated to each other. The plant noise covariance matrix is given by

$$Q(k) = \begin{bmatrix} ts^2 & 0 & ts^3/2 & 0 \\ 0 & ts^2 & 0 & ts^3/2 \\ ts^3/2 & 0 & ts^4/2 & 0 \\ 0 & ts^3/2 & 0 & ts^4/2 \end{bmatrix} * d(k) \tag{6}$$

Where d(k) is given by d(k) = $E[\omega(k)\omega^T(k)]$

B. Unscented Kalman Filter Algorithm

Detailed literature on UKF is available in [7], [8]. However a small brief of UKF is as follows. The state equation is given by

$$X(k+1) = F\big(X(k), \emptyset(k)\big) + \omega(k) \tag{7}$$

where, $\omega(k)$ is the plant noise. The Unscented Kalman Filter (UKF) uses $(2n+1)$ scalar weights (mean and covariance), which can be calculated as

$$W_0^{(m)} = \frac{\lambda}{n+\lambda}, W_0^{(c)} = \frac{\lambda}{n+\lambda} + \beta, W_i^{(m)} = W_i^{(c)} = \frac{1}{2(n+\lambda)} \tag{8}$$

where $i = 1,2,\ldots,2n$.

where $\lambda = (a^2 - 1)n$ is a scaling parameter, 'a' determines the spread of the sigma points around the mean $\bar{x}$ and is usually set to a small positive value and β is used to incorporate prior knowledge[9][10-13] of the state distribution x (for Gaussian distribution, $\beta = 2$ is optimal.) The standard UKF implementation consists of the following steps:

Calculation of the $(2n+1)$ sigma points starting from the initial conditions $x(k)=x(0)$ and P(k)=P(0)

$$X(k) = \lfloor x(k) \quad x(k) + \sqrt{(n+\lambda)P(k)} \quad x(k) - \sqrt{(n+\lambda)P(k)} \rfloor \tag{9}$$

Transformation of these sigma points through the process model using Eqn. (12). The prediction of the state estimate at time k with measurement up to time $k+1$ is given as

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

As the process noise is additive and independent, the predicted covariance is given as

$$\mathrm{P(k+1/k)} = \sum_{i=0}^{2n} [\mathrm{W_i^c}[\mathrm{x(i,k+1/k) - x(k+1/k)}][\mathrm{x(i,k+1/k) - x(k+1/k)}]^{\mathrm{T}}] + \mathrm{Q(k)}] \tag{11}$$

Next step is updating the sigma points with the predicted mean and covariance. The updated sigma points are given as

$$\mathrm{X(k+1/k)} = \left[\mathrm{x(k+1/k)} \quad \mathrm{x(k+1/k)} + \sqrt{(\mathrm{n}+\lambda)\mathrm{P(k+1/k)}} \quad \mathrm{x(k+1/k)} - \sqrt{(\mathrm{n}+\lambda)\mathrm{P(k+1/k)}}\right] \tag{12}$$

After updating, transformation of each of the predicted points happens through the measurement equation. Prediction of measurement (innovation), given as

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

Since the measurement noise is also additive and independent, the innovation covariance is given as

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(m)} [Y(i,k+1/k) - y(k+1/k)][Y(i,k+1/k) - y(k+1/k)]^T + R(k) \tag{14}$$

The cross covariance is given as

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

Kalman gain is calculated as

$$K(k+1) = P_{xy} P_{yy}{}^{-1} \tag{16}$$

The estimated state is given as

$$\mathrm{X(k+1/k) = X(k+1/k) + K(k+1)y(k+1/k+1) - y(k+1/k))} \tag{17}$$

where y(k) is true measurement. Estimated error covariance is given as

$$P(k+1/k+1) = P(k+1/k) - K(k+1)P_{yy}K(k+1)^T \quad (18)$$

C. Generic IMM Algorithm

a. Interaction:

Interaction involves computation of mixing probabilities of model i and j with previous mode probabilities and transition probabilities. The mixing probabilities are calculated as

$$u_{i/j}\left(k-1/_{k-1}\right) = \frac{1}{c} p_{ij} u_i(k-1) \quad (19)$$

where $i, j = 1, ..., n$ and the normalizing constant

$$c_j = \sum_{i=1}^{n} p_{ij} u(k-1) \quad (20)$$

$j = 1, ..., n$ and $u_{i/j}$ is mixing probability to reach model j from i. $p_{i/j}$ = Transition probability to reach model j from i.

b. Mixing:

Mixing involves computation of resultant state and covariance matrices of all models according to mixing probabilities. Mixing of state vector

$$x^{\sim oj}\left(k-1/_{k-1}\right) \sum_{i=1}^{n} x^{\sim i}\left(k-1/_{k-1}\right) u_{i/j}\left(k-1/_{k-1}\right) \quad (21)$$

where j=1, 2,..., n.

c. Mixing of covariance matrices

$$P^{0j}\left(k-1/_{k-1}\right) = \sum_{i=1}^{r} u_{i/j}\left(k-1/_{k-1}\right)\left\{P^{i}\left(k-1/_{k-1}\right) + \begin{bmatrix}\hat{x}^{j}\left(k-1/_{k-1}\right) - \\ \hat{x}^{oj}\left(k-1/_{k-1}\right)\end{bmatrix}\begin{bmatrix}\hat{x}^{j}\left(k-1/_{k-1}\right) - \\ \hat{x}^{oj}\left(k-1/_{k-1}\right)\end{bmatrix}^T\right\} \quad (22)$$

d. Computing likelihood

$$\Lambda_j(k) = N(\hat{z}^j, S^j) \quad (23)$$

Where $\hat{z}^j$, is the measurement residue for and S^j is the innovation covariance of filter j

e. Updating Mode Probability

$$u_j(k) = \left(\frac{1}{c}\right) * \Lambda_j(k)c_j \text{ where } c_j = \sum_{j=1}^{n} \Lambda_j(k)c_j \quad (24)$$

f. Computing Resultant State and Covariance vectors

$$\hat{x}(k/k) = \sum_{j=1}^{n} \hat{x}^{j}\left(\frac{k}{k}\right) u_j(k)$$

$$P(k/k) = \sum_{j=1}^{n} u_j\left(\frac{k}{k}\right)\left\{P^{j}(k/k) + \left[\hat{x}^{j}(k/k) - \hat{x}(k/k)\right]\left[\hat{x}^{j}(k/k) - \hat{x}(k/k\right]^{T}\right\}$$

(25)

D. IMM-UKF

Three UKFs are combined to form IMM-UKF. Three models, one Constant Velocity (CV) and two Coordinated Turn (CT) models were used to develop IMM-UKF. It assumed that the target is a submarine which occasionally changes its course at 1 deg/sec.

For CV Model:

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

(26)

For CT Model:

$$\emptyset(k+1/k) = \begin{bmatrix} \cos(\Omega t) & \sin(\Omega t) & 0 & 0 \\ -\sin(\Omega t) & \cos(\Omega t) & 0 & 0 \\ \frac{\sin(\Omega t)}{\sin(\Omega)} & \frac{(1-\cos(\Omega t))}{\Omega} & 1 & 0 \\ -\frac{(1-\cos(\Omega t))}{\Omega} & \frac{\sin(\Omega t)}{\sin(\Omega)} & 0 & 1 \end{bmatrix}$$

(27)

Where Ω is the turn rate, with-1 deg/s for left CT model and 1 deg/s for right CT model. The measurement relation vector and measurement noise covariance matrices are given by:

$$H(k) = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

(28)

$$R(k) = \frac{\sigma_R^2 - R(k)^2\sigma_\beta^2}{2}\begin{bmatrix} L + \cos(2\beta) & \sin(2\beta) \\ \sin(2\beta) & L - \cos(2\beta) \end{bmatrix}$$

(29)

Where

$$L = \frac{\sigma_R^2 + R(k)^2\sigma_\beta^2}{\sigma_R^2 - R(k)^2\sigma_\beta^2}$$

III. SIMULATION AND RESULTS

a. Simulation:

The IMM-UKF was tested with the following scenarios. The trajectory of the target and observer is simulated in Matlab. Range and bearing measurements are computed by taking sonar maximum acquisition range as 8000m. Sampling time of these measurements are computed assuming sound velocity in water as 1500 m/s. Hence sampling time is 2*8000 / 1500 = 10. 6 seconds. Total simulation time is 1000 seconds. These measurements are corrupted by adding zero-mean white Gaussian noise. The IMM UKF algorithm uses the following transition and mode probabilities.
Transition probability matrix is

$$\begin{bmatrix} 0.99 & 0.005 & 0.005 \\ 0.005 & 0.99 & 0.005 \\ 0.005 & 0.005 & 0.99 \end{bmatrix} \tag{30}$$

Initial Mode probability matrix

$$[0.99 \quad 0.005 \quad 0.005]$$

The above values are arrived at by rigorous simulations using different transition and mode probabilities for every scenario. The choices have been simulation intensive factors as there are no patterns in the results that could be utilized to generate an empirical formula for calculating these probabilities.
Ownship is taken to be moving with course 90 deg and speed 4. 1m/s for both test cases as in TABLE 1. The noise in the measured range is taken as 10m S. D. while the noise of the measured bearing is taken to be 0. 565 deg S. D. for simulation purposes. The noise is assumed to be Gaussian. The turn rate for the target ship is taken as 1 deg/s. The acceptance criteria taken for error in course and speed convergence are ±5 deg and 20 % of true speed respectively.

TABLE 1

Target		Scenario1	Scenario2
Range (m)		5000	3000
Initial Bearing (deg)		50	60
Straight Path Before Maneuver			
Course (deg)		270	120
Speed (m/s)		7. 71	9. 19
Course Maneuver	Start Sample	37 (400 s)	37 (400 s)
	End Sample	58 (640 s)	56 (620 s)
Straight Path After Maneuver			
Course (deg)		30	340
Speed (m/s)		7. 71	9. 19
Own Ship			
Course (deg)		90	90
Speed (m/s)		4. 1	6. 16

b. Results

TABLE 2: CONVERGENCE TIME IN SECONDS

	Scenario1	Scenario2
Straight Path Before Maneuver		
Course	52	49
Speed	30	38
Delay in Course Maneuver Detection		
Course	33	33
Speed	10	11
Straight Path After Maneuver		
Course	70	54
Speed	10	11

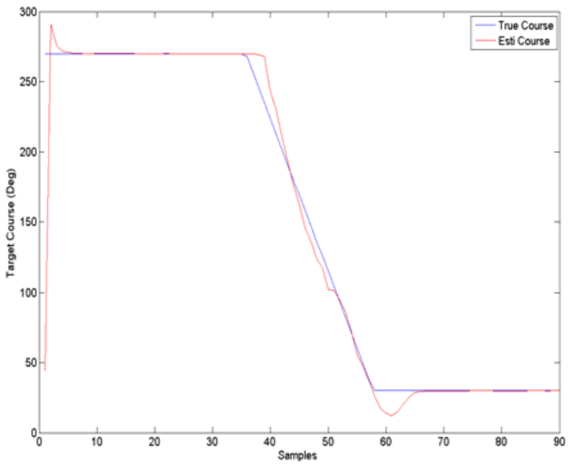

Figure 2: Estimated Course and True Course (Scenario 1)

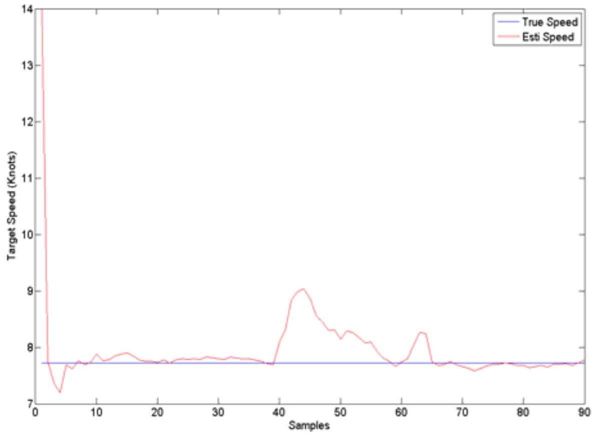

Figure 3: Estimated Speed and True Speed (Scenario 1)

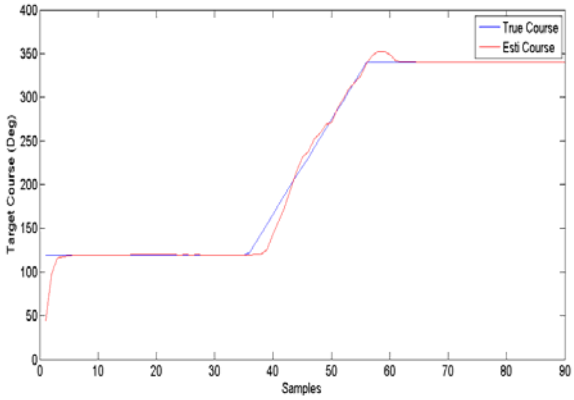

Figure 4: Estimated Course and True Course (Scenario 2)

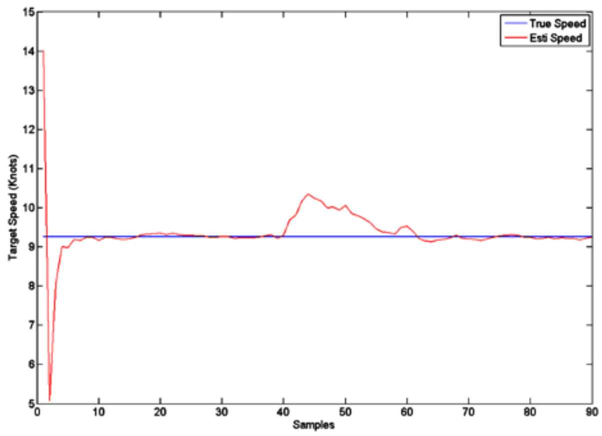

Figure 5: Estimated Speed and True Speed (Scenario 2)

From the figures 1 and 3, it is evident that the target ship is being tracked accurately by the IMM-UKF algorithm in both the scenarios even in its maneuvering phases. The course maneuvers in the first and second scenarios are 240 degrees and 220 degrees respectively. It is seen that large course changes have been tracked correctly by the algorithm. The slacks in the estimated course at both the time of maneuver start and maneuver stop are indicative of the time that algorithm takes time to respond to the target maneuvers.

IV. Conclusion

The performance of the proposed IMM-UKF algorithm to active underwater target tracking is found to be satisfactory. Selection of transition probability and model probabilities are the key factors to tune the IMM performance. It is observed that, even though the model switching occurred at precise instants, the reflection of switch in convergence times had a noticeable delay. The performance of the IMM-UKF can be improved by further investigation on the role of covariance matrices.

REFERENCES

[1] X. Rong Li, V. P. Jilkov, “Survey of Maneuvering Target Tracking Part I:Dynamic Models, ” IEEE Transactions on Aerospace and Electronic Systems, Vol. 39, No. 4, October 2003.

[2] X. R. Li, Engineer’s Guide to Variable Structure Multiple Model Estmation for Tracking in Multitarget-Multisensor Tracking:Applications and Advances, vol. 3. pp. 499-567, Boston, MA:Arctech House, 2000.

[3] D. T. Magill, “Optimal Adaptive Estimation of Sampled Stochastic Processes, ”, IEEE Trans. Automatic Control, AC-10:434-439, 1965..

[4] P. S. Maybeck, “Stochastic Models, Estimation and Control”, Vols. II, III. New York: Academic Press, 1982.

[5] H. A. P. Blom, “An Efficient Filter for Abruptly Changing Systems, ” in Proc. 23rd IEEE Conf. Decision and Control, (Las Vegas, NV), Dec. 1984.

[6] B. Ristic, S. Arulampalam, N. Gordon, “Beyond Kalman Filters-Particle filters for tracking applications”, Artech House, DSTO, 2004.

[7] James V. Candy, “ Bayesian Signal Processing: Classical, Modern and Particle Filtering, ”, Wiley Intersceince, 2009.

[8] James V. Candy, “Model based Signal Processing ”, IEEE press, 2006.

[9] A. Sampath Dakshina Murthy, S. Koteswara Rao, K. Srinavasa Naik, Rudra Pratap Das, Kausar Jahan, and K. Lova Raju. "Tracking of a Manoeuvering Target Ship using Radar Measurements. " Indian Journal of Science and Technology 8, no. 28 (2015). (0974-5645)

[10] A. Sampath Dakshina Murthy, S. Koteswara Rao, A. Naga Jyothi, and Rudra Pratap Das. "Analysis of Effect of Ballistic Coefficient in the Formulations and Performance of EKF with Emphasis on Air Drag. " Indian Journal of Science and Technology 8, no. 31 (2015). (0974-5645).

[11] Raju, K. Lova, S. Koteswara Rao, Rudra Pratap Das, M. Nalini Santhosh, and A. Sampath Dakshina Murthy. "Passive Target Tracking using Unscented Kalman Filter based on Monte Carlo Simulation. " Indian Journal of Science and Technology 8, no. 29 (2015). (0974-5645).

[12] Annabattula Jawahar, S. Koteswara Rao, A. Sampath Dakshina Murthy, K. S. Srikanth, and Rudra Pratap Das. "Multi-Sensor Submarine Surveillance System using MGBEKF. " Indian Journal of Science and Technology 8, no. 35 (2015). (0974-5645).

[13] Annabattula Jawahar, S. Koteswara Rao, A. Sampath Dakshina Murthy, K. S. Srikanth, and Rudra Pratap Das. "Advanced Submarine Integrated Weapon Control System. " Indian Journal of Science and Technology 8, no. 35 (2015). (0974-5645).

[14] Annabattula Jawahar, S. Koteswara Rao, A. Sampath Dakshina Murthy, K. S. Srikanth, and Rudra Pratap Das. "Underwater Passive Target Tracking in Constrained Environment. " Indian Journal of Science and Technology 8, no. 35 (2015). (0974-5645).

[15] Jahan, Kausar, A. Sampath Dakshina Murthy, and S. Koteswara Rao. "Particle Filter Based Ownship Evasive Maneuver under Torpedo Attack. " Volume 6, Issue 1, January 2015.
[16] A. Sampath Dakshina Murthy, and A. Naga Jyothi. "Minimization of Degeneracy Problem by Roughening Particle Filter. " Volume-4 Issue-3 May 2016.
[17] A. Sampath Dakshina Murthy1, T. Pavani and K. Lakshmi "An Application of Firefly Hybrid Extended Kalman Filter Tracking a Reentry Object". Indian Journal of Science and Technology 9, no. 28 (2016). (0974-5645).