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Performance Analysis of Unscented Kalman Filter using Fuzzy Logic for Tracking Applications

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***Abstract:*-- Target tracking is one of the major aspects often used in sonar applications, surveillance systems, communication systems, embedded applications etc. To obtain kinematic components of a moving target such as position, velocity, and acceleration, one of the most used approaches in target tracking is stochastic estimation approach. Movement of the target is described by state space dynamic system. Stochastic estimation is carried out using state estimators (filters). Some of the estimators are Kalman Filter, Extended Kalman Filter, Unscented Kalman Filter, Particle Filter, Interactive Multiple Model etc. The approach in this paper is to analyze Unscented Kalman Filter(UKF) using Fuzzy Logic.**

Keywords: - State estimator, Fuzzy Logic, Target tracking, Unscented Kalman Filter

I. INTRODUCTION

In this paper, the objective is to achieve underwater maneuvering target tracking using passive sonar bearing measurements. In the underwater the sonar's are fixed to ships and submarines to get target localization by sending acoustic energy into the water. The energy virtually illuminates the target and by using this target range and bearing measurements are taken in the presence of noise. Then noisy range and bearing measurements are filtered and estimate the course and speed of the target. The own ship course and speed are considered without noise .In general target tracking can be classified into two different categories [3,7]. i.e., Tracking a maneuvering target and Tracking a non-maneuvering or constant velocity target. Maneuvering target tracking is very important than the non maneuvering target tracking. Non-maneuvering target tracking has been discussed earlier and implemented with the help of Kalman filter, Extended Kalman filter. So, in this paper mainly concentrate on manuvering target tracking using unscented Kalman filter (UKF). Maneuvering target tracking is very difficult because of those state 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. UKF is proven to be one of the best algorithms for tracking a non maneuvering target.

II. 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 [1]. The unscented transformation coupled with certain parts of the classic Kalman filter, provides a more accurate method than the EKF for nonlinear state estimation. It is more accurate, easier to implement and uses the same order of calculations. Instead of linearizing the functions, UKF transform uses a set of points and propagates them through the actual nonlinear function, eliminating linearization altogether. The points are chosen such that their mean, covariance and higher order moments match the Gaussian random variable. Mean and covariance can be recalculated from the propagated points, to yield more accurate results compared to Taylor's series ordinary function linearization [2,4]. Selection of sample points is not arbitrary. Gaussian random variable in N dimensions uses 2N+1sample points. Matrix square root and Covariance definitions are used to select sigma points in such a way that their covariance is same as the Gaussian random variable. The unscented Transform approach has the advantage that noise is treated as a nonlinear function to account for non-Gaussian or non-additive noises. The strategy for doing so involves propagation of noise through functions by first augmenting the state vector to include noise sources. Sigma points are then selected from the augmented state, which includes noise values also. The net result is that any nonlinear effects of process and measurement noise are captured with the same accuracy as the rest of the state, which in turn increases estimation accuracy in presence of additive noise sources.
The state equation is given by

X(k+1)=F(X(k),A(k))+w(k) (1)

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

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

$$W_i^{(m)} = W_i^{(c)} = \frac{1}{2(n+\lambda)} \quad (3)$$

Where i = 1,2, ... , 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 isusually 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-1)=x(0) and P(k-1)=P(0) (4)

X(k-1)=[x(k-1) x(k1)+$\sqrt{(n+\lambda)P(k-1)}$
x(k-1)-$\sqrt{(n+\lambda)P(k-1)}$] (5)
Transformation of these sigma points through the process model. The prediction of the state estimate at time k with measurement up to time k-1 is given as

x(k/k-1)=$\sum_{i=0}^{2n} W_i^{(m)}\, x(i, \mathrm{k/k}-1)$ (6)

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

P(k/k-1)=$\sum_{i=0}^{2n} W_i^{(c)}\, [x(i, \mathrm{k/k}-1) - x(\mathrm{k/k}-1)]$
$[x(i, \mathrm{k/k}-1) - x(\mathrm{k/k}-1)]^T$+Q(k) (7)

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

X(k/k-1)=[x(k/k-1)x(k/k-1)+ $\sqrt{(n+\lambda)P(k/k-1)}$
x(k/k-1)-$\sqrt{(n+\lambda)P(k/k-1)}$] (8)

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

y(k/k-1)=$\sum_{i=0}^{2n} W_i^{(m)}\, Y(i, \mathrm{k/k}-1)$ (9)

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

R_{zz}=$\sum_{i=0}^{2q} W_i^{(c)}\, [C(i, \kappa/\kappa-1) - z(\kappa/\kappa-1)]$
$[Z(i, \kappa/\kappa-1) - z(\kappa/\kappa-1)]^T$ + V(□) (10)

The cross covariance is given as

R_{sz}=$\sum_{i=0}^{2q} W_i^{(c)}\, [M(i, \kappa/\kappa-1) - m(\kappa/\kappa-1)]$
$[Z(i, \kappa/\kappa-1) - z(\kappa/\kappa-1)]^T$ + V(□) (11)

Kalman gain is calculated as
K(□)=$R_{sz}{R_{zz}}^{-1}$ (12)

The estimated state is given as

X(k /k-1)= X(k /k-1)+ K(k)((y(k /k)-y(k /k-1) (13)

Where y(k-1)is true measurement. Estimated error covariance is given as

P(k/k)=P(k/k-1)-K(k)$P_{yy}K(k)^T$ (14)

III. FUZZY LOGIC

Fuzzy logic is a system of rule-based decision making used for expert systems and process control. Fuzzy logic is different from Boolean logic in that fuzzy logic allows partial membership in a set. Boolean logic is two-valued in the sense that a member either belongs to a set or does not. One and zero represent the values to membership of a member to the set with one represents absolute membership and zero represents no membership [6]. A fuzzy system is a system of variables that are associated when using fuzzy logic. A fuzzy controller uses defined rules to control a fuzzy system based on the current values of input variables. Fuzzy systems consist of three main parts: linguistic variables, membership functions, and rules. A general model of a Fuzzy Inference System (FIS) is shown in Figure 1 Fuzzy logic mainly consists of four types. They are Fuzzification, Knowledge base, Inference engine and Defuzzification

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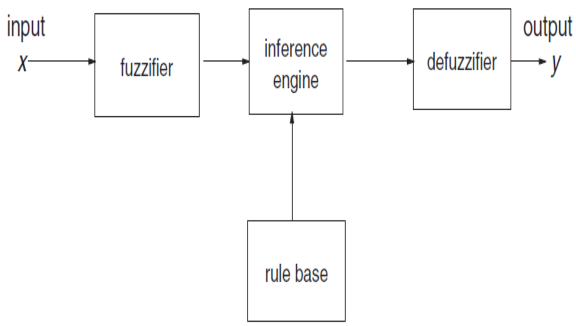

Figure: 1 Block diagram of a Fuzzy Inference System

IV. TOPOLOGICAL DEPICTION OF TARGET OWN SHIP COUNTER

In the ocean environment, movement of the Target and own ship is considered as shown in Fig2

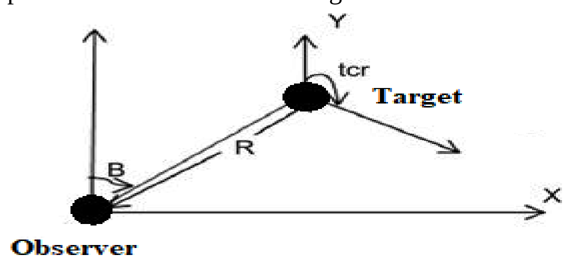

Fig 2: Target and observer positions

Line of Sight (LOS) is the line joining the target and own ship. Bearing is calculated by taking angle of LOS with Y-axis. Range is taken as the total length of LOS of the target. Own ship Course (OCR) and Target Course (TCR) is obtained by making angle of own ship and target with Y-axis respectively [5,8].

Case studies for Target Motion Parameters

Target is assumed to move with an initial speed and course of 4 knots and 135 degrees respectively. The approach in this paper is to track the maneuvering target using bearing only measurements in sonar applications using Fuzzy Logic.

Initially distance between target and observer is considered as 5000 meters and 0 bearing value. Complete target motion is analyzed for 1800 samples. Initial values are assumed as with Speed of 4 knots, course of 135 degrees. The bearing measurements are corrupted with maximum noise level by 0.5 degrees. The measurements are recorded for every 1sec.

Case studies for Observer Motion Parameters

Observer is assumed to be moving in 'S' maneuver on LOS with a speed of 6 knots. Here Observer motion is assumed to be 'S' maneuver on LOS for better tracking and Initial Course of observer is 90 degrees for the first 120 samples,270 degrees for next 420 samples,90 degrees for next 420 samples, 270 degrees for next 420 samples and 90 degrees for remaining 420 samples.

The performance of UKF-FUZZY can be analysed by mathematical modeling and it was shown below.

Problem Modelling

Let us consider the state vector is M(□) ,

Where

$$M(\square)=\left[\overline{m(\kappa)z(\kappa)}V_s(\kappa)V_z(\kappa)\right]^T \qquad (15)$$

$\overline{m(\kappa)}$ and $\overline{z(\kappa)}$ are object velocity components and, $R_s(\kappa) = R*\sin(B)$and $R_z(\kappa) = R*\cos(B)$ are range components in x and y directions.

General state dynamic equation of an object is represented as follows.

$$M(\square+1)=B(\square+1/\square)M(\square)+D(\square+1)+w(\square) \qquad (16)$$

Where

B= transition matrix and D= deterministic vector

'D' can be defined as follows

$$D(\square+1)=[00–[m_0(\square+1)\text{-}m(\square)]\text{-}[z_0(\square+1)\text{-}z_0(\square)] \qquad (17)$$

Where m_0 and z_0 are position components of observer. w(□) is process noise. Here we have to take all angles with reference to y-axis.The range measurement (Rm) and bearing measurement (Bm) are modelled as

$$D_m(\square+1)=tan^{-1}[R_s(\kappa+1)/R_z(\kappa+1)]+\varepsilon d(\square) \qquad (18)$$

$$R_m(\square+1)=\sqrt{R_s(\kappa+1)^{\,2}+R_z(\kappa+1)^{\,2}}+\varepsilon r(n) \qquad (19)$$

Here εd(□) = bearing error ,εr(n) = range error

The process and measurement noises are considered being not correlated to each other.

The process noise covariance matrix is taken as

Q(□) =

$$\begin{bmatrix} ts^2 & 0 & ts^3/2 & 0 \\ 0 & ts^2 & 0 & ts^3/2 \\ ts^3/2 & 0 & ts^4/4 & 0 \\ 0 & ts^3/2 & 0 & ts^4/4 \end{bmatrix} *e(\square) \qquad (20)$$

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Where

$e(\square)=E[v(\square)*v^{T}(\kappa)]$ (21)

V. RESULTS

Performance of UKF-FUZZY for sonar application is simulated using MATLAB. Fig3 shows the estimation errors of Range and Fig4 shows the estimated errors of bearing.

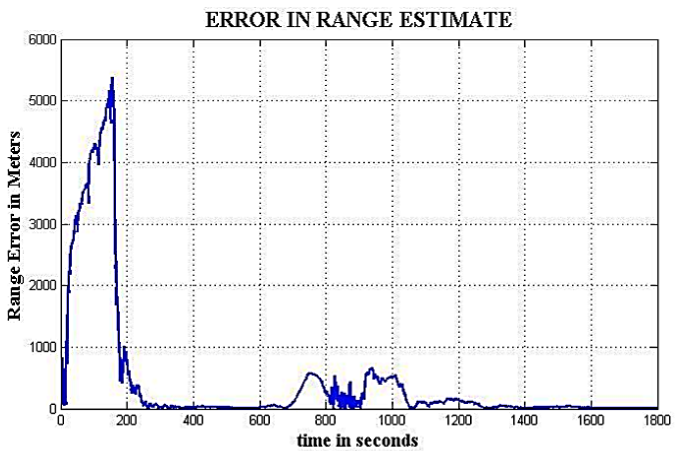

Fig 3: Error in Range estimate of UKF-FUZZY

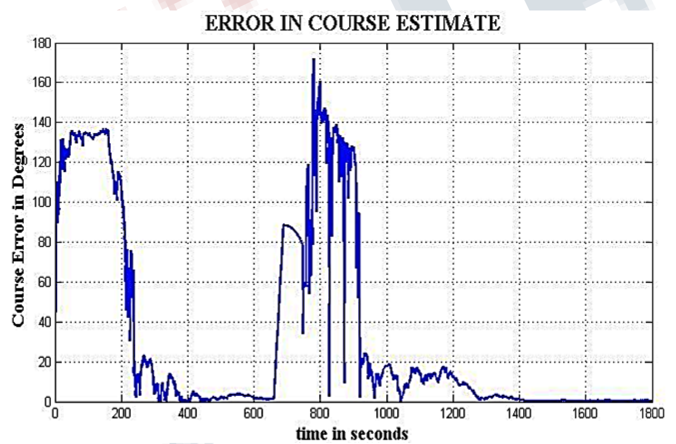

Fig 4: Error in Course estimate of UKF-FUZZY

Performance analysis of UKF-FUZZY

The maneuvering of before and after target tracking values of estimated Range and estimated Course converges with 213 and 1032 samples, 310 and 1032 samples samples respectively. Overall all the parameters are converged at 310th and 1032th sample before and after maneuvering tracking respectively. The initial maneuvering time sample and post maneuvering time samples and their corresponding errors are shown in the tables given below.

	Range	Course
Initial acquisition time(sample)	213	310
Post maneuvering acquisition time(sample)	1032	1032

Table 1: Individual Parameter Acquisition and Reacquisition Time for UKF-FUZZY

Time (sec)	Range Error (meter)	Course Error(degree)
213	347.79	67.98
310	15.54	6.86
988	488.43	14.15
1032	302.8	8.57

Table 2: Errors in Estimated Parameters using UKF-FUZZY

VI. CONCLUSION

The paper began with the simulation of the motion of the target and determining the initial target parameter namely Range and Course. We get the noisy measurements by using Extended Kalman Filter and it can filter the noisy measurements and extend the target motion parameters but is having computational difficulties. The Unscented Kalman Filter algorithm reduces this noise. Maneuvering of the own ship was detected using relative Bearing algorithm and the state of the target was corrected by using S-maneuvering. So that we may conclude that performance of Unscented Kalman Filter using Fuzzy Logic get better results. The performance can be further improved by using Particle Filter.

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