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Application of Unscented Kalman Filter for Sonar Signal Processing

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Abstract—***State estimation theory is one of the best mathematical approaches to analyze variants in the states of the system or process. The state of the system is defined by a set of variables that provide a complete representation of the internal condition at any given instant of time. Filtering of Random processes is referred to as Estimation, and is a well defined statistical technique. There are two types of state estimation processes, Linear and Nonlinear. Linear estimation of a system can easily be analyzed by using Kalman Filter (KF) and is used to compute the target state parameters with a priori information under noisy environment. But the traditional KF is optimal only when the model is linear and its performance is well defined under the assumptions that the system model and noise statistics are well known. Most of the state estimation problems are nonlinear, thereby limiting the practical applications of the KF. The modified KF, aka EKF, Unscented Kalman filter and Particle filter are best known for nonlinear estimates. Extended Kalman filter (EKF) is the nonlinear version of the Kalman filter which linearizes about the current mean and covariance. The EKF has been considered the standard in the theory of nonlinear state estimation. Since linear systems do not really exist, a novel transformation is adopted. Unscented Kalman filter and Particle filter are best known nonlinear estimates. The approach in this paper is to analyze the algorithm for maneuvering target tracking using bearing only measurements where UKF provides better probability of state estimation.***

Keywords-Kalman filter, Extended Kalman filter, Unscented Kalman filter,Bearing.

I. INTRODUCTION

Control of any process modeling, obtained from a priori knowledge of certain observable parameters is standard practice for Engineers. For many of the applications simple models with linear approximations around a design point suffice the requirement. Since all the natural phenomena are non-linear, it is very important to study the nonlinear models and their control for the following reasons:

1) Some systems have a linear approximation that is non controllable near interesting working points. Linearization is ineffective even locally for such cases.

2) Even if the linearized model is controllable one may wish to extend the operational domain beyond the validity domain into nonlinear region for better prediction.

3) Some control problems are external to the process and cannot be answered by a linearly approached model.

The success of the linear model in identification or in control has its cause in the good understanding of it. A better mastery of invariants of nonlinear models for some transformations is a prerequisite to a true theory of nonlinear identification and control. And all nonlinear systems are supposed to have a state space of finite dimension. State Estimation techniques are handled by filtering technique models for performance.

A common approach to overcome this problem is to linearize the system before using the Kalman filter, resulting in an extended Kalman filter. This linearization does however pose some problems, e.g. it can result in nonrealistic estimates [1, 2] over a period of time. The development of better estimator algorithms for nonlinear Systems has therefore attracted a great deal of interest in the scientific community, because the improvements will undoubtedly have great impact in a wide range of engineering fields. The EKF has been considered the standard in the theory of nonlinear state estimation. This paper deals with how to estimate a nonlinear model with unscented kalman filter (UKF). The approach in this paper is to analyze **Unscented** Kalman filter where UKF provides better probability of state estimation for a free falling body towards earth.

II. LINEAR AND NONLINEAR MODELS

Kalman Filter (KF), Extended KF (EKF), Unscented KF (UKF) and Particle filter (PF) are models popularly used for state estimation.

The traditional Kalman Filter is optimal only when the model is linear. . The practical application of the KF is limited because most of the state estimation problems like tracking of the target are nonlinear. If the system is linear, the state estimation parameters like the mean and covariance can be exactly updated with the KF.

The EKF works on the principal that a linearized transformation is approximately equal to the true nonlinear transformation. But the approximation could be unsatisfactory and the application of EKF is also limited. If the system is nonlinear, EKF updates the mean and covariance.

Hence the feasibility of the novel transformation known as UKF is explored. The unscented transformation coupled with certain properties of classical KF, provides a more accurate method than the EKF for nonlinear state estimation. Unscented transformations are more accurate than linearization for propagating means and covariance. The UKF performance is estimated better in a noisy environment also. The particle filter is expected to perform better than UKF as the nonlinearity level is enhanced.

UKF is based on two fundamental principles.

- It is easy to perform a nonlinear transformation on a single point (rather than an entire pdf)

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- It is not too difficult to find a set of individual points in state space whose sample pdf approximates the true pdf of a state vector.

In this paper, UKF for State Estimation have been considered for their relative performance levels and to give an idea as to their applications with sample State Estimation case study.

III. UNSCENTED KALMAN FILTER

Instead of linearising 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.

Selection of sample points is not arbitrary. Gaussian random variable in N dimensions uses 2N+1 sample 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.

IV. MODELLING EXAMPLE FOR MANEUVERING TARGET TRACKING USING BEARING ONLY MEASUREMENTS

There are many methods available to obtain target motion parameters in sonar signal processing[3-8].Target is assumed moving at constant course and constant speed. Its motion is updated every second. The own ship is also assumed to be stationary. It is assumed that noise in one bearing measurement is uncorrelated with that of the other. Another assumption is that the mean value of the noise is zero. In the simulator, random numbers are generated using central limit theorem. The output of Gaussian random generator is used as Gaussian noise for the Bearing measurements. The raw bearings are corrupted with the Gaussian noise. The output of another Gaussian random generator with given percentage input error is used to corrupt the frequency measurements.

The obtained bearing is modified according to the quadrant in which it exists such that its range is from 0-360 deg. (clock wise positive). The bearing is considered with respect to North.

Target parameters [R, B, C and S] and Own ship parameters [ocr and ospd] are read and taken as input by the simulator. Assumed error in Bearing measurement (sigma_b) and range measurement (sigma_r) are also fed as input.

Assumptions:

Following are the assumptions made in the simulator.

1. At start, own ship is at the origin.
2. Target is moving at constant velocity and
3. All angles are considered with respect to Y-axis.

a. Own ship motion

The own ship motion is introduced as follows. Consider the fig 2 shown below. The own ship is moving with a velocity v_0,x_0 is the distance of the own ship from the x-coordinate, y_0 is the distance of the own ship from the y and Ocr is the angle making with north. From fig 1.

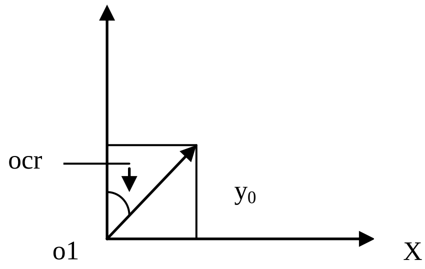

Fig 1

$$\text{Sin (ocr)} = x_0 / v_0 \quad (1)$$
$$\text{Cos (ocr)} = y_0 / v_0 \quad (2)$$

For every second change in X and Y component of own ship position is found and added to the previous X, Y components of own ship position.

For t_s=1sec

$$dX_0=v_0*\sin (Ocr)*ts \quad (3)$$
$$dY_0=v_0*\cos (Ocr)*ts \quad (4)$$

Where dX_0 is change in X-component of own ship position in 1 sec.

dY_0 is change in Y-component of own ship position in 1 sec.

v_0 is own ship velocity.

Ocr is own ship course.

(X_0 Y_0) is own ship position. Then

$$X_0 = (X_0 +dX_0) \quad \& \quad Y_0 = (Y_0 +dY_0) \quad (5)$$

b. Initial target position

From input bearing, initial position of target is known as follows.

Considering Fig 2. Shown below.

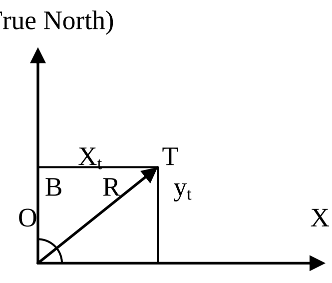

Fig 2

R-Range T-Target

For t_s=1sec

$$X_t = \text{range}*\sin (\text{bearing}) \quad (6)$$
$$Y_t = \text{range}*\cos (\text{bearing}) \quad (7)$$

Where (X_t , Y_t) is target position with respect to own ship as the origin.

c. Target Motion

The target motion is introduced as follows. Consider the Fig 3.shown below.

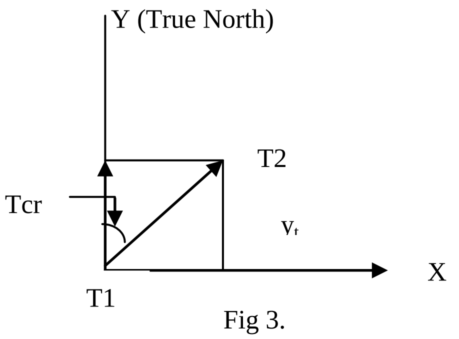

Fig 3.

F rom input range and Bearing initial position of target is known,

X_t=Range*sin(Bearing) (8)

Y_t=Range*cos (Bearing) (9)

(X_t, Y_t) is target position with respect to own ship as the origin.

For every 1 sec, change in X_t, and Y_t are calculated and added to previous target position.

dX_t= v_t*sin (Tcr)*ts (10)

dY_t=v_t*cos (Tcr)*ts (11)

X_t = (X_t +dX_t)and Y_t = (Y_t +dY_t) (12)

Where dX_t is change in X-component of target position in 1 sec dY_t is change in Y-component of target position in 1 sec.

V_t is target velocity.Tcr is target course with respect to true ϕ north.

X_t = (X_t +dX_t) and Y_t = (Y_t +dY_t).

The target is assumed to maintain fixed course and velocity through the observation duration.

d. Target tracking and mathematical modeling

State and measurement equations**:**

The target is assumed to be moving with constant velocity as shown in the fig1. And is defined to have the state vector.

$$Xs\ (k) = [\ \dot{x}\ (k)\ \ \dot{y}\ (k)\ R_x\ (k) R_y\ (k)\ W_x(k)\ W_y(k)]^T \quad (13)$$

Where $R_x\ (k) R_y(k)$ denote the relative range components between observer and target. The observer state is similarly defined as

$$X_0 = [\ \dot{x}_0\ \dot{y}_0\ x_0\ y_0]^T \quad (14)$$

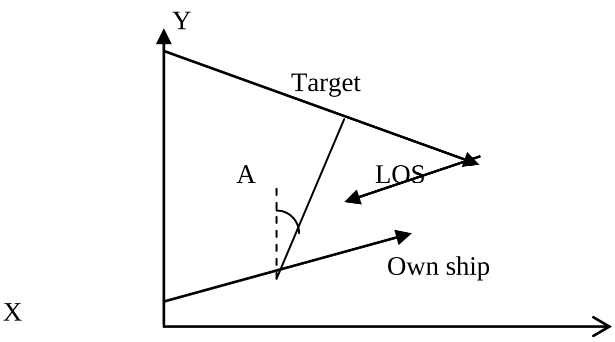

Fig 4.Target and observer encounter

The target state dynamic equation is given by

Xs (k+1) = Φ(k+1/k) Xs (k) +b (k+1) +W (k) (15)

Where Φ(k+1/k), b (k+1) and W (k) are transient matrix, deterministic vector and plant noise respectively.

The transient matrix is given by

$$\Phi(K+1/k)= \begin{pmatrix} 1 & 0 & 0 & 0 & t_s & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & t_s & 0 \\ t_s & 0 & 1 & 0 & t_s^2/2 & 0 & 0 \\ 0 & t_s & 0 & 1 & 0 & t_s^2/2 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

Where t_s is sample time and b (k+1) is given by

b (k+1)=[0 0 -(X(k+1)-X(k)) -(y(k+1)-y(k)) 0 0 0]^T(16)

W (K) IS A ZERO MEAN GAUSSIAN NOISE VECTOR WITH

E [W (k) W (k) ^{T}] =$Q\delta_{kj}$. It is assumed that the measurement noise and plant noise are uncorrelated. The bearing measurement, modeled as

$$B_m\ (k+1) = \tan^{-1} \frac{Rx(k+1)}{R\ y(k+1)} \quad (17)$$

Where δ_{kj} the Kronecker delta function, and ς(k) is error in the measurement and this error is assumed to be zero mean Gaussian with variance σ^2.The measurement and plant noises are to be uncorrelated to each other.

Kronecker Delta Function:

δ_{kj} =1 if k=j

0 if k≠j (18)

V. FILTER MODEL FORMULATION

a. *Augmentation of State Vector*

The filter starts by augmenting the state vector to N Dimensions, where N is the sum of dimensions in the original state-vector, model noise and measurement noise.

The covariance matrix is similarly augmented to a N^2 matrix. Together this forms the augmented state$\mathcal{X}^a$ estimate vector and covariance matrix P^a**:**

$$x^a_{k-1} = \begin{pmatrix} x_{k-1} \\ 0w \\ 0v \end{pmatrix} \quad (19)$$

$$P^a_{k-1} = E(x^a_{k-1} - \hat{x}^a_{k-1})(x^a_{k-1} - \hat{x}^a_{k-1})^T \begin{bmatrix} P^{k-1} & 0 & 0 \\ 0 & q_{k-1} & 0 \\ 0 & 0 & R_{k-1} \end{bmatrix} \quad (20)$$

b. Creating 2N+1 sigma-points

The $\mathcal{X}^a$matrix is chosen to contain these points, and its columns are calculated as follows:

$$\chi^a_{0,k-1} = X^a_{k-1} \qquad i = 0$$

$$\chi^a_{i,k-1} = X^a_{k-1} + (\alpha\sqrt{NP^a_{k-1}})_i \qquad i = 1 \cdots, N$$

$$\chi^a_{i,k-1} = X^a_{k-1} - (\alpha\sqrt{NP^a_{k-1}})_i,)_{i-N} i = N+1 \cdots, 2N$$

(21)

Subscript ‘ i ’means ith column of the square root of thecovariance matrix. The parameter α , in the interval 0 <α<1, determines sigma-point spread. This parameter is typically quite low, normally around 0.001, to avoid non-local effects. The resulting matrix$\mathcal{X}^a_{k-1}$ can now be decomposed vertically into the$\mathcal{X}^x_{k-1}$ rows, which contains the state;

The rows $\mathcal{X}^W_{k-1}$, which contain sampled process noise and

The rows $\mathcal{X}^V_{k-1}$, which contain sampled measurement noise.

c. *Weightage in Estimation*

Each sigma-point is also assigned a weight. The resulting weights for mean and covariance (C) estimates then become:

$$w_0^{(m)} = 1 - 1/\alpha^2 i = 0$$

$$w_0^{(c)} = 4 - 1/\alpha^2 - \alpha^2 i = 0$$
$$w_0^{(m)} = w_0^{(c)} = 1/2\alpha^2 N i = 1 \cdots, 2N \quad (22)$$

d. Estimation

The filter then predicts next state by propagating the sigma-points through the state and measurement models, and then calculating weighted averages and covariance matrices of the results:

$$\chi^x_{k/k-1} = f(\chi^x_{k-1}, u_k, \chi^w_{k-1})$$
$$\hat{x}_{k/k} = \sum_{i=0}^{2N} W_i^{(m)} \chi^x_{k-1}$$
$$P_{k/k-1} = \sum_{i=0}^{2N} W_i^{(c)} [\chi^x_{k-1} - \hat{x}_{k/k-1}][\chi^x_{k/k-1} - \hat{x}_{k/k-1}]^T$$

$$z_{k/k-1} = h(\chi^x_{k/k-1}, \chi^v_{k-1})$$
$$\hat{z}_{k/k-1} = \sum_{i=0}^{2N} W_i^{(m)} z_{i,k/k-1} \quad (23)$$

e. Mean and Covariance

The predictions are then updated with new measurements by first calculating the measurement covariance and state measurement cross correlation matrices, which are then used to determine Kalman gain - New state of the system; - Its associated covariance - Expected observation; - Cross-correlation matrix - Kalman Gain

$$P_{zz} = \sum_{i=0}^{2N} W_i^{(c)} [z_{i,k/k-1} - \hat{z}_{k/k-1}][z_{i,k/k-1} - \hat{z}_{k/k-1}]^T \quad (24)$$
$$P_{xz} = \sum_{i=0}^{2N} W_i^{(c)} [\chi^x_{i,k/k-1} - \hat{x}_{k/k-1}][z_{i,k/k-1} - \hat{z}_{k/k-1}]^T \quad (25)$$
$$K_k = P_{xz} P^{-1} \quad (26)$$
$$\hat{x}_{k/k} = \hat{x}_{k\{k-1} + K_k(z_k - \hat{z}_{k/k-1}) \quad (27)$$
$$P_{k/k} = P_{k/k-1} - K_k P_{yy} K_k{}^T \quad (28)$$

$\hat{x}_{k/k}$ -New state of the system;

$P_{k/k}$ - Its associated covariance

$\hat{z}_{k/k-1}$- Expected observation;

P_{xz} - Cross-correlation matrix K_k- Kalman Gain

The properties of this algorithm:

1. Since the mean and covariance of x are captured precisely up to the second order, the calculated values of the mean and covariance of Nonlinear function (Yi = f [Xi]) are correct to the second order as well. This means that the mean is calculated to a higher order of accuracy than the EKF, whereas the covariance is calculated to the same order of accuracy. However, there are further performance benefits. Since the distribution of x is being approximated rather than the function, its series expansion is not truncated in a particular order. It can be shown that the unscented algorithm is able to partially incorporate information from the higher orders, leading to even greater accuracy.
2. The sigma points capture the same mean and covariance irrespective of the choice of matrix square root which is used.
3. The mean and covariance are calculated using standard vector and matrix operations. This means that the algorithm is suitable for any choice of process model, and implementation is extremely rapid because it is not necessary to evaluate the Jacobeans which are needed in an EKF.

VI. FILTER IMPLEMENTATION AND SIMULATION

All raw bearings and frequency measurements are corrupted by additive zero mean Gaussian noise. The performance of this Algorithm is evaluated against number of geometries. For the purpose of presentation, the results of the scenario considered as shown in Table 1. (Scenario1 is for ship and the scenario 2 is for submarine). The measurement interval is one second and the period of simulation is 1800 seconds. Here all angle are considered with respect to true north 0 to 360 degrees, clockwise positive.

All one second samples are corrupted by additive zero mean Gaussian noise with a r.m.s level of 0.33 degree. The observer is assumed to be doing 'S' maneuver on the line of sight at a given constant speed and at a turning rate of 3 deg/sec.The observer moves initially at 90 degrees course for a period of 2 minutes and and then it changes its course to 270 degrees. At ninth, sixteenth and twenty third minutes, the observer changes its course from 270 to 90, 90 to 270 and 270to 90 degrees respectively. It is also assumed that the bearing measurements are available continuously every second. Numbers of scenarios are tested by changing the course of the target in steps of 3 degree in such a way that the angle between the target course and line of sight is always less than 60 degrees, as only closing targets are of interest to the observer. The results of these scenarios in Monte-Carlo simulation are noted and it is found that the observability in the target motion parameters has taken place after the completion of the observer's first maneuver. In general, the error allowed in the estimated target motion parameters in under water is ten percent in range, three degrees in course and four meters/sec in velocity estimates.Arond 80[% required solution is realized after observer's second maneuver and 90 to 95% required solution is realized after the third. From the results, it is observed that the solution with required accuracy is obtained from sixth minute onwards. The theoretical value of chi-square value with 5 degrees of freedom at 90% confidence level is 9.24.The higher value of *d(ς)* is due to the consideration of EKF using Taylor's series expansion up to the first order. When there is a target maneuver it is changing from around 200 to 500 in 20 seconds initially afterwards in next 4 to 5 seconds, it is changing more than 2000.In this scenario the observer moves from origin in S-maneuver on initial line of sight at 2.0 m/sec with turning rate of 3deg/sec.After the completion of four maneuvers it maintains 90 degrees course throughout the simulation period. It is assumed that the target is maneuvering from 135 degrees to 235 degrees with a turning rate of 3 deg/sec at 660 seconds. The target has maneuvered from 135 to 235 degrees at 660 seconds. Target maneuver is declared when the normalized squared innovations exceed the threshold. Sufficient state noise is inputted to the covariance matrix during the period of target maneuver so that the filter comes back to steady state experiencing only acceptable disturbance during target maneuvering period. When the maneuver is completed, i.e., when the normalized squared innovations less than the threshold, the process noise level is lowered to 1.

For each scenario, the errors in the estimated range, course and speed are shown in figures.

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Parameter	Scenario1	Scenario2
Initial range, meters	5000	5000
Initial bearing, deg	**0**	**0**
Target speed,	2	2
Target course,deg	135	135
Observer speed,	10	3
Observer course, deg	90	90
Error in the bearing, deg(one sigma)	0.33	0.33

For the implementation of the algorithm, the initial estimate of the target state vector is chosen as follows. As range measurements are not available, it is difficult to guess the velocity components of the target. So these components are each assumed as 5 m/sec, which are roughly close to the general speeds of the vehicles in underwater. The sonar range of day (SRD), say 5000 meters, is utilized in the calculation of initial position components of the target state vector as follows.

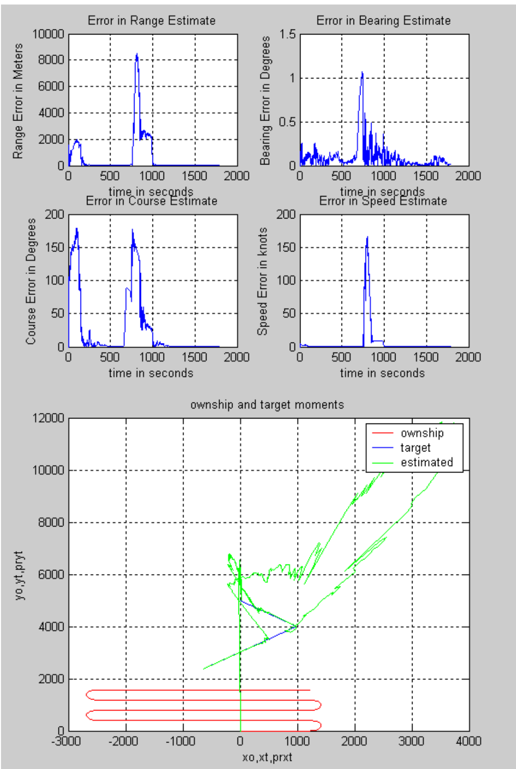
The augmented target state vector is

$X_s^{(a)}(0)=[5\ 5\ \ 5000\sin B_m(0)\ 5000\cos Bm(0)]^T$

Where B_m (0) is the initial bearing measurement. W_x (k) and W_y (k) are the Disturbances in acceleration component along X and Y-axis. The initial covariance matrix P (0/0) is a diagonal matrix with the elements are given byP (0/0) =Diagonal (4* $X_s^{(a)}(I)^2/12$) here I=1, 2, 3…10.

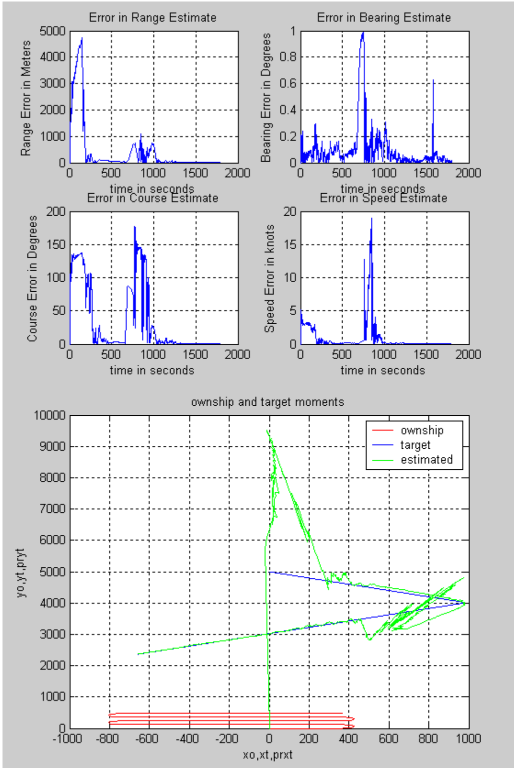
VII. RESULTS

a. plots of scenario 1



Duration of run: 1800 sec.
Targets maneuver detection:
Maneuver is given at 660 sec
The solution is converged at 275 sec before maneuver the target.
Total solution is converged at 1014 sec after maneuvering the target
Time taken for convergence of the solution is 354 sec after target maneuver

b. plots of scenario 2



Duration of run: 1800 sec.
Target maneuvers detection:
Maneuver is given at 660 sec
The solution is converged at 312 sec before maneuver the target.
Total solution is converged at 1035 sec after maneuvering the target
Time taken for convergence of the solution is 375 sec after target maneuver.

VIII. CONCLUSIONS

Application of KF to nonlinear systems results in highly inaccurate estimates. This paper looks into the need to consistently predict the new state and observation of the system with the presentation of UKF for nonlinear systems. We have introduced a new Filtering algorithm, called the unscented Filter. By virtue of the unscented transformation, this algorithm has two great advantages over the KF. First, it is able to predict the state of the system more accurately. Second, it is much less difficult to implement. The benefits of the algorithm were demonstrated in a realistic example, a free falling body towards earth.. This paper has considered one specific form of the unscented transform for one particular set of assumptions. It is shown that the number of sigma points can be extended to yield a Filter which matches moments up to the fourth order. This higher order extension effectively de-biases almost all common nonlinear coordinate transformations.

The project work began with the simulation of the motion of the target and determining the initial target parameter namely bearing. This parameter was then corrupted with noise to get the noisy measurements. Extended Kalman Filter can filter the noisy measurements and extend the target motion parameters but is having computational difficulties. The unscented Kalman Filter algorithm reduces this difficulty. Subsequently, maneuvering of the own ship was detected using relative Bearing algorithm and CPA algorithm. Then the state of the target was corrected accordingly after the detection of correct own ship evasion. Monte-Carlo simulation was carried out in the end in a number of scenarios.

The results confirm that the failure rate of UKF is insignificant. For the UKF the initial errors in x position were more than 160m. Therefore we may conclude that UKF is robust algorithm.

In this paper Unscented Kalman Filter for bearings only underwater target tracking in Monte Carlo simulation it is observed that the results are satisfactory. Hence Unscented Kalman Filter is recommended for this application.

IX. FUTURE SCOPE

Angle on Target Bow (ATB) is the angle between the target course and line of sight. When ATB is more than 60 degrees, the distance between the target and observer increases as time increases and hence bearing rate decreases. The algorithm cannot provide good results when the measurement noise is more than 1^0 rms or when the target is going away with respect to observer.

In general, the sonar can listen to a target when SNR is sufficiently high. When SNR becomes less, auto tracking of the target fails, the sonar tracks the target in manual mode and the measurements are not available continuously. The bearings available in manual mode are highly inconsistent and are not useful for good tracking targeting under water it is also possible that sonar measurement sometimes is spurious(the difference between the present and previous measurement being very high) and the same is treated as invalid. In this algorithm, it is assumed that good track continuity is maintained over the simulation period. This means that propagation conditions are satisfactory during this period as well as track continuity is maintained during own ship maneuvers. The algorithm cannot provide good results when the measurement noise is more than 1^0 rms or when the target is going away with respect to observer. The particle filter is expected to perform better than the UKF as the nonlinearity level is enhanced

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