# DOPPLER-BEARING PASSIVE TARGET TRACKING SYSTEM FOR UNDERWATER TARGET DETECTION USING MODIFIED GAIN EKF

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## ABSTRACT

Range, Bearing, Course, Doppler and speed of a moving target are parameters that define a target motion. The present work concerns the estimation of Target Motion parameters (TMP) in a noisy environment from data obtained through sensor. The sensor gives the Frequency and Bearing measurements of the target.

Doppler Bearing passive target tracking is the determination of the trajectory of a target solely from measurements (both bearing and Doppler) of signals originating from the target. In the underwater scenario, the passive SONAR, which utilizes a number of hydrophones, is capable of sensing the sound waves in water. These sensors get the frequency and bearing information of the underwater target or the surface target as noise corrupted data (acoustic disturbances generated by underwater bodies).

The objective of this paper is to predict the current target position in terms of Range, Bearing, Course, Speed and frequency. This prediction is done by analyzing the data obtained from first contact instance with the target. PASSIVE SONAR sensors are used to obtain the data.

**Key words:** TMA, Doppler Bearing, kalman filter, EKF, underwater tracking, passive sonar.

## I INTRODUCTION

TMA provides a means to track targets using bearing data received from passive sonar (Streit and Walsh) [1]. This is primarily used in naval vessels where tracking of vessels around ownship is essential in deciding an appropriate course of action. In the naval terms used in TMA, ownship refers to the current observation platform for the bearings. A bearing is essentially an indication of direction. Target or source refers to a single vessel being tracked by ownship. The problem space is the set of all possible location scenarios and movement of the target confirmed by the bearings. Therefore a solution is considered to be a single resolution to the location and movement of a target based in the problem space.

Passive sonar, the main source of data for TMA, utilises an array of hydrophones and a technique known as beamforming to infer bearings corresponding to a tracked target. Beamforming works on the assumption that every naval vessel radiates a factor of noise from the engines and other heavy mechanical processes, to which the hydrophones of ownship listen. The passive sonar process takes this radiated noise signal, caliberates for any ambient noise from the ocean and ownship self-noise, and approximates a bearing based on signal strength received by the individual hydrophones. This received signal has a low signal-to-noise ratio due to the background ocean noise, ownship noise, and ambient reflections (Waite)[2], and in turn the bearings have a relative uncertainty factor associated with them.

The Target motion analysis (TMA) using conventional passive bearing together with frequency measurements is explored in S.Koteswararao study. This approach offers one tactical advantage over the classical bearings-only TMA. It makes the ownship maneuver superfluous. The inclusion of range, course, and speed parameterization is proposed in the UKF target state vector to obtain the convergence of the solution fast [3].

An ownship monitors noisy sonar bearings from a radiating target, which is assumed to be travelling with a uniform velocity. The ownship processes these measurements and finds out target motion parameters. Here the measurement is nonlinear, making the whole process nonlinear. Since bearing measurements are extracted from a single sensor, the process remains unobservable until ownship executes a proper maneuver. However, there are other methods found in literature [4-9] to obtain target motion parameters in the above situation.

The noise in the measurements is assumed to be zero mean Gaussian and the noise in the frequency measurement is not correlated with that of bearing measurement. It is also assumed that the measurements are continuously available every second. Here the sum of the tonals is taken as a state variable in the state vector. The concept of Chan and Rudnick's constant state vector formulation [10] that the dimension of state vector does not increase with the number of frequency tonals is followed.

Richard [11] examines the problem of adaptively tracking, in the horizontal ocean plane, an underwater maneuvering target using passive, time delay measurements. The target is free to make large scale random changes in velocity and bearing at times that are unknown to the observer. Tracking is accomplished by utilizing the basic linearized polar or "spherical" model of target and observer motion previously developed for radar tracking of airborne maneuvering vehicles. The addition of a nonlinear system block to the tracking system leads to a partial decoupling of both bearing and polar range estimators which not only reduces computational burden, but also significantly reduces any tendency toward tracking divergence. A modified method to obtain closed-form expressions for the measurement error statistics is presented which replaces conventional extensive off-line simulation procedures. Finally, test results are shown which validate the elimination of all extended Kalman filters in the measurement processing. This makes the passive tracking system very "robust" with respect to convergence characteristics in the presence of adverse target maneuvers.

## II KALMAN FILTERING

Ever since the manual tracing of "blips" on radar and sonar systems evolved into computer controlled tracking algorithms, tracking of any kind of sensor data has continued to develop significantly. Tracking is the processing of measurements obtained from a target in order to maintain an estimate of its current state [25].

The Kalman filter algorithm has proven to be quite successful in filtering sonar data [13]. The Kalman filter is an estimation algorithm that takes the current state, the control input, noisy observations and produces the optimal linear estimate of its current state along with the associated error variance. Kalman Filtering attracted considerable attention because of its general validity, mathematical elegance and widespread technical application [14]. Another striking feature of the Kalman Filter is the number of different ways the solution equations can be derived. The maximum likelihood method, the method of minimum variance and the least-squares method are derivation methods that were discovered following the initial system of differential equations derived by Bucy and Kalman [15].

### *A. Underwater scenario*

In the ocean environment, two dimensional Doppler-Bearing tracking target motion analyses are generally used. An own ship monitors noisy sonar bearings and frequency from a radiating target and finds out target motion parameters (TMP).

When the source emits harmonic components, the harmonic signals will experience Doppler shifts at the own ship so that the frequency measurements can be explored to improve the estimation accuracy. The use of both Doppler shifts and bearing angles to analyze a moving target is termed Doppler-Bearing Tracking (DBT).

As the true bearings and Doppler are not available in real environment, it was replaced by the measured bearing and Doppler (Measurement signal = Actual signal + noise) by the simulator. The problem is inherently nonlinear as the measurement is nonlinear. In this passive target tracking, a single own ship monitors a sequence of Bearing-Doppler measurements, which are assumed to be available at equi-spaced discrete times. The target motion analysis can be viewed as target localization and its tracking.

The basic assumptions are that the target moves at constant velocity most of the time. The ownship motion is unrestricted (either maneuvering or non-maneuvering). But as Doppler-Bearing tracking is preferred, target motion parameters can also be obtained for own ship non-maneuvering (straight line path).

### *B. Tracking: Own ship and target motion*

Passive target tracking is the determination of the trajectory of a target solely from measurements of signals originating from the target. These signals could be machine noise from a target and its detection is usually indicated by an increase in energy above the ambient at a certain bearing. The energy is mostly broadband but in some instances, the signal spectrum may contain a few tonal as well. In Doppler-Bearing passive target tracking, a single own ship monitors a sequence of both bearing and frequency measurements, which are assumed to be available at equi-spaced discrete times.

*C. Ownship motion: Initial own ship position*

Initial own ship position is assumed to be at the origin. For $t_s$ = 1 sec, and shown in Figure-1.

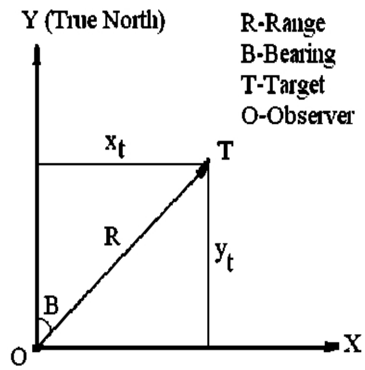


Fig. 1. Initial target position

From input bearing, initial position of target is known as follows. For $t_s$ = 1 sec

$x_t$ = range * sin (bearing)

$y_t$ = range * cos (bearing)

Where ($x_t$, $y_t$) is target position with respect to own ship as the origin.

*D. Tracking algorithms: least squares, kalman, EKF, PMGDBEKF*

From Karl Gauss the basic idea of least square estimation is that: "the most probable value of the unknown quantities will be that in which the sum of the squares of differences between the actually observed and the computed values multiplied by numbers that measure the degree of precision is a minimum".

The measurements are not always linear, some may be noisier or some less noisy than others. It implies that we have less confidence in some measurements than in others. With this weighted least square estimation came into existence. If the number of measurements becomes too large, the computational effort becomes prohibitive. Therefore recursive model of weighted least square estimation is utilized which reduces computational effort. If the correction term is zero or if the gain matrix is zero, then the estimate does not change from time step (k-1) to k.

A linear recursive estimator can be written in the form:

$$Y_k = H_k X + v_k$$

$$X_k = X_{k-1} + K_k\,(y_k - H_k X_{k-1})$$

Where $(y_k - H_k X_{k-1})$ is the correction term.

$K_k$ is the estimator gain matrix.

$X_{k-1}$ is the previous estimate.

$y_k$ is the new measurement.

Kalman filter is an efficient recursive filter that estimates the state of a dynamic system from a series of noisy measurements.

The error between the true state $X_k$ and the estimated state $X_k$ is denoted as Xk~:

$$Xk\sim \;=\; X_k + Xk$$

Since the state is partly determined by the stochastic process, Xk is a random variable. Since the state estimate is determined by the measurement sequence { *yk* }, which in turn is partly determined by the stochastic process { *vk* }, *Xk* is a random variable. Therefore, Xk~ is also a random Every time, get the measurement and update the mean and covariance of the state. variable. Kalman filter operates by propagating the mean and covariance of the state through time.

But in real time applications as the measurements obatained are not linear, Extended Kalman Filter (EKF) is the widely used state estimation algorithm to linearize the nonlinear systems around kalman filter estimate (since the kalman filter estimates the state of the system, we can use the kalman filter estimate as the normal state trajectory). To overcome the difficulties and to enhance the convergence rate Modified Gain Doppler Bearing Extension Kalman Filter (MGDBEKF) is used.

*E. Doppler bearing tracking (DBT) using MGDBEKF to compute target motion analysis*

- In the ocean environment, two-dimensional target motion analysis (TMA) is generally used.
- Passive sonar, which makes use of acoustic signals for reception of signals, is considered and used for tracking enemy targets.
- When passive sonar is to be simulated, bearings and frequency measurements are generated.
- The passive sonar positioned on a ship observes noisy bearing and frequency measurements of a target that may either be a ship or a submarine. The observer is assumed to be moving in straight line and the target is assumed to be moving mostly in straight line.
- The observer processes the measurements and estimates the target motion parameters. Typical Target- observer encounter is shown in Figure-2.

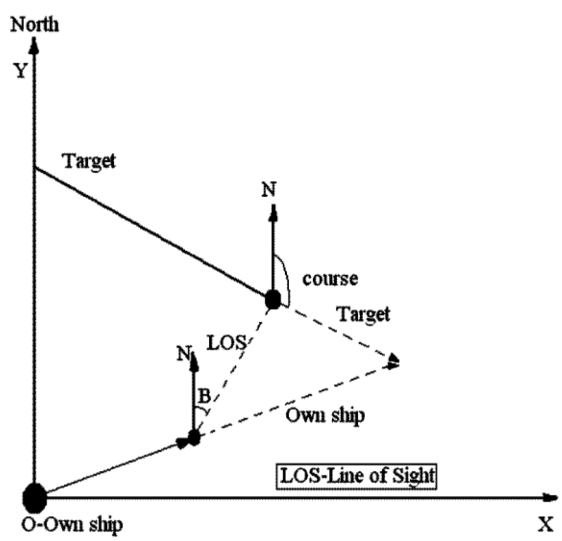


Fig. 2. Typical Target- observer encounter

Doppler-Bearing Tracking (DBT): The use of both Doppler shifts and Bearing angles to analyze a moving target is termed as Doppler-Bearing Tracking. The noise in these measurements is assumed to be Zero mean Gaussian and the noise in the frequency measurements is not correlated with that of bearing measurement. It is also assumed that the measurements are continuously available every second.

Bearings Only Tracking (BOT): It is the determination of trajectory of a target solely from bearing measurements. If bearing measurements are only extracted from single passive sonar, the process remains unobservable until own ship executes proper maneuver.

The noise in the bearing and frequency is assumed to be additive in nature and follows normal distribution. Random numbers are generated by using "randn" function present in Matlab. The noise in the bearing is assumed to be additive in nature and follows normal distribution. Using PI generator random number is generated. Using Central Limit Theorem, pseudo random numbers are used to derive the data in normal distribution. The input to the noise is in terms of standard deviation. If input value is 0.5 standard deviation, then maximum gaussian number will be three times the given standard deviation number.

Noise in the bearing measurement is generated with sigma_b as SD and it is added to the actual bearing, to get measured bearing. Similarly the noise in the frequency measurement is generated with sigma_d as SD and it is added to the actual frequency, to get measured frequency.

Input to simulator:

Target parameters (R, C, B, and S) and own ship parameters (C, S) are read and taken as input by the simulator. Assumed error in bearing measurement (sigma_b) and error on the frequency measurement (sigma_d) is fed as input.

Output to simulator:

Measured bearing = True bearing + noise

Where, true bearing = $\tan^{-1}((x_t - x_o) / (y_t - y_o))$

Measured Doppler = True Doppler + noise

Where, true doppler = relative velocity/lambda,

Relative velocity, $= \sin B \cdot (X_4) + \cos B \cdot (Y_r)$,

$X_r =$ Change in relative velocity in X-direction

$Y_r =$ Change in relative velocity in Y-direction

## III RESULTS

With and without maneuver, target versus ownship plots are shown in Figure-3 & 4. To investigate the performance of the MGDBEKF trackers for single target applications, a Monte Carlo simulation is

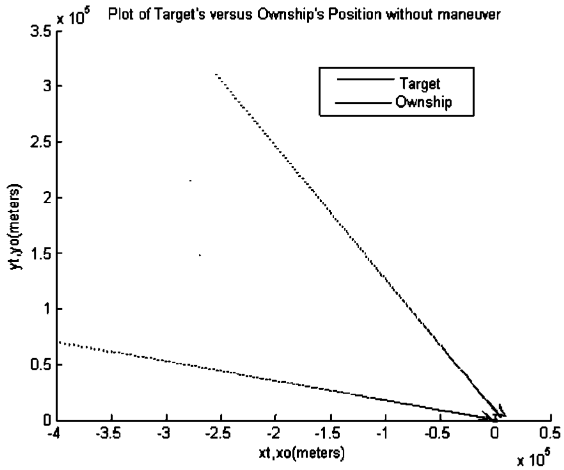


Fig. 3. Plot of target's versus ownship's position without maneuver

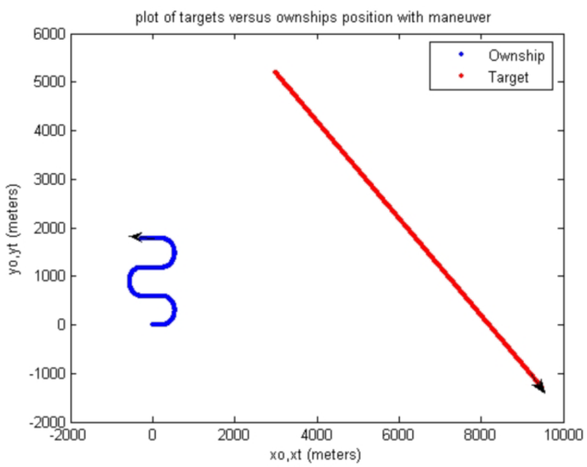


Fig. 4. Plot of target's versus ownship's position with maneuver

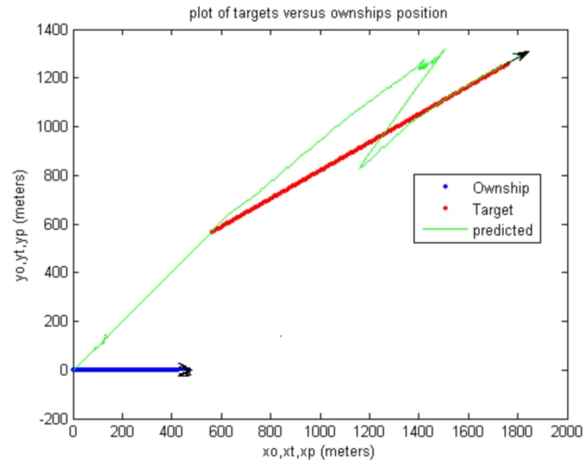


Fig. 5. Plot of ownship versus target position (Actual and predicted)

undertaken. In the scenario, a hull-mounted sonar is fitted on a ship (the own ship), which emits Linear Frequency Modulated (LFM) pings. This scenario consists of Initial Velocity of the Target = 15.00 mts, Initial Velocity of the Own ship = 10.00 mts, Initial Target Course = 60.00 degrees, Initial Observer Course = 90.00 degrees, Initial Range = 1800 meters, Initial Bearing = 10.00 degrees, Initial Position of the observer = (0.0, 0.0), Sigma in bearing = 0.17 deg, Sigma in frequency = 0.33 Hz, Target Frequency = 800.00 Hz.

A tool has been developed in Matlab, which automates the entire tracking process using the MGDBEKF algorithms described both actual and

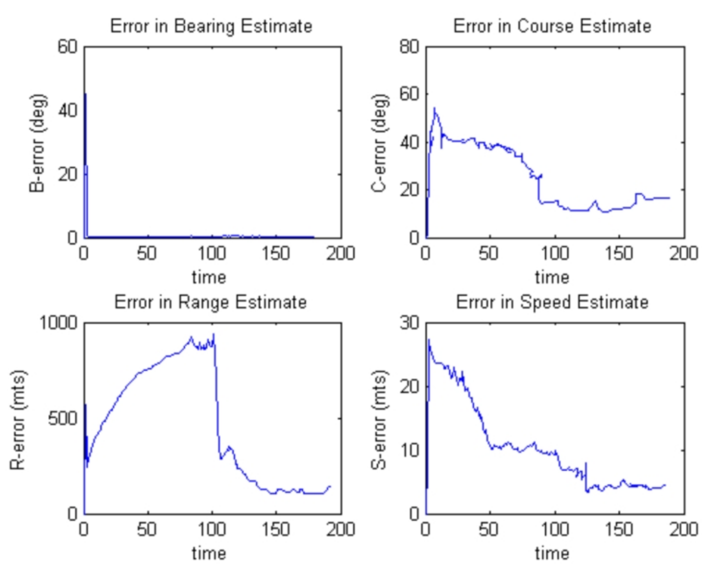


Fig. 6. Range, Bearing, Course and Speed error plots

predicted results shown in Figure-5 and Range, Bearing, Course and Speed error plots are shown in Figure-6. In all these plots the own ship trajectory is shown in BLUE and the true target trajectories are in RED.

## IV. CONCLUSION

The Paper deals with the Simulation of the motion of the target and determining the initial target parameters namely Frequency and Bearing. In basic simulator ownship with and without maneuvering was observed. These parameters were then corrupted with noise to get the noisy measurements. DBT is a right method to obtain target motion parameters without using ownship maneuver. This method can be easily adopted for underwater passive target tracking application. In this paper, an approach using a Modified Gain Extended Kalman Filter (which is useful for nonlinear applications) is proposed to estimate target motion parameters without using ownship maneuver in passive target tracking. Monte-carlo simulation was carried out in the scenarios.

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## REFERENCES

[1] Streit, R. L., and M. J. Walsh. “Bearings-Only Target Motion Analysis With Acoustic Propagation Models of Uncertain Fidelity.” Aerospace and Electronic Systems, IEEE Transactions on Aerospace and Electronic Systems, IEEE Transactions on 4 (2002): 1122-37.

[2] Waite, A, 2002, Sonar for Practising Engineers, John Wiley and Sons Ltd.

[3] S. Koteswara Rao, “Doppler-bearing Passive Target Tracking Using a Parameterized Unscented Kalman Filter”,(2010) IETE journal, 56(1), pg: 69-75

[4] A.G Lindgren, and K.F Gong, Position and velocity estimation via bearing Observations, IEEE Transactions on Aerospace and Electronic Systems, AES-14, pp. 564-77, Jul. 1978

[5] V.J Aidala, Kalman filter behaviour in bearings-only tracking applications, IEEE Transactions on Aerospace and Electronic Systems, AES-15, pp. 29-39, Jan. 1979.

[6] S.C Nardone, A.G Lindgren, and K.F Gong, Fundamental properties and performance of conventional bearings-only target motion analysis, IEEE Transactions on Automatic Control, AC-29, pp. 775-87, Sep. 1984.

[7] V.J Aidala, and S.E Hammel, Utilization of modified polar coordinates for bearings-only tracking, IEEE Transactions on Automatic Control, AC-28, pp. 283-94, Mar. 1983.

[8] T.L Song, and J.L Speyer, A stochastic analysis of a modified gain extended Kalman filter with applications to estimation with bearing-only measurements, IEEE Transactions on Automatic Control, AC-30, No. 10, pp. 940-9. Oct. 1985.

[9] W Grossman, Bearings only tracking: A hybrid coordinate system approach, J. Guidance, Vol. 17, No. 3, pp. 451-9, May-Jun. 1994.

[10] Y T Chan, and S W Rudnick, Bearings-only and Doppler-bearing tracking using instrumental variables, IEEE Transactions on Aerospace and Electronic Systems, AES-28, pp. 1076-82, Oct. 1992.

[11] Richard L M, “Passive Range Estimation of an Underwater Maneuvering Target”, IEEE transactions on acoustics, speech, and signal processing, vol. Assp-35, no. 3, march 1987, pg:274-285

[12] Bar-Shalom, Y. and Fortmann, T. E. Tracking and Data Association. Academic Press, 1988.

[13] Leonard, John J. and Durrant-Whyte, Hugh F., “A Unified Approach to Mobile-Robot Navigation”) Technical Report, Department of Engineering Science, University of Oxford, September 1989.

[14] Brammer, Karl and Siffiing, Gerhard. Kalman-Bucy Filters. Norwood, MA., Artech House, Inc., 1989.

[15] Kalman, R.E. and Bucy, R.S. New results in linear filtering and prediction theory, Trans. ASME, Ser. D, J. Basic Eng., 83: 95-108, 1961.