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Research Article

ROBUST STOCHASTIC UNDERSEA NONLINEAR SIGNAL ESTIMATOR FOR ACTIVE SONAR APPLICATIONS

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ABSTRACT

Objective: This paper presents the interacting multiple model (IMM) method of tracking underwater maneuvering targets using active sonar measurements.

Methods: The IMM algorithm is a widely accepted state estimation scheme for solving maneuvering target tracking problems.

Results: In the underwater scenario, algorithms that assume constant velocity model are suitable for tracking nonmaneuvering targets but fail if target is maneuvering.

Conclusion: Unscented Kalman filter is used throughout the process, and the simulation results for two scenarios are presented.

Keywords: Estimation, Sonar, Target tracking, Maneuver, Kalman filter, Interacting multiple model.

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 nonmaneuvering or constant velocity (CV) target. Needless to say, the challenges posed by maneuvering target tracking are much greater as compared to the nonmaneuvering case. Tracking a nonmaneuvering target has been historically a well-discussed problem and has been mainly solved using the unscented Kalman filter (UKF) and 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 [1]. UKF is proven to be one of the best algorithms for tracking a nonmaneuvering target. However, when the target model being used by the UKF is that of a CV one, due to the mismatch of the target motion model, it fails to get convergence.

Multiple model (MM) introduction

Hence for tracking a maneuvering target, the need is felt to use an MM approach. The MM approach gets around the difficulty due to model uncertainty in different legs of target run 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 MM algorithms have been discussed [2]. With MM 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 Maybeck [4]. The second generation, Blom's "Interacting MM" (IMM), has been practically evaluated in trackingscenarios and demonstrated by Bar-Shalom [5]. 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 such as air traffic control, the IMM approach is chosen to design the algorithm.

Unscented Kalman filter (UKF)

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, nonlinearity in models exist thereby limiting the practical usefulness of the Kalman filter, and the extended Kalman filter (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 nonlinear 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 model set used in the algorithm presented contains three UKFs catering to the CV model and the coordinated turn (CT) model. The CV 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 tracks it in the left maneuvering phase.

Section II contains mathematical modeling of measurements, target, and ownship path. It also contains a brief introduction of UKF and

IMM algorithms. Detailed simulation is carried out, and the results are presented in Section III. Finally, the paper is concluded in Section IV.

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). The length of LOS is called range (R) of the target.

State and measurement equations

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

$$X(k) = \begin{bmatrix} \dot{x}(k) & \dot{y}(k) & R_x(k) & R_y(k) \end{bmatrix}^T \quad (1)$$

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-axis, respectively.

The target state dynamic equation is given by:

$$X(k+1)=\phi(k+1/k)X(k)+b(k+1)+\Gamma\omega(k) \quad (2)$$

Where, ϕ and b are transition matrix and deterministic vector, respectively.

$$b(k+1) = \begin{bmatrix} 0 & 0 & -\left(x_0(k+1)-x_0(k)\right) & -\left(y_0(k+1)-y_0(k)\right) \end{bmatrix} \quad (3)$$

Where, x_0 and y_0 are observer position components. The plant noise: $w(k) = \begin{bmatrix} w_{\ddot{x}} \\ w_{\ddot{y}} \end{bmatrix}$ is assumed to be zero mean white Gaussian with $E\left[w(k)w'(j)\right] = Q\delta_{kj}$.

In this paper, all angles are assumed to be w.r.t. y-axis. This convention is to reduce mathematical complexity and for easy implementation. The bearing measurement B_m, and range measurement R_m is modeled as:

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

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

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.

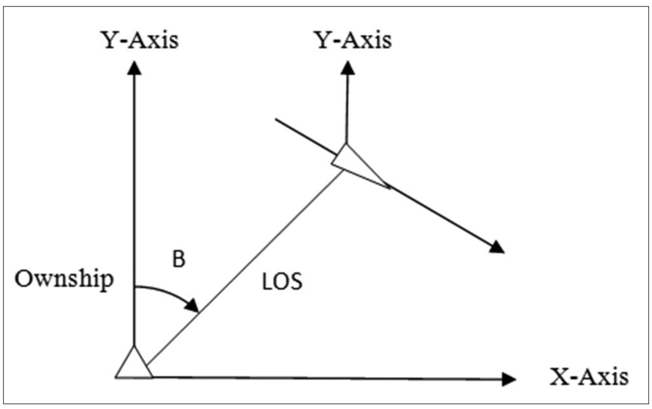

Fig. 1: Target and ownship encounter

The plant noise covariance matrix is given by:

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

Where $d(k)$ is given by $d(k) = E\left[w(k)w^T(k)\right]$.

UKF algorithm

Detailed literature on UKF is available in Candy [7,8]. However, a small brief of UKF is as follows.

The state equation is given by:

$$X(k+1)=F(X(k), \phi(k))+\omega(k) \quad (7)$$

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

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

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 and is usually set to a small positive value and β is used to incorporate prior knowledge 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 $P(k)=P(0)$

$$X(k) = \begin{bmatrix} x(k) & x(k)+\sqrt{(n+\lambda)P(k)} & x(k)-\sqrt{(n+\lambda)P(k)} \end{bmatrix} \quad (9)$$

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

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

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

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

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

$$X(k+1|k) = \begin{bmatrix} x(k+1|k) & x(k+1|k)+\sqrt{(n+\lambda)P(k+1|k)} & x(k+1|k)-\sqrt{(n+\lambda)P(k+1|k)} \end{bmatrix} \quad (12)$$

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

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

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

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

The cross covariance is given as:

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

Kalman gain is calculated as:

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

The estimated state is given as:

$$X(k+1|k) = X(k+1|k) + K(k+1)(y(k+1|k+1) - y(k+1|k)) \quad (17)$$

Where, $y(k)$ is true measurement. Estimated error covariance is given as:

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

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

where *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:

$$\hat{x}^{oj}(k-1/k-1) = \sum_{i=1}^{n} \hat{x}^i(k-1/k-1) u_{i/j}(k-1/k-1) \quad (20)$$

Where, *j*=1, 2…, *n*.

c. Mixing of covariance matrices:

$$P^{0j}(k-1/k-1) = \sum_{i=1}^{r} u_{i/j}(k-1/k-1) \left\{ P^i(k-1/k-1) + \left[\begin{array}{l} \hat{x}^i(k-1/k-1) - \\ \hat{x}^{0i}(k-1/k-1) \end{array} \right] \cdot \left[\begin{array}{l} \hat{x}^i(k-1/k-1) - \\ \hat{x}^{0i}(k-1/k-1) \end{array} \right]^T \right\} \quad (21)$$

d. Computing likelihood:

$$\Lambda_j(k) = N\left(\hat{z}^j, S^j\right) \quad (22)$$

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

e. Updating mode probability:

$$u_j(k) = \left(\frac{1}{c}\right) * \Lambda_j(k) c_j \quad \text{where } c_j = \sum_{j=1}^{n} \Lambda_j(k) c_j \quad (23)$$

f. Computing resultant state and covariance vectors:

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

$$P(k/k) = \sum_{j=1}^{n} u_j(k) \left\{ P^j(k/k) + \left[\hat{x}^j(k/k) - \hat{x}(k/k)\right]\left[\hat{x}^j(k/k) - \hat{x}(k/k)\right]^T \right\} \quad (24)$$

IMM-UKF

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

For CV model:

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

For CT model:

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

Where Ω is the turn rate, with −1°/s for left CT model and 1°/s for right CT model.

The measurement relation vector and measurement noise covariance matrices are given by:

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

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

Where, $L = \dfrac{\sigma_R^2 + R(k)^2 \sigma_B^2}{\sigma_R^2 - R(k)^2 \sigma_B^2}$.

SIMULATION AND RESULTS

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 8000 m. The sampling time of these measurements is computed assuming sound velocity in water as 1500 m/s. Hence, the 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: $\begin{bmatrix} 0.99 & 0.005 & 0.005 \\ 0.005 & 0.99 & 0.005 \\ 0.005 & 0.005 & 0.99 \end{bmatrix}$

Initial mode probability matrix: $\begin{bmatrix} 0.99 & 0.005 & 0.005 \end{bmatrix}$

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

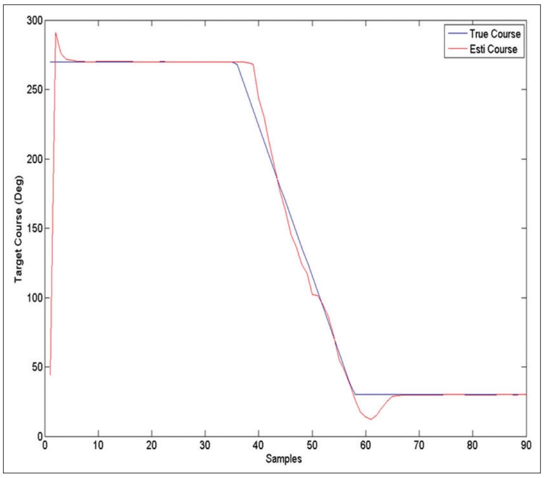

Fig. 2: Estimated course and true course (Scenario 1)

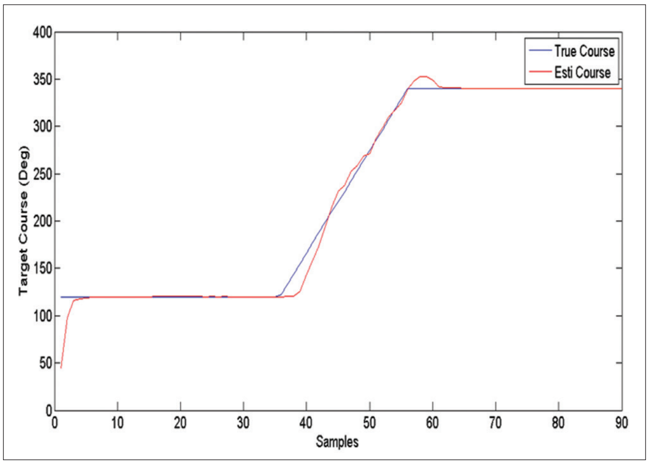

Fig. 4: Estimated course and true course (Scenario 2)

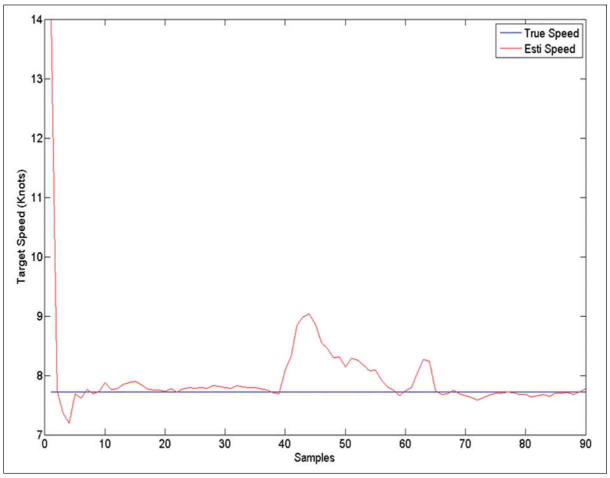

Fig. 3: Estimated speed and true speed (Scenario 1)

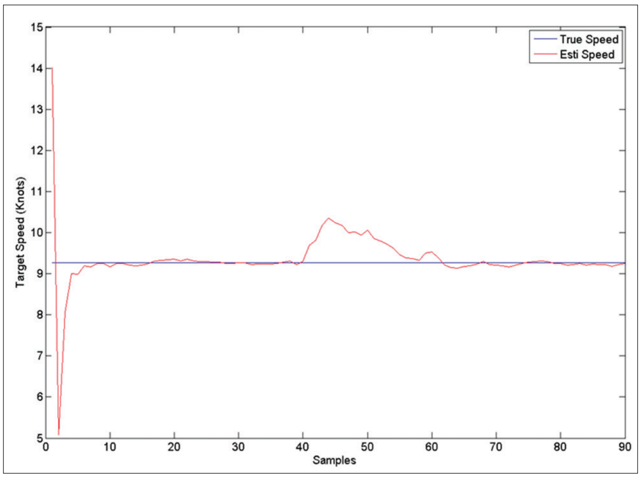

Fig. 5: Estimated speed and true speed (Scenario 2)

that could be utilized to generate an empirical formula for calculating these probabilities.

Ownship is taken to be moving with course 90° and speed 4.1 m/s for both test cases as in Table 1. The noise in the measured range is taken as 10 m S.D. while the noise of the measured bearing is taken to be 0.565° S.D. for simulation purposes. The noise is assumed to be Gaussian. The turn rate for the target ship is taken as 1°/s. The acceptance criteria taken for error in course and speed convergence are ±5° and 20% of true speed, respectively.

Results

From Figs. 2-5, 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° and 220°, 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 as shown in Table 2.

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-

Table 1: Scenarios considered

Target	Scenario 1	Scenario 2
Range (m)	5000	3000
Initial bearing (°)	50	60
Straight path before maneuver		
Course (°)	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 (°)	30	340
Speed (m/s)	7.71	9.19
Ownship		
Course (°)	90	90
Speed (m/s)	4.1	6.16

Table 2: Convergence time in seconds

Tactical geometry	Scenario 1	Scenario 2
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

UKF can be improved by further investigation on the role of covariance matrices.

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