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# Passive Underwater Target Tracking using Extended Kalman Filtering Algorithm

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## Abstract

Nonlinear Kalman Filtering is a well-established field in applied probability and control systems which plays an important role in many practical applications such as target tracking. In this project, nonlinear Kalman filtering algorithm named Extended Kalman Filter (EKF) is presented to estimate the location of the target using bearing and Doppler-frequency measurements. The tracking using bearing and doppler-frequency measurements are popularly known as Doppler-Bearing tracking. Here the measurements, that is, bearings and doppler-frequency, are considered to be corrupted with Gaussian noise. Target Motion Analysis (TMA) using bearing together with doppler-frequency measurements are explored. In this project, TMA is carried out using and EKF. Range, course and speed parameters are proposed in the EKF state vector to obtain the convergence of solution fast. Finally, the results of one scenario in Monte-Carlo simulation are presented.

## 1 Introduction

Owing to the lack of global positioning signals that are normally available in areas reachable by satellites, passive underwater target detection is a great difficulty. Underwater Target detection is a way of finding a swimming body's location within the water. An underwater vehicle tracks an underwater target in this case, requiring an accurate approximation of the

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target location. Here the location of the target will be discovered using acoustic signals originating from the target. In our mission, the observer continuously monitors the signals produced by the radiated noise or the sounds of the target machinery [1]. Advantages in acoustic and instrumentation technologies now allow the discovery of underwater resources. Underwater target monitoring has a vital exploration aspect and has a wide range of attention in both military and civil fields. The underwater world is a very complicated environment, but many number people will get better tracking results of tracking techniques have been proposed. The main aim of tracking is to find the state of a Persons should get good detection outcomes with monitoring techniques have been suggested. With the assistance of nonlinear calculations, the purpose behind monitoring is to approximate the status of a moving target. The numerical approximation is used mostly for many methods of estimation. The important facets of target detection are electronic warfare and underwater surveillance [2-4]. The observations obtained from the instruments are usually carried out, such as the hull-mounted series. The noise is a combination of Gaussian distributions and non-Gaussian.

The monitoring methods are designed to do with both Non-Gaussian and Gaussian noise. The acoustic signature observed is typically demonstrated by a rise in the energy of a certain bearing above the ambient. The energy is mainly broadband, although the signal spectrum may contain some tonal in certain instances. The tonal measures derived from the frequency spectrum of the target are referred to as the Doppler effect [5-9]. Doppler changes at the own-ship will occur as the source emits harmonic signals such that the frequency measurements can be tested to enhance the precision of the calculation. The distinct frequency lines are taken in the frequency spectrum to find the enemy position. If all frequency and bearing calculations are possible between distinct lines, the enemy is claimed to be entirely measurable. To evaluate a moving object, the use of both Doppler changes and bearing angles need to be used. The position of the target will be determined on the basis of bearing observations and a time series of Doppler from a single observer using Doppler-bearing monitoring. A significant area of study is passive target detection using the line of sight and angle-only measurements that links the enemy and the observer. Estimated target motion parameters can be derived more precisely by taking Doppler-bearing measurements [10].

The Kalman filter theory has been developed for linear Gaussian models that are discrete in time and are optimal filters. As the working environment is extremely non-linear, the Kalman filter is not suitable, so due to its sub-optimality, the Extended Kalman filter was introduced. The nonlinear difference of the Kalman filter that linearizes an approximation of the current mean and covariance is the extended Kalman filter the difficult task for DBT is the value of nonlinearity in the equations defined by the relationship between the measurements of the target area and Doppler-bearing.

## 2 Literature Survey

A thorough study of the Pseudolinear Kalman Filter (PLKF) bias is to nearly same-speed target dynamics in the PLKF bearings-only target tracking applications. This research not covered the basic reasons for bias in state finding and contributes to the enhanced bias efficiency of a modern bias-compensated PLKF algorithm. The bias resulting from the association that is resolved by a new instrumental-variable Kalman filter is between the pseudolinear noise and the measurement vector. The efficiency enhancement over the traditional PLKF of the proposed recursive.

The problem of nonlinear multi-response parameter estimation is nothing but unknown inhomogeneous general covariance, passive sonar bearing target trajectory estimation and frequency measurements in the presence of normally distributed multivariate noise. In this case, it is shown that the maximum probability estimate is equivalent to optimizing a determinant criterion that has a succinct shape and contains no unknown covariance matrix elements. The results of the simulation show that the typical noise assumption is not superior to the success of the method of maximum probability estimation with the above noise model [11].

Goal detection is the method of figuring out the target position. For the estimation process, decomposition is also useful, monitoring the video is the first step in this process, and then the video is transformed into frames during the initialization cycle and each frame consists of a piece of film. In another step, the targets in each frame will be identified by means of colour recognition. Next the centre coordinates and the moving target are identified and the coordinates of the present and previous frames are entered in the last step and the position of the moving target, the current frame, is determined. And the filter will approximate the frame. Monitoring is very important for multiple goals. With the assistance of the Kalman filter, the targets can be monitored. This filter can be used for pixel wise subtraction of the current frame. The error between the real ball location and the expected position value can be detected with the aid of this filter[12,13,14,15,16].

## 3 Proposed Methodology

To confirm that the accuracy of distance estimation was enhanced by using the reliability function, an Extended Kalman Filter (EKF) was developed. In the case of high attitude dynamics, the efficiency of current attitude monitoring algorithms degenerates easily. This paper introduces an Extended Kalman Filter attitude monitoring algorithm based on filtering. The filter is constructed with the three degree-of-freedom attitude quaternion and angular velocity given by the state estimate as a nonlinear stochastic system.

In this research, used extended Kalman filter (EKF) monitor the frequency of the signal instead of linearizing the performance of the optical frequency to enhance the precision of the phase extraction, so the phase will be calculated by averaging the monitored frequency over time. This algorithm will remove the effects of nonlinear optical frequency obtaining on phase extraction. In this paper we propose an EKF model that uses a robotic model and ideology of living motion to find displacement using measurements of gyroscope. Although some past researchers have been used Kalman filters to find displacement, he appears to be using INS, which incorporate accelerometers and gyroscopes to provide speed.

Backpropagation over time real-time recurrent study and EKF are the more common training algorithms. Different methodologies have been proposed to increase the convergence of that methods in training. For example, a manipulated back propagation algorithm is finding to be good than the actual back propagation algorithm based on generalization and convergence efficiency. Unfortunately, convergence of EKF-based training is unstudied. Only a few researches on the convergence of EKF-based training such as training have been performed to date. Unfortunately, the we have incorporated some estimations to made these innovative experiments generic and successful. Some normal research on training integration had been carried out and tested on implementations in order to integrate EKF-based training effectively.

## 4 Mathematical Modelling

The target is believed to travel in a linear direction and at a constant velocity. From the collection of measured data, two types of measurements are available; these are measurements of frequency and bearing. The calculated bearing equation is

$$\boldsymbol{\alpha_k^m = \alpha_k + B_k^\alpha} \tag{1}$$

where $\boldsymbol{\alpha_k^m}$, $\boldsymbol{\alpha_k}$ and $\boldsymbol{\beta_K^\alpha}$ are the bearing with was measured, true bearing and noise in the calculation of the bearing at k. True bearing is acquired as

$$\tan \boldsymbol{\alpha_k} = \frac{\boldsymbol{P_k^x}}{\boldsymbol{P_k^y}} \tag{2}$$

where $\boldsymbol{P_k^x}$ is range parameter of x and $\boldsymbol{P_k^y}$ is range parameters of y.

Due to the Doppler shift, the observer obtains the measured frequency as follows.

$$\boldsymbol{H_k^m = H_k^S \times \left[1 + \left(\frac{v_k^r}{c}\right)\right] + \beta_k^F} \tag{3}$$

Where, $\boldsymbol{H_k^m}$ and $\boldsymbol{H_k^S}$ are calculated frequencies; c is signal propagation and $\boldsymbol{\beta_k^F}$ is frequency error. Velocity is expressed by velocity

$$\boldsymbol{v_k^r = \dot{x}_k^r sin\alpha_k + \dot{y}_k^r cos\alpha_k}$$

where $\boldsymbol{\dot{x}_k^r\ and\ \dot{y}_k^r}$ are the target's relative x and y positions with respect to observer

$$\boldsymbol{\dot{x}_k^r = \left(\dot{x}_k^0 - \dot{x}_k^t\right)\dot{y}_k^r = \left(\dot{y}_k^0 - \dot{y}_k^t\right)}$$

Equation (3) in the terms of frequency is rewritten as

$$\boldsymbol{H_k^m = H_k^S * [1 + (x_k^r \sin\alpha_k + \dot{y}_k^r cos\alpha_k \,/\, c)] + \beta_k^H} \qquad (4)$$

Therefore,

Measured frequency = Change in frequency + noise

Measurement vector ($\boldsymbol{W_k^1}$) is

$$\boldsymbol{W_k^1 = [\alpha_k^m \;\; H_k^m]^T} \qquad (5)$$

Where bearing is $\boldsymbol{\alpha_k^m}$ and frequency is $\boldsymbol{H_k^m}$

Sate vector of the target, $\boldsymbol{L_k^t}$, is

$$\boldsymbol{L_k^t = [\dot{x}_k^t \;\; \dot{y}_k^t \;\; \dot{P}_k^x \;\; \dot{P}_k^y \;\; H_k^S]^T} \qquad (6)$$

where $\boldsymbol{\dot{x}_k^t \; and \; \dot{y}_k^t}$ are velocity components of target for x and y; $\boldsymbol{\dot{P}_k^x \; and \; \dot{P}_k^y}$ are target's range components and source frequency is $\boldsymbol{H_k^S}$.

Sate vector of the observer, $\boldsymbol{\dot{L}_k^0}$, is

$$\boldsymbol{\dot{L}_k^0 = \left[\dot{x}_k^0 \;\; \dot{y}_k^0 \;\; x_k^0 \;\; y_k^0\right]^T} \qquad (7)$$

where $\boldsymbol{\dot{x}_k^0 \; and \; \dot{y}_k^0}$ are velocity components of target for x and y; $\boldsymbol{x_k^0 \; and \; y_k^0}$ are observer's range components.

### *4.1 DBEKF Algorithm*

EKF is used for single bearing calculation in BOT and applications in nonlinear environment. But there are two components in the DBEKF. The measurement part of the method is therefore a bit critical and involves adjustments in algorithm simulation, too. It is thus, called the DBEKF algorithm. The target state equation is

$$\boldsymbol{L_{k+1/k+1}^S = \Omega_{k+1/k} L_k^S + \phi_k w_k} \qquad (8)$$

Where the given state transient matrix is $\boldsymbol{\Omega_{k+1/k}}$, $\boldsymbol{w_k}$ denotes plant noise. The gain matrix of plant noise is $\boldsymbol{\phi_k}$. The target's state transient matrix is

$$\boldsymbol{\Omega_{k+1/k} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ \Delta g & 0 & 1 & 0 & 0 \\ 0 & \Delta g & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}}$$

where $\boldsymbol{\Delta t}$ is the target state's time for all transition and plant noise variance is given below

$$\boldsymbol{f\left[\phi_k \; w_k \;\; w_k^1 \;\; \phi_k^T\right] = d \times G_k}$$

Where 'd' is the matrix variance of plant noise gain, $\boldsymbol{G_k}$is plant noise covariance's matrix and is calculated as

$$\boldsymbol{G_k = \phi_k \, \phi_k^T =}$$

$$\boldsymbol{\begin{bmatrix} \Delta g & 0 \\ 0 & \Delta g \\ \Delta g^2 / 2 & 0 \\ 0 & \Delta g^2 / 2 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta g & 0 & \Delta g^2 / 2 & 0 & 0 \\ 0 & \Delta g & 0 & \Delta g^2 / 2 & 0 \end{bmatrix}} \qquad (9)$$

$$G_k = \begin{bmatrix} \Delta g^2 & 0 & \Delta g^3/2 & 0 & 0 \\ 0 & \Delta g^2 & 0 & \Delta g^3/2 & 0 \\ \Delta g^3/2 & 0 & \Delta g^4/4 & 0 & 0 \\ 0 & \Delta g^3/2 & 0 & \Delta g^4/4 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Below equation is about Measurement equation

$$W_k = M_k L_k^s + v_k \tag{10}$$

We have shown the Measurement matrix below

$$M_k = \begin{bmatrix} 0 & 0 & \cos\hat{\alpha}/\hat{P} & -\sin\hat{\alpha}/\hat{P} & 0 \\ -\hat{H}\sin\hat{\alpha}/c & -\hat{H}\cos\hat{\alpha}/c & 0 & 0 & [1 + V_k/C] \end{bmatrix} \tag{11}$$

where $\hat{P}$ is bearing, $\hat{\alpha}$ is range, $V_k$ is velocity and **C** is speed.
Measurement equation's noise is given below

$$v_k = (0, \delta)$$

$$\delta = \begin{bmatrix} \sigma_b^2 & 0 \\ 0 & (2\pi\sigma_f)^2 \end{bmatrix} \tag{12}$$

Measurement covariance matrix is represented as $\delta$
Estimated co variance error's time update is

$$\mathbf{Q_{k+1/k}} = (\mathbf{\Omega_{k+1/k}} \times \mathbf{Q_{k+1/k+1}} \times \mathbf{\Omega^T_{k+1/k}}) + \mathbf{G_k} \tag{13}$$

State estimation time update is

$$\mathbf{L^S_{k+1/k}} = \mathbf{\Omega_{k+1/k}} \times \mathbf{L^S_{k+1/k+1}} \tag{14}$$

Representation of Kalman gain is

$$\mathbf{N_{k+1/k+1}} = \mathbf{Q_{k+1/k}} \mathbf{M^T_{k+1/k+1}} \times (\mathbf{M_{k+1/k+1}} \times \mathbf{Q_{k+1/k}} \times \mathbf{M^T_{k+1/k+1}} + \mathbf{\delta_k})^{-1} \tag{15}$$

We have shown the state error covariance measurement below

$$\mathbf{L^S_{k+1/k+1}} = \mathbf{L^S_{k+1/k}} + (\mathbf{N_{k+1/k+1}} \times W_k) \tag{16}$$

where $B_k = B_k^1 + B_k^2$

$$B_k^1 = \begin{bmatrix} \alpha_k^m \\ H_k^m \end{bmatrix}, B_k^2 = \begin{bmatrix} \hat{\alpha}_k^m \\ \hat{H}_k^m \end{bmatrix}$$

$$\mathbf{Q_{k+1/k+1}} = [\mathrm{I} - [\mathbf{N_{k+1/k+1}} \mathbf{M_{k+1/k+1}}]] \times \mathbf{Q_{k+1/k}} \tag{17}$$

For DBEKF algorithm mathematical modelling is given in [16].

## 5 Simulation Results

The aim is to evaluate the efficiency of CKF, the desired condition is assumed to occur at the time of the experiment, and therefore the measurements are continuously available for any second. In MATLAB program, the algorithm is taken with hundred Monte-Carlo runs. It is presumed that the scenarios in Table-1 are target and observer scenarios. The solution's acceptance requirements for this algorithm are as follows: error in the expected range is about 8/3% of the estimated range, error, true range in the estimated course is about $1^0$ and error in the estimated speed is 0.33 m/sec.

The estimates and true target paths for the scenarios 1 is shown in below Figure 1. Observer and target scenarios are shown in Table 1. For clarification of this concept, detailed estimation of target path and error in target motion parameters (range, course and speed) for scenario 1 is shown in Figure-2, Figure-3 and Figure-4. From the above answer the convergence times of the obtained solution is given in Table 2. From the Table 2 it is shown the convergence time for range, course and speed are 264, 277 and 260 seconds. From these times the solution is said to be converged at 277 second.

**Table 1** Observer and Target Scenarios

| Scenario | Initial Bearing | Initial Range | Observer Speed | Target Course | Target Speed |
|---|---|---|---|---|---|
| 1 | 0 | 3500 | 6 | 149 | 8 |
| 2 | 0 | 3500 | 6 | 156 | 8 |

**Table 2** Convergence time for solution in seconds for 100 runs

| Scenario | Range | Course | Speed | Total solution |
|---|---|---|---|---|
| 1 | 264 | 277 | 260 | 277 |
| 2 | 300 | NC | 704 | NC |

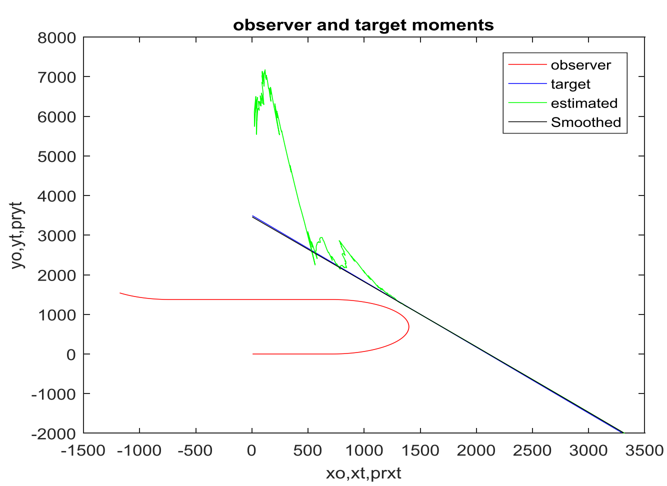


**Figure 1** Target-Observer Estimated Path

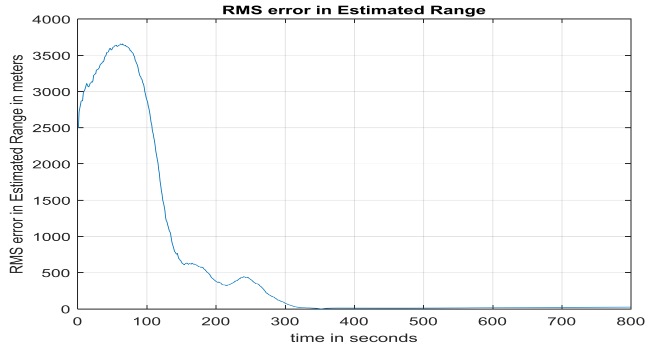


**Figure 2** Error Estimate in Range

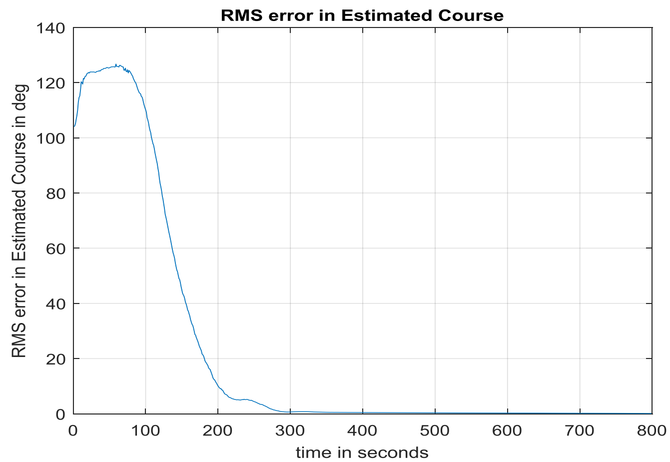


**Figure 3** Error Estimate in Course

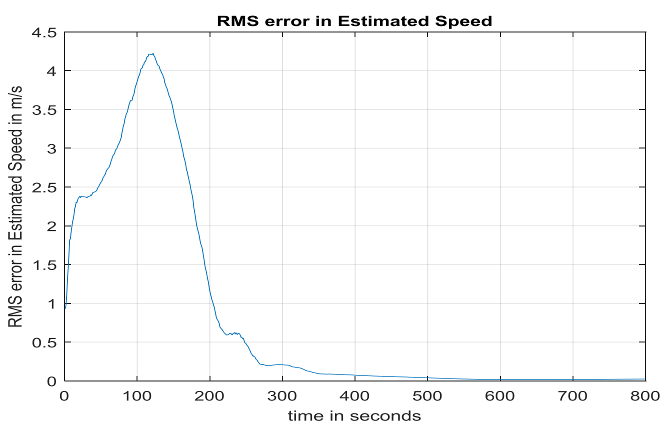


**Figure 4** Error Estimate in Speed

## 6 Conclusion

With the growing attention paid to the monitoring of undersea target technologies in marine science, full attention has been drawn. Because of the accuracy and difficulty of the deep-water environment, acoustic waves have become the most used technique for tracking underwater targets. The DBEKF algorithm is considered for performance evaluation with regard to the convergence of the solution and the solution is taken for hundred Monte-Carlo runs.

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