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Improved Particle Filtering Algorithm for Underwater Target Tracking using Bearing and Frequency Measurements

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Abstract

The topic of this article is the problem of far-range non-active (passive) tracking of a target through a stationary multi-static sonar location. This challenge seems difficult enough. In our case, the observations accessible first are the bearings towards the target with the Doppler change of the signal obtained induced by the motion of the target relative to the sonar. The tracking initiation problem is discussed in the sense of Doppler-Bearing Tracking for a single target that appears/disappears (DBT). At present, in nonlinear contexts, the particle filtering (PF) algorithm has found growing use in many areas. An improved combination of the PF algorithm along with the Extended Kalman Filter (PF-EKF) to fix degeneracy deficiencies is suggested in this research. The position of the underwater-moving-target and target motion parameters such as range, direction and velocity need to be accurately determined in a situation in which autonomous underwater vehicles (AUVs) perform tasks. It finds that by simulating iteration operations in Matlab, the proposed algorithm provides greater accuracy in convergence times.

1 Introduction

Tracking is a very difficult activity in an underwater environment. The

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active sonar is fitted with an acoustic sensor to obtain the object's approximate direction. Object monitoring is achieved in our research paper via implementation of the PF-EKF algorithm. Active sonar provides the world today with successful airborne warfare. The data obtained by the passive sonar is processed and sent to the submarine via a hull-mounted sensor for further processing of the received signal. The object tracking is carried out with the PF and EKF. The important contribution in this paper is the tracking of an underwater object, as indicated, with simple processing techniques the object can track. Achieving the right coordinates together with no loss of time is an important component here. The Particle Filter(PF) and Extended Kalman Filter are used to achieve this (EKF).

No linear system is explicitly needed for the Kalman Filter (KF) from which the EKF is inherited. The models of transformation and observation may also be non-linear, which is also the case in the atmosphere under water. From the predicted state, we calculate predicted measurements. But as it is a non-linear filtering method, the EKF is not an efficient estimator. In addition to this because of its linearization, if the initial state is incorrect, the filter can diverge rapidly. We combine it with a PF to overcome this problem, which is slightly costly when compared to EKF, but gives better output in return. [3]

Only target motion analysis (TMA) of the two-dimensional bearings is mainly used in the ocean environment. An owner tracks a radiating target's noisy sonar bearings, which are assumed to travel at the same speed. The owner analyzes these measurements and determines target motion parameters, namely the range, direction, bearing, and velocity of the target. The estimate here is nonlinear, which renders the entire mechanism nonlinear. Added to the current, when the bearing readings are taken from a single sensor, the device remains invisible[4-6] until the property performs a correct maneuver. However several techniques for thinning any such scenario with target motion parameters are available. Aidala's modified polar extended Kalman filter, Song and Speyer's modified gain extended Kalman filter (MGEKF), and even the hybrid system method of Walter Grossman are among the active contributions in this field. The TMA approach to a specific case is referred to as bearings-only passive target tracking is that a target's path is determined solely by tracking (BOT).

To determine the position of a point, passive object detection is based solely on observations of signals originating from the target. These signals may be machinery noise from a target and their detection is often seen by an energy spike at a certain bearing above the atmosphere. The energy is typically broadband, but in some cases, the signal spectrum can require few tonals in the same way. As the source emits harmonic components, the harmonic signals may undergo Doppler property shifts, so the frequency measurements are analyzed in order to improve the accuracy of the calculation. A moving object is referred to as Doppler-bearing tracking by using both Doppler changes and bearing angles to inspect a moving object (DBT).

DBT's dominance over BOT, i.e. DBT doesn't need ownership to traverse to obtain target motion parameters.

2 Literature Survey

Kalman filtering is an algorithm in statistics and control theory that applies a series of observations observed for a particular period of time, including factual noise and different mistakes, and generates possibilities of unknown samples that tend to be more authentic than those built on just mathematics alone by computing a joint distribution of probability over each timeframe over the variables. From Rudolf E. Kálmán, the filter takes its name. It is an algorithm that is used when there are linear conditions. But the environment is extremely non-linear in an underwater setting. Under such circumstances, Kalman Filter can not be used as incorrect observations will be given. This is when the Kalman Extended Filter(EKF) enters the picture.

The Extended Kalman Filter (EKF) is the nonlinear version of the evaluation theorem of the Kalman Filter, linearizing the current gauge of mean and covariance. In the nonlinear state evaluation hypothesis of submerged settings, the EKF was used as the norm, taking all the characterized models of improvement into account. In order to linearize a construct around a working point, the EKF adapted calculus methods, including multi-variate Taylor series expansions. If the system model is not known enough or highly non-linear (as mentioned below, Monte Carlo techniques are used for estimation, particularly particle filters. Monte Carlo techniques predate the EKF's existence, but for any reasonably sized state-space they are more computationally intensive.

The definition of particle filtration (PF) is based on the Monte Carlo methods, which use particle sets to indicate the possibilities that can be used in any kind of state space. The central idea is to express its distribution excluding random state cells from the reverse potential. It is a continuous method of model significance (sequential significance model). Simply put, the particle filtration method refers to the process of obtaining the state minimum variant distribution by selecting a set of random samples propagated at the state level to estimate the potential density performance and to replace the entire process with the sample medium.

A group of particles is defined by the samples from the distribution; each sample has a probability weight applied to it that enhances likelihood of the probability density function being sampled from that particle. Particle filters get their prediction in an approximate (statistical way. Weight difference that leads to collapse in weights is an usual issue found in such algorithms; however it can be diminished by inserting a re-sampling process before weights get too irregular. Multiple adaptive resampling parameters are compared to uniform distribution, including weight variance and relative entropy - using these is a choice. In the resampling process, in the vicinity of the samples with marginal masses are replaced by new samples or particles with heavier weights[5]-[17].

We use both the Extended Kalman Filter (EKF) and the Particle Filter in this article (PF). Both of these are mixed together and EKF is used to obtain precise estimates and observations on each filtered particle.

3 Proposed Methodology

Usually, Kalman Filter is an algorithm for predicting an object's exact position (object tracking). But this only gives us predictable values in a linear setting. This algorithm fails when a non-linear environment is observed. This is when we come across the Kalman Extended Filter (EKF). This is a new Kalman Filter variant that can track artifacts in a non-linear setting. EKF is the best algorithm to be used as the non-linear setting does not give us Gaussian values. Here the EKF requires no linear functions for models of state change and observation. It could have differential equations instead. But EKF is not an optimal estimator, and this algorithm fails if the order of the equations is above the second order. A new Unscented Kalman Filter in such scenarios (UKF).

In a non-linear environment with the order of equations up to the fifth order, an Unscented Kalman Filter(UKF) may be used. The UKF can not predict an accurate position above these conditions. UKF has a deterministic theory of sampling called Unscented Transformation to achieve a minimum range of sigmaa points called across the mean as sampled points. Mean and the covariance returned by non-linear functions are now passed through them. UKF is more detailed in certain processes and gives us better outcomes. With Monte Carlo's methods, this can be verified. This is used in the Algorithm for Particle Filtering.

The Sequential Monte Carlo (SMC) method is also known as the Particle Filter (PF), an algorithm used in extremely non-linear environments where the differential equations are greater than the seventh order. PF is ideal in such cases. The posterior density function (PDF) of a random process that produces a significant amount of noise is obtained using a collection of particles. We can produce samples from the appropriate distribution in this technique without any prior imagination of the state-space model.

The theory of the particle filter is used to resolve problems with the Hidden Markov model and nonlinear filtering. Mireille Chaleyat-Maurel and Dominique Michel demonstrated in 1984 that there is no selective recursive recursion in the succession of back dispersions of the irregular conditions of the sign provided the perceptions (a.k.a. ideal filter) with the important exemption of linear-Gaussian sign perception models (Kalman filter) or more comprehensive groups of models. Markov Chain Monte Carlo methods (MCMC), ordinary linearization, extended Kalman filters, or determining the best linear system (in the usual cost-blunder sense) do not adjust to enormous scope systems, unstable cycles, or when the nonlinearities are not sufficiently smooth. Different other mathematical strategies based on fixed network approximations.

In order to find the exact position of an AUV, we apply EKF on any particle or sample produced by the Particle Filtering algorithm to bring out the best of both algorithms.

4 Mathematical Modeling

Equations for state and calculation

The goal is expected to travel at an unbroken pace and along a very linear direction. There are two sorts of measurements available from the measured data collection; namely bearing angle and frequency. The calculated equation of bearing is

$$\boldsymbol{\beta}^m{}_k = \boldsymbol{\beta}_k + \gamma^{\beta}{}_k$$

where $\boldsymbol{\beta}^m{}_k$, $\boldsymbol{\beta}_k$ and $\gamma^{\beta}{}_k$ are the measured bearing, actual bearing and noise in bearing measure at time instant k, respectively. True bearing is non-inheritable as being

$$\tan \boldsymbol{\beta}_k = R^x{}_k / R^y{}_k$$

where $R^x{}_k$ and $R^y{}_k$ are elements of the vary x and y. The observer obtains the calculated frequency because of the propagation as follows.

$$F_k{}^m = F_k{}^s * [1 + (v_k{}^r / c)] + \gamma_k{}^F$$

Where $F_k{}^m$ and $F_k{}^s$ are measured, c and $\gamma_k{}^F$ are signal speed propagation speeds

and error in frequency, respectively. Relative rate is expressed by relative velocity

$$V_k{}^r = x_k{}^r \sin\boldsymbol{\beta}_k + y_k{}^r \cos \boldsymbol{\beta}_k$$

Where the relative x and y targeted positions with relevant observer are $x_k{}^r$ and $y_k{}^r$ and is as follows

$$x_k{}^r = (x_k{}^o - x_k{}^t)$$
$$y_k{}^r = (y_k{}^o - y_k{}^t)$$

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

$$F_k{}^m = F_k{}^s * [1 + (x_k{}^r \sin\boldsymbol{\beta}_k + y_k{}^r \cos \boldsymbol{\beta}_k /c)] + \gamma_k{}^F$$

Therefore,

Measured frequency=Change in frequency + noise

Measurement vector ($Z^1{}_k$) is given as follows

$$Z^1{}_k = [\ \boldsymbol{\beta}^m{}_k\ F_k{}^m\ ]^T$$

where $\boldsymbol{\beta}^m{}_k$ is that the measured bearing and the measured frequency is $F_k{}^m$. The target's state vector $x_k{}^t$, is

$$x_k{}^t = [\ x_k{}^t\ y_k{}^t\ R^x{}_k\ \ R^y{}_k\ \ F_k{}^s\ ]^T$$

where x_k^t and y_k^t are x and y target speed parts respectively, R^x_k and R^y_k are firing range components, and F_k^s is the supply frequency. The observer state vector, xko ,is

$$x_k^o = [x_k^o, y_k^o, x_k^o, y_k^o]^T$$

where x_k^o and y_k^o are x and y target velocity elements, x_k^o and y_k^o are the observer's range components.

5 Results and Discussions

The aim is to evaluate the efficiency of CKF, the desired condition is presumed to occur at the time of the experiment, and thus the measurements are continuously available for any second. In MATLAB program, the algorithm is executed. It is presumed that the scenarios in Table.1 are observational and aim scenarios. The approval conditions for this algorithm's solution are given as: The estimated error in range is about 8% of the original range, the estimated error in course is about 3°, and the estimated speed error is about 1 m/s.

The projections and true goal paths are shown below for scenarios 1 and 2. Figures 1(a) and 2(a), 1(b) and 2(b), 1(c) and 2(c), 1(d) and 2(2) provide a detailed estimate of the target path and error in target motion parameters (speed, range and course) for scenarios 1 and 2 for clarification of this definition (d). The convergence times for the solution obtained are given from the above solution in Table 2.

Table 1 Observer and Target Scenarios

Scenario	Initial Range	Initial Bearing	Observer Speed	Target Speed	Target course
1	3500	0	6	8	149
2	3500	0	6	8	156

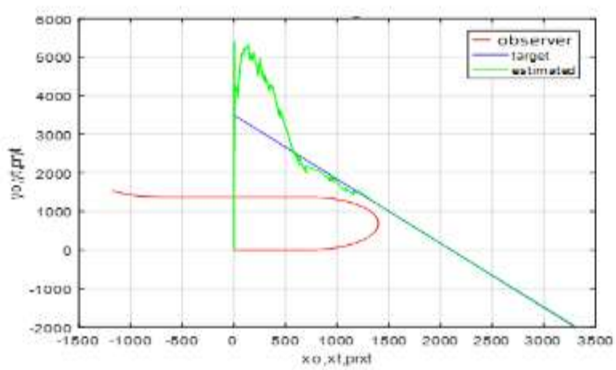

Figure 1 (a) Target-Observer Estimated Path

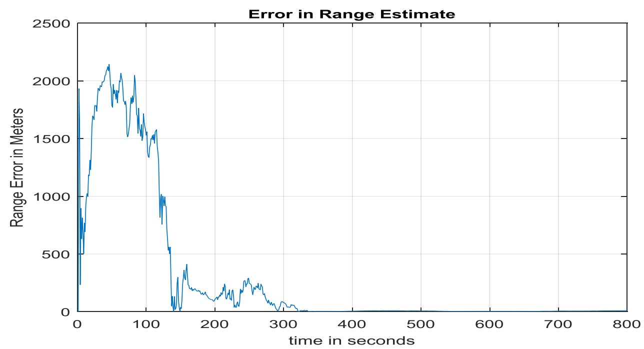

Figure 1 (b) Error Estimate in Range

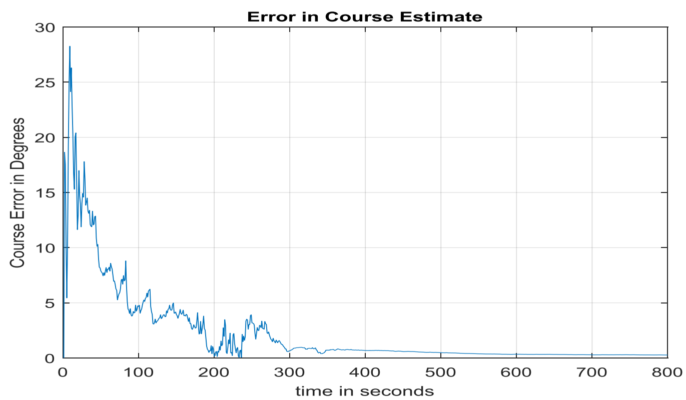

Figure 1 (c) Error Estimate in Course

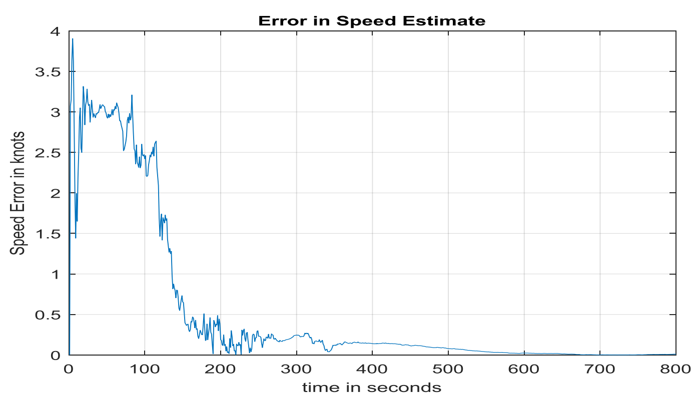

Figure 1 (d) Error Estimate in Speed

Figure 1 Detailed Estimation of Target Path and Error in Target Motion Parameters for Scenario 1 are given the above Figures

Table 2 Convergence Time for Solution in Seconds

Scenario	Range	Course	Speed	Total solution
1	317	270	136	317
2	323	320	313	323

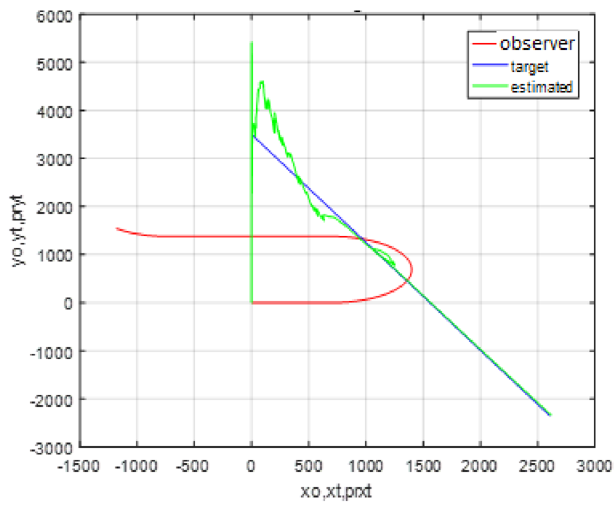

Figure 2 (A) Target-Observer Estimated Path

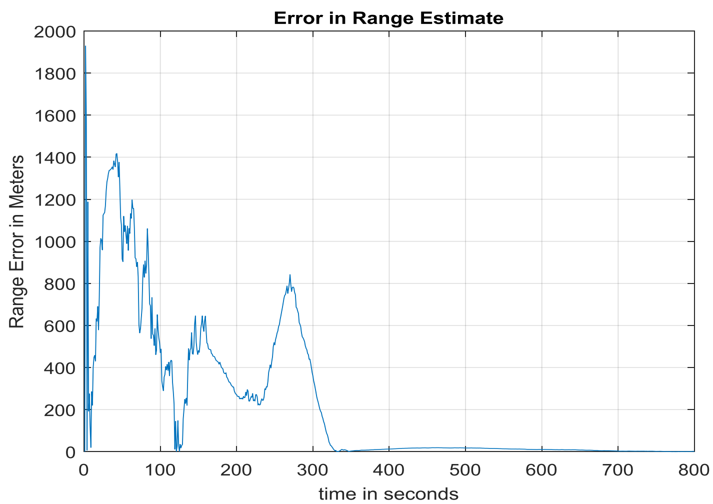

Figure 2 (B) Error Estimate in Range

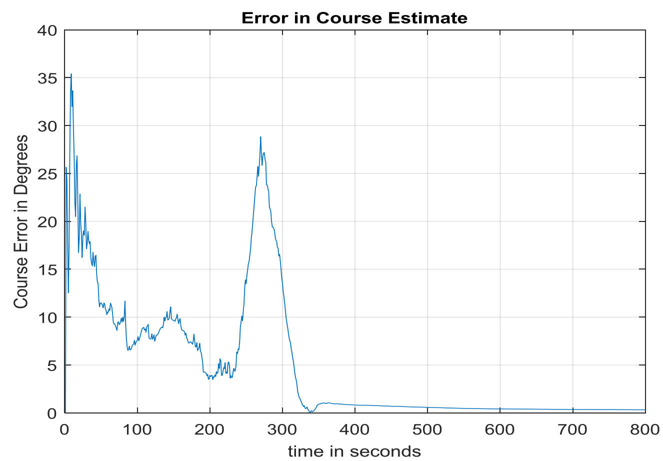

Figure 2 (C) Error Estimate in Course

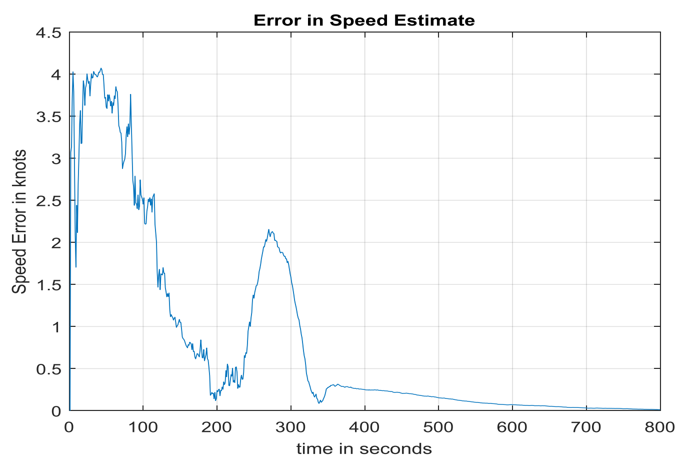

Figure 2 (C) Error Estimate in Speed

Figure 2 Detailed Estimation of Target Path and Error in Target Motion Parameters for Scenario 2 are given the above Figures

6 Conclusion

With the growing focus of marine science, complete attention has been drawn to the surveillance of underwater target technologies. Because of the accuracy and difficulty of the deep-water environment, acoustic waves have become the most used technique for tracking underwater targets. The DBPF-EKF algorithm is considered for performance evaluation with regard to the convergence of the solution.

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