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Research Article

AN INNOVATIVE APPROACH TO MORE RELIABLE AND AUTOMATED TARGET CLASSIFICATION FOR UNDERWATER MARITIME SURVELLIANCE

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ABSTRACT

Objective: Target motion analysis (TMA) using conventional passive bearing together with frequency measurements is explored.

Methods: This approach offers one tactical advantage over the classical bearings-only TMA. It makes the ownship maneuver superfluous.

Results: In this paper, TMA is carried out using Unscented Kalman Filter (UKF). Inclusion of range, course and speed parameterization is proposed in UKF target state vector to obtain the convergence of the solution fast.

Conclusion: Finally the results of various scenarios in Monte-Carlo simulation are presented. This method can be easily adopted for underwater passive target tracking application.

Keyword: classical bearings-only TMA, Target Motion Analysis (TMA)

INTRODUCTION

In the ocean environment, two dimensional bearings-only target motion analysis (TMA) is generally used. An ownship monitors noisy sonar bearings from a radiating target, which is assumed to be traveling with a uniform velocity. The ownship processes these measurements and finds out target motion parameters-Viz., range, course, bearing and speed of the target. Here the measurement is nonlinear, making the whole process nonlinear. Added to this, since bearing measurements are extracted from a single sensor, the process remains unobservable until ownship executes a proper maneuver. However, there are many methods available [1]-[6] to obtain target motion parameters in the above situation. The modified polar extended Kalman filter by Aidala [4], the modified gain extended Kalman filter (MGEKF) developed by Song and Speyer [5] and hybrid coordinate system approach by Walter Grossman [6] are among the successful contributions in this field. TMA method dealing with this specific case is known as Bearings-Only Tracking (BOT). 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 machinery 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. When the source emits harmonic components, the harmonic signals will experience Doppler shifts at the ownship 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) [7-12]. DBT has the advantage over BOT in that DBT does not require the ownship to maneuver to obtain target motion parameters. Target Motion Analysis (TMA) so far carried out for DBT can be divided into two groups: recursive method based on Instrumental Variables (IV) [8] and batch processing methods such as Maximum Likelihood Estimator (MLE) [9]. The work carried out by. Xiuo-Jiao Tao, Cai –Rong Zou and Zhen-Ya He [9] cannot be implemented in the real scenario as solution is found out using search methods, which are not suitable for real time applications. In practice, an improved estimate is required at each sample on every arrival of new measurement. Chan and Rudnicki's recursive Instrumental Variable method [8] is based on pseudo linear formation. In their work, the strong bias generated by pseudo linear formation is reduced by using the estimated bearing in the place of measured bearing. The estimation accuracy of the IV technique can reach the Cramer-Rao lower bound for Gaussian noise at moderate noise levels. Recently K.C. Ho and Y. T. Chan [12] proposed "constrained least squares minimization" with sequential processing. This is proven to be asymptotically unbiased. It avoids the difficulties of initial condition sensitivity and possible convergence problem associated with the IV or numerical Maximum Likelihood techniques.

The author is motivated by the work presented by 'Branko Ristic, Sanjeev Arulampalam and Neil Gordon' in 'Beyond the Kalman Filter- Particle filters for tracking applications' [13]. These scientists divided the range interval of interest into a number of sub- intervals, and each sub-interval is dealt with an independent Kalman filter. They suggested that this method can be extended to course and speed parameterization, if prior knowledge of target course and speed respectively are vague. Parameterization in initialization reduces the dependence of convergence of the solution on initialisation. In underwater scenario, prior knowledge of torpedo range, course and speed is vague. In this situation, time to obtain convergence has an important role and this is achieved using parameterization. Inclusion of range, course and speed parameterization is proposed for Unscented Kalman Filter (UKF) to track a target using bearings and frequency measurements and this algorithm is named as Parameterized Doppler-Bearing Unscented Kalman Filter (PDBUKF). The measurements are assumed to be available from hull mounted array of the ownship. Ownship uses estimated target motion parameters to calculate weapon preset parameters to release weapon on to target.

In this paper, the Doppler shift in the frequency measurement is described in terms of target & ownship speed components and the velocity of the sound in water. The noise in the measurements is assumed 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 Rudnicki's constant state vector formulation [8], that the dimension of state vector does not increase with the number of frequency tonals is followed.

Section 2 describes mathematical modeling of measurements, formulation of PDBUKF and initialization of state vector and its covariance. Section 3 is about simulation and results. The limitations of the algorithm are presented in section 4 and the paper is concluded in section 5.

MATHEMATICAL MODELING

State and Measurement Equations

The target is assumed to be moving with constant velocity as shown in Fig.1 and is defined to have the state vector

$$X_S(k) = [\dot{x} \quad \dot{y} \quad r_x \quad r_y \quad F_s \quad \omega_x \quad \omega_y \quad \omega_f \quad \sigma_b \quad \sigma_f]^T \tag{1}$$

where (r_x, r_y) denote the relative range components between ownship and target. F_s is source frequencyr and superscript T denotes transpose. The ownship state is similarly defined as

$$X_o = [\dot{x}_o \quad \dot{y}_o \quad x_o \quad y_o]^T \tag{2}$$

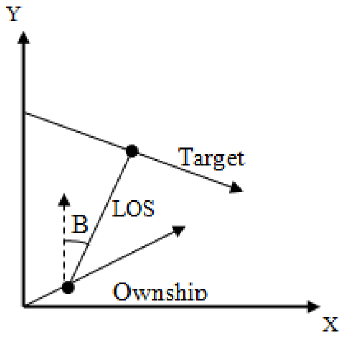

Fig. 1: Target and Ownship encounter

The set of measured data consists of two types of measurements: bearing angles and frequency measurements. The bearing measurement is modeled as

$$B_m(k) = B(k) + \gamma_B(k) \tag{3}$$

where $B_m(k)$ is the measured bearing, relative to the y axis of the ownship, at k^{th} instant (k=1, …, n), B(k) is the actual bearing and $\gamma_B(k)$ a Gaussian random variable with zero mean and variance $\sigma_B^2(k)$. The actual bearing B(k) is given by

$$\tan B(k) = \frac{r_x(k)}{r_y(k)} \tag{4}$$

In Sonar, a broadband noise is generally accompanied by one or more tonals. These tonals are constant in frequency and because of Doppler shift; a particular frequency measured by the ownship is given by

$$f_m^{(j)}(k) = f_s^{(j)}(k)\left(1 + \frac{\dot{x}_r(k)\ \mathrm{Sin}\ B(k) + \dot{y}_r(k)\ \mathrm{Cos}\ B(k)}{C}\right) + \gamma_f^{(j)}(k) \tag{5}$$

where $f_m^{(j)}(k)$ denotes the j^{th} (j=1, 2,3…n) frequency measured by the ownship at k^{th} instant, $f_s^{(j)}$ is the j^{th} unknown constant source frequency, C is the speed of propagation of the signal, $\gamma_f^{(j)}(k)$ is the zero mean Gaussian random frequency measurement error with variance σ_f^2 and $\dot{x}_r$ & $\dot{y}_r$ are components of relative velocity between target and ownship. (Derivation of eqn.(5) is given in Appendix-A.) Constant state vector formulation [8] (the size of the state vector does not increase with the increase in no. of tonals) is obtained as follows:

Let

$$F_m(k) = \sum_{j=1}^{n} f_m^{(j)}(k) \tag{6}$$

$$F_s(k) = \sum_{j=1}^{n} f_s^{(j)}(k)$$

$$N(k) = \sum_{j=1}^{n} \gamma_f^{(j)}(k)$$

Using eqn. (6), eqn. (5) can be rewritten as

$$F_m(k) = F_s(k)\left(1 + \frac{\dot{x}_r(k)\ \mathrm{Sin}\ B(k) + \dot{y}_r(k)\ \mathrm{Cos}\ B(k)}{C}\right) + N(k) \tag{7}$$

The measurement vector Z is given by

$$Z = \begin{bmatrix} B_m(k) \\ F_m(k) \end{bmatrix} \tag{8}$$

In this tracking problem, the aim is to estimate the state vector X_s, from a set of measurements Z. It is assumed that the noises in bearing and frequency measurements are not correlated. The target state dynamic equation is given by

$$X_s(k+1) = \varphi(k+1/k)Xs(k) + b(k+1) + \omega(k) \tag{9}$$

where φ(k+1/k), b(k+1) and ω(k) are transient matrix, deterministic vector and plant noise respectively. The transient ma[illegible]en by

X

$$\varphi(k+1/k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & t & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & t & 0 & 0 & 0 \\ t & 0 & 1 & 0 & 0 & t^2/2 & 0 & 0 & 0 & 0 \\ 0 & t & 0 & 1 & 0 & 0 & t^2/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{10}$$

where t is sample time and b(k+1) is given by

$$b(k+1) = [0 \quad 0 \quad -(x(k+1) - x(k)) \quad -(y(k+1) - y(k)) \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]^T \tag{11}$$

$\omega(k)$ is a zero mean Gaussian noise vector with E [$\omega(k)$ $\omega(k)^T$]= Q δ_{kj}.

Unscented Kalman Filter Algorithm

Unscented Transformation (UT) is a method for calculating the statistics of a random variable which undergoes a nonlinear transformation. Consider a random variable x (dimension L) propagating through a nonlinear function, y = g(x). Assume x has mean and covariance P_X. To calculate the statistics of y, we form a matrix χ of 2L + 1 sigma vectors χ_i (with corresponding weights W_i), according to the following [11]:

$$\chi_0 = \bar{x}$$
$$\chi_i = \bar{x} + \left(\sqrt{(L+\lambda)P_x}\right)_i \quad i = 1,\ldots,L$$
$$\chi_i = \bar{x} - \left(\sqrt{(L+\lambda)P_x}\right)_{i-L} \quad i = L+1,\ldots,2L$$
$$W_0^{(m)} = \lambda/(L+\lambda)$$
$$W_0^{(c)} = \lambda/(L+\lambda) + (1-\alpha^2+\beta)$$
$$W_i^{(m)} = W_i^{(c)} 1/\{2(L+\lambda)\} \quad i = 1,\ldots,2L \qquad (12)$$

where $\lambda = \alpha^2(L+\kappa) - L$ is a scaling parameter. α determines the spread of the sigma points around $\bar{x}$ and is usually set to a small positive value (e.g., 1e-3), κ is a secondary scaling parameter which is usually set to 0, and β is used to incorporate prior knowledge of the distribution of x (for Gaussian distributions, $\beta = 2$ is optimal). $\left(\sqrt{(L+\lambda)P_x}\right)_i$ is the i[th] row of the matrix square root. These sigma vectors are propagated through the nonlinear function,

$$y_i = g(\chi_i) \quad i = 1,\ldots,2L \qquad (13)$$

and the mean and covariance are approximated using a weighted sample mean and covariance of the posterior sigma points [11].

UKF is a straightforward extension of the UT to the recursive estimation. In UKF, the state random variable is redefined as the concatenation of the original state and noise variables. The UT sigma point selection scheme is applied to this new augmented state random variable to calculate the corresponding sigma matrix. The standard UKF implementation consists of the following steps:2.2.1 Calculation of the (2n+1) state vectors with sigma points starting from the initial conditions

$$X(k) = \left[X_s(k) \quad X_s(k) + \sqrt{(n+\lambda)P(k)} \quad X_s(k) - \sqrt{(n+\lambda)P(k)}\right] \qquad (14)$$

2.2.2 Transformation of these sigma points through the process model using eqn.(9).

2.2.3 The prediction of the state estimate at time k with measurement up to time k+1 is given as

$$X_s(k+1|k) = \sum_{i=0}^{2n} W_i^{(m)} * X_s(i,k+1|k) \qquad (15)$$

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

$$P(k+1|k) = \sum_{i=0}^{2n} W_i^{(c)} [X_s(i,k+1|k) - X_s(k+1|k)] * [X_s(i,k+1|k) - X_s(k+1|k)]^T + Q(k) \qquad (16)$$

2.2.5. Updation of the sigma points with the predicted mean and covariance. The updated sigma points are given as

$$X(k+1|k) = \left[X_s(k+1|k) \quad X_s(k+1|k) + \sqrt{(n+\lambda)P(k+1|k)} \quad X_s(k+1|k) - \sqrt{(n+\lambda)P(k+1|k)}\right] \qquad (17)$$

2.2.6. Transformation of each of the predicted points through measurement model eqn.(10)

2.2.7. Prediction of measurement, given as

$$y(k+1|k) = \sum_{i=0}^{2n} W_i^{(m)} . Y(k+1|k) \qquad (18)$$

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

$$P_{yy} = \sum_{i=0}^{2n} W_i^{(c)} [Y(i,k+1)|k) - y(k+1|k)][Y(i,k+1|k) - y(k+1|k)]^T + R(k) \qquad (19)$$

2.2.9. The cross covariance is given as

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(c)} [X(i,k+1|k) - x](k+1|k).[Y(i,k+1|k) - y(k+1|k)]^T \qquad (20)$$

2.2.10. Kalman gain is calculated as

$$K(k+1) = P_{xy}.P_{yy}^{-1} \qquad (21)$$

2.2.11. The estimated state is given as

$$X(k+1|k+1) = X(k+1|k) + K(k+1)(y(k+1|k+1) - y(k+1|k) \qquad (22)$$

where y(k) is true measurement.

2.2.12. Estimated error covariance is given as

$$P(k+1|k+1) = P(k+1|k) - K(k+1).P_{yy}.K(k+1)^T \qquad (23)$$

Parameterized Doppler-Bearing Unscented Kalman Filter

The ownship is assumed to be getting the bearing measurements available from sonar. Prior knowledge of target range, course or speed is not available. The aim is to obtain target motion parameters accurately at the earliest. Time to obtain convergence greatly depends on the accuracy of the initialisation of the target state vector. Parameterization in initialization reduces the dependence of convergence of the solution on initialisation. Inclusion of range, course and speed parameterization is proposed for Doppler-Bearing Unscented Kalman Filter (DBUKF) to track a target using bearings and Doppler frequency measurements**.** The basic idea is to use a number of independent DBUKF trackers in parallel, each with a different initial estimate. To do so, the range, course and speed interval of interest is divided into a number of sub-intervals, and each sub-interval is dealt with an independent DBUKF. Let the range, course and speed intervals of interest are $(range_{min}, range_{max}), (course_{min}, course_{max})$ and $(speed_{min}, speed_{max})$ respectively with range, course, speed subintervals. For example, the sub-intervals can be chosen as 1000 meters, 1 degree, 1 m/sec in range, course, and speed respectively. Let

$$a = (range_{max} - range_{min})/1000$$
$$b = (course_{max} - course_{min})/1$$
$$c = (speed_{max} - speed_{min})/1 \qquad (24)$$

So number of filters, N is given by (a*b*c). If hardware support for sufficient computation capacity is available, the size of the sub-intervals can be increased as much as possible to improve the accuracy of the estimated target motion parameters. The initial weights of each DBUKF is set to $1/N$. Subsequently, the weight of filter i at time k is given by

$$\omega^i(k) = \frac{p(B(k)|i)\omega^i(k-1)}{\sum_{j=1}^{N} p(B(k)|j)\omega^j(k-1)} \qquad (25)$$

where $p(B(k)|i)$ is the likelihood of measurement $B(k)$. Assuming Gaussian statistics, the likelihood $p(B(k)|i)$ can be computed as

$$p(B(k)|i) = \frac{1}{\sqrt{2\pi{\sigma^{i}}_{inv}^{2}}} \exp\left[-\frac{1}{2}\left(\frac{B(k)-\hat{B}^{i}(k|k-1)}{\sigma^{i}_{inv}}\right)^{2}\right] \qquad (26)$$

where $\hat{B}^{i}(k|k-1)$ is the predicted angle at k for filter i ,and

${\sigma^{i}}_{inv}^{2}$ is the innovation variance for filter i given by

$${\sigma^{i}}_{inv}^{2} = \hat{H}^{i}(k)P^{i}(k|k-1)\hat{H}^{i\,T}(k)+\sigma^{2} \qquad (27)$$

The combined estimate of parameterized DBUKF is computed using the Gaussian mixture formulas.

SIMULATION AND RESULTS

Initialization of state vector

It is assumed that HMA of the ownship can track the target in auto-tracking mode from 20000 meters (maximum range) onwards and the target speed is in the range of 20 m/sec to 5 m/sec. The search area in target course is 0 to 359 deg. Here sub-interval size is chosen in such away that minimum filters give the same accuracy within the required time. The target state vector is initialized as

$$X_s(0|0) = [V_T \sin(\theta) \quad V_T \cos(\theta) \quad r\sin(B_m(0)) \quad r\cos(B_m(0)) \quad F_s(k)$$

$$\omega_x(k) \quad \omega_y(k) \quad \omega_f(k) \quad \sigma_b \quad \sigma_f]^T \qquad (28)$$

where $B_m(0)$ *and* $F_m(0)$ are the initial bearing and Doppler frequency measurements $\omega_x(k), \omega_y(k)$ and $F_m(0)$ are the disturbances in acceleration component along x axis,

y axis and in frequency component.

r, initial range in meters= [20000 19000 18000 ……3000].

φ , target course in deg = [0 1 2 ..359]

V_T, target speed in m/sec = [20 19 18 ….5]. (29)

There will be number of DBUKFs working in parallel with different initialization of state vectors.

Initialization of covariance matrix

It is assumed that the components of the initial target state vector follow uniform density function and accordingly the initial covariance matrix $P(0/0)$ is chosen as a diagonal matrix with the elements are given by

$$P(0/0) = \text{diagonal}\left(4\,X_s(i)^2/12\right) \quad \textit{where i = 1,2 …10}$$

Scenario	Parameters						
	Initial Range (m)	Initial Bearing (deg)	Sum of tonal frequencies (Hz)	Target Speed (m/sec)	Target Course (deg)	Ownship Course (deg)	Ownship Speed (m/sec)
1	3000	45	800	15	120	90	4.635

Simulation of algorithm

All raw bearings and frequency measurements are corrupted by additive zero mean Gaussian noise with a maximum level of 0.5 degrees and 0.9 Hz respectively. The performance of this algorithm is evaluated against no. of geometries. A typical scenario as shown in Table. 1 is chosen for evaluation of the algorithm. The measurement interval is one second and the period of simulation is 1800 seconds. Here all angles are considered with respect to True North 0 to 360 degrees, clockwise positive. The errors in the estimated range, course and speed are shown in figures. In underwater applications the acceptable errors in estimated range, course and speed are less than or equal to 10 %, 5 degrees and 20% respectively. As per the required accuracies the entire solution of the estimated parameter range, course and speed are obtained around at **80** seconds.

Limitations of this algorithm

In some scenarios, there will not be applicable change in the bearing from beginning to end of the process. As change in frequency measurement depend on bearing rate and hence change in frequency measurement is negligible. So, convergence of solution is not possible in these scenarios, unless ownship maneuvers in such a way that there is an appreciable change in bearing measurements.

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 of the target. 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. The algorithm cannot provide accurate results when the measurement noise is more than 1^0 rms.

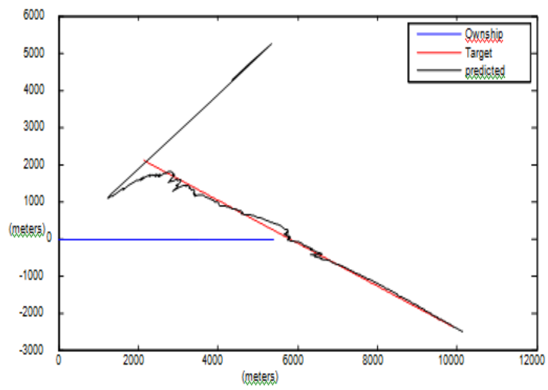

Fig: 1. Simulated and predicted target paths

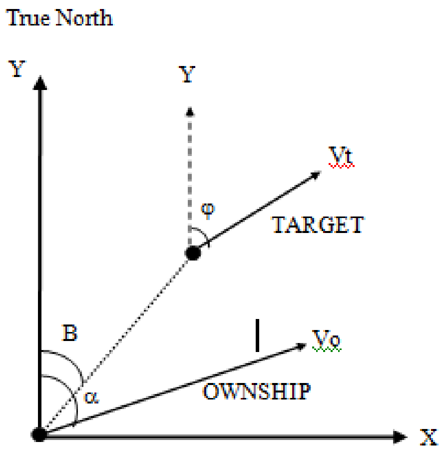

Fig. 2. Target and ownship in a pursuit geometry

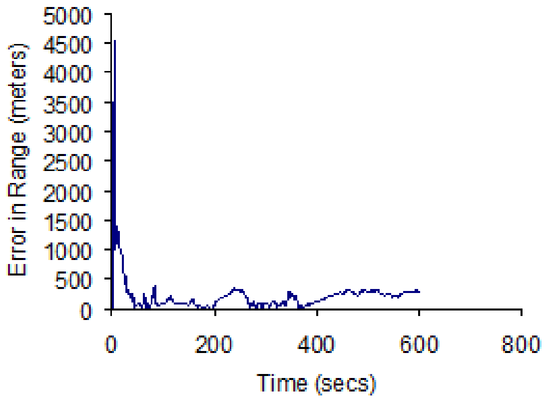

Fig. 1(a). Error in range estimate

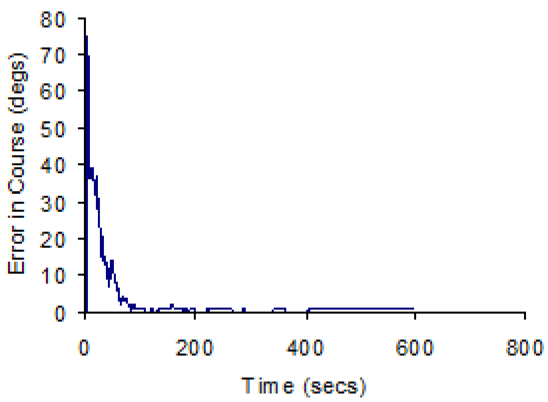

Fig. 1(b). Error in course estimate

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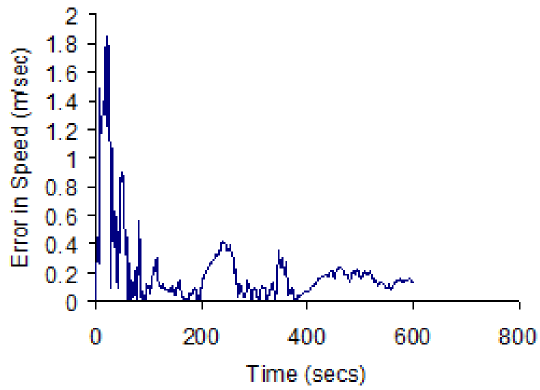

Fig. 1(c). Error in speed estimate

CONCLUSION

Recently much importance is given to obtain the target motion parameters using passive sonar installed in ownship (submarine, ship or underwater weapon) without using ownship maneuver. In many tactical situations, it is very difficult to carry out number of maneuvers until the required accuracy in the estimated target motion parameters. Researchers try to use Data fusion techniques if more tracking sensors are available. But in many situations only single platform with single sensor is available for tracking application in underwater. So, DBT is a right candidate 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 Unscented Kalman Filter (which is useful for non-linear applications) is proposed to estimate target motion parameters without using ownship maneuver in passive target tracking.

Mathematical modeling of frequency measurement

Let V_o & V_t, α & φ be the ownship and target speeds and courses respectively. The relative velocity along line of sight (LOS), as shown in Fig.2, is as follows.

$$V_C\text{, relative velocity} = V_0\cos(\varphi - B) - V_T\cos(\varphi - B) \quad \text{(A.1)}$$

$$= \cos B(\dot{y}_0 - \dot{y}_t) + \sin B(\dot{x}_0 - \dot{x}_t)$$

$$= \cos B(V_0\cos\varphi - V_T\cos\varphi) + \sin B(V_0\sin\varphi - V_T\sin\varphi)$$

$$= \sin B(\dot{x}_r) + \cos B(\dot{y}_r) \quad \text{(A.2)}$$

Doppler shift is defined as the ratio of relative velocity to wavelength. It is given by

$$\text{Doppler shift} = \frac{\text{relative velocity}}{\text{wave length}} = \frac{\text{relative velocity}}{\frac{C}{f_s}} \quad \text{(A.3)}$$

So the frequency measured as ownship is given by

$$f_m(k) = f_s(k) + \frac{\text{relaive velocity (k)}}{C} f_s(k) + \gamma_f(k) \quad \text{(A.4)}$$

$$= f_s(k)\left[1 + \frac{\text{relative velocity}}{C}\right] + \gamma_f(k)$$

$$= f_s(k)\left[1+\frac{\dot{x}_r(k)\sin B(k)+\dot{y}_r\cos B(k)}{C}\right]+\gamma_f(k) \tag{A.5}$$

$$= f_s(k)\left[1+\frac{(\dot{x}_0-\dot{x}_t)\sin B(k)+(\dot{y}_0-\dot{y}_t)\cos B(k)}{C}\right]+\gamma_f(k)$$

$$= f_s(k)\left[1+\frac{\dot{x}_0\sin B(k)+\dot{y}_0\cos B(k)}{C}\right]-\frac{\dot{x}_t f_s(k)\sin B(k)}{C}-\frac{\dot{y}_t f_s(k)\cos B(k)}{C}+\gamma_f(k) \tag{A.6}$$

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