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Tracking of a Manoeuvering Target Ship using Radar Measurements

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Abstract

For on sea water measurements of range on bearing in naval operations various types of Kalman filters including extended Kalman filter have been used. In this paper ,input estimation techniques applied normally to in air applications are applied to on sea measurements using chi – square distribution random sequence residual techniques. In which the algorithm estimates target motion parameters covering maneuvering. After detecting the target maneuvering, the algorithm corrects the velocity and position components based on acceleration noise input estimation method. Monte – Carlo simulation has proved the efficiency of the method. Practical applications of these methods are quite immense. Further test can be carried out on such cases.

Keywords: Chi-Square Distribution, Extended Kalman Filter, Linear Maneuvering, Monte-Carlo Simulator, Radar Measurements

1. Introduction

Kalman Filter for the sea scenario using the input estimation technique to detect target manoeuvre, estimate target acceleration and correct the target state vector accordingly. There are mainly two versions of Kalman Filter – a Linearised Kalman Filter (LKF) in which polar measurements are converted into Cartesian coordinates and the well-known Extended Kalman Filter (EKF) in which polar measurements are directly considered. Recently S. T. Pork and L. E. Lee[1,2] presented a detailed theoretical comparative study of the above two methods and stated that both the methods perform well. Here, EKF is used throughout the paper. The detection of target manoeuvre is carried out as follows. In this process, it is assumed that the estimator EKF is of high quality in the sense that solution is possible for all scenarios including all quadrants (Several geometries are tested using EKF and the solution is invariably obtained). It is also assumed that the solution diverges only when target maneuvers. When target is not maneuvering, it is observed from much geometry that the bearing residuals of the EKF are almost zero and their small scatter around the zero bearing line is the random noise[3,4].

It is also noted that the bearing residuals are not close to zero when the target is maneuvering. It is very difficult to confirm whether the target has maneuvered or not just by visual inspection of the bearing residual plot, due to the corruption of the bearing measurement with random noise. Hence, zero mean chi-square distributed random sequence residuals of the non-maneuvering model, in sliding window format are used for the detection of target maneuvers. Target maneuver is declared when the normalized squared innovations exceed the threshold. At the same time using these innovations of the Kalman Filter, the acceleration input is estimated and used to correct the state estimate. During the window period the acceleration input is assumed to be constant. This procedure is called

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input estimation and is given in detail, in references[3,4]. In this paper the authors try to extend the input estimation technique being used for in-air applications to on-sea water applications.

2. Mathematical Model

2.1 Target Motion Parameters

Let the target state vector be X_s (k) and is given by

$$X_S(k) = \begin{bmatrix} \dot{x}(k) & \dot{y}(k) & Rx(k) & Ry(k) \end{bmatrix}^T \quad (1)$$

Where $\dot{x}(k)$ and $\dot{y}(k)$ are target velocity components, and R_x (k) and R_y(k) are range components. For the purpose of introducing concepts, to start with target is assumed to be non-manoeuvreing. The target state dynamic equation is given by

$$X_S(k+1) = \Phi(k+1/k)X_s(k) + b(k+1) + \omega(k) \quad (2)$$

Where ω(k) is zero mean Gaussian plant noise Φ(k + 1/k) and b(k + 1) is transient matrix and the deterministic vector respectively. These are given by

$$\Phi(k+1/k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ t & 0 & 1 & 0 \\ 0 & t & 0 & 1 \end{bmatrix} \quad (3)$$

Where it is a sample time between measurements, and

$$b(k+1) = [0 \quad 0 - [x_o(k+1) + x_o(k)] - [y_o(k+1) + y_o(k)]^T \quad (4)$$

Where x_o (k) and y_o (k) are own ship position components respectively. The true North convention is followed for all angles to reduce mathematical complexity and easy implementation. The measurement vector Z (k) is given by

$$Z(k) = \begin{bmatrix} B_m & (k) \\ R_m & (k) \end{bmatrix} \quad (5)$$

Where B_m(k) and R_m(k) are bearing and range measurements and are given by

$$B_m(k) = B(k) + \gamma(k)$$
$$R_m(k) = R(k) + \eta(k) \quad (6)$$

Where B(k) and R(k) are actual bearing and range respectively. These are given by

$$B(k) = \tan^{-1}\left(\frac{R_x(k)}{R_y(k)}\right)$$
$$R(k) = \sqrt{R_x^2(k) + R_y^2(k)} \quad (7)$$

where η(k) and γ(k) are zero mean uncorrelated Gaussian noises in range and bearing measurements respectively. Using (5) and (6), the following equations can be written

$$Z(k) = H(k)X_s(k) + \xi(k) \quad (8)$$

Where

$$H(k) = \begin{bmatrix} 0 & 0 & \dfrac{\cos B(k)}{R(k)} & \dfrac{-\sin B(k)}{R(k)} \\ 0 & 0 & \sin B(k) & \cos B(k) \end{bmatrix} \quad (9)$$

It is assumed that the plant and measurement noises are uncorrelated to each other. The covariance prediction is

$$P(k+1|k) = \phi(k+1|k)P(k|k)\phi^T(k+1|k) + Q(k+1) \quad (10)$$

where Q is the covariance of the plant noise. The Kalman gain is

$$G(k+1) = P(k+1|k)H^T(k+1)[r(k+1) + H(k+1)P(k+1|k)H^T(k+1)]^{-1} \quad (11)$$

Where are (k + 1) is input measurement error covariance matrix. The state and its covariance corrections are given by

State:

$$X(k+1/k+1) = X(k+1/k) + G(k+1)[Z(k+1) - \hat{Z}(k+1)] \quad (12)$$

Covariance:

$$P(k+1/k+1) = [I - G(k+1)H(k+1)]P(k+1/k) \quad (13)$$

2.2 Tracking of a Maneuvering Target

Maneuvering targets are characterized by

$$X(k+1/k) = \Phi((k+1/k)X(k) + Fu(k) + \omega(k) \quad (14)$$

Where u(k) is an unknown input modelling the target maneuvers (u = 0 when there is no maneuver). In the modelling of the dynamics of non-maneuvering targets, the process noise is assumed to be low. A maneuver manifests itself into a large innovation, when target maneuver exists.

Estimation of the state is done using the model without input (non-maneuvering model). From the innovations of the Kalman Filter based on the non-maneuvering model, the input u(k) is detected, estimated and used to correct the state estimate. Zero mean chi-square distributed random sequence residuals, in sliding window format are used for the detection of target manoeuvre. During this window period, the input is assumed constant. Target manoeuvre is declared when the normalized innovations exceed the threshold. This procedure is called input estimation and is given in detail in[5,6]. Here the final equations are reproduced from the [7,8]. Assume that the target starts manoeuvreing at time k. It's unknown inputs during the time interval [k, k +s] are u(i), i = k,…..k + s – 1. An asterisk denotes the state estimates from the non-manoeuvreing model. The innovation of manoeuvreing target model is zero mean, white and is given by

$$\nu(k+1) = Z(k+1) - HX(k+1/k) \tag{15}$$

The innovations corresponding to non-manoeuvreing target model is given by

$$\nu^*(k+1) = Z(k+1) - H\hat{X}^*(k+1/k) \tag{16}$$

This innovation has the white noise sequence plus a term related to the inputs.

$$\nu*(i=1) = \nu(i+1) + H\sum_{j=k}^{i}\left[\prod_{m=j+1}^{i}\varphi(m)\right]Fu(j) \tag{17}$$

Can be rewritten as

$$\nu^*(i+1) = \Psi(i+1)u + \nu(i+1), \quad i = k, \ldots\ldots, k+s-1 \tag{18}$$

Where

$$\Psi(i+1) = H\sum_{j=k}^{i}\left[\prod_{m=j+1}^{i}\varphi(m)\right]F \tag{19}$$

ν^* of the non-manoeuvreing model is a linear measurement of the input manoeuvre u in the presence of the additive white noise ν. The input can be estimated using least squares criterion from y = φu + ζ

where

$$y = \begin{bmatrix} v^*(k+1) \\ . \\ . \\ . \\ v^*(k+s) \end{bmatrix} \text{and } \Psi \begin{bmatrix} \Psi(k+1) \\ . \\ . \\ . \\ \Psi(k+s) \end{bmatrix} \tag{20}$$

are the stacked "measurement " vector and matrix, and the "noise".

$$\zeta = \begin{bmatrix} \nu(k+1) \\ . \\ . \\ . \\ \nu(k+s) \end{bmatrix} \tag{21}$$

is zero mean with block-diagonal covariance matrix.

$$S = \text{diag}\,[S\,(i)] \tag{22}$$

The estimation can be done in batch form as

$$\hat{u} = (\Psi^T S^{-1} \Psi)^{-1} \Psi^T S^{-1} y \tag{23}$$

Where S is given by

$$S(k+1) = (H(k+1)P(k+1/k)H^T(k+1) + r(k+1)^{-1}$$

with the resulting covariance matrix

$$L = (\Psi^T s^{-1} \Psi)^{-1} \tag{24}$$

Estimation of u is accepted, i.e, a manoeuvre is declared only if it is "statistically accepted". The significance for the vector estimate u is

$$d(\hat{u}) = \hat{u}^T L^{-1} \hat{u} \geq c \tag{25}$$

Where c is a threshold. The choice of the threshold is as follows. If the input is zero, then

$$u \sim N(0, L). \tag{26}$$

i.e., the estimate is a normal random variable with mean zero and covariance P. Then the statistic d from equation (25) is

Chi-squared distributed with n_u degrees of freedom and c is chosen such that the probability of false alarm is

$$p\{d(\hat{u}) \geq c\} = \alpha$$
$$\text{with } \alpha = 10^{-2} \text{ or smaller} \tag{27}$$

If a manoeuvre is detected, then the state has to be corrected, as follows. The input term is used with the estimated input.

$$\hat{x}^u(k+s+1/k+s) = \hat{x}^*(k+s+1/k+s) + M\hat{u}$$
$$\text{where } M = \sum_{j=k}^{k+s}\left[\prod_{m=j+1}^{k+a}\varphi(m)\right]F \tag{28}$$

The covariance associated with the estimate equation (28) is

$$P^u(k+s+1/k+s) = P(k+s+1/k+s) + MLM^T \tag{29}$$

A manoeuvre is considered finished when the input estimate based on measurements from the sliding window of length s becomes insignificant. The length s is a design parameter. In cases where the duration of a manoeuvre is short relative to a sample interval, an input pulse length of s = 1 or 2 is appropriate.

3. Implementation of the Algorithm

Using first and second sets of bearing and range measurements, the speed components of the target are calculated and the actual computation of the Kalman filter starts from second measurement onwards.

The initial estimate of target state vector X(2/2) is given by

$$X(2/2) = [\text{term}1 \;\; \text{term}2 \;\; R_m(2)\sin B_m(2)\cos B_m(2)]^T \qquad (30)$$

where

$$\text{term}1 = R_m(2)\sin B_m(2) - R_m(1)\sin B_m(1)/t$$

$$\text{term}2 = R_m(2)\cos B_m(2) - R_m(1)\cos B_m(1)/t \qquad (31)$$

It is assumed that the initial estimate, X (2|2) is uniformly distributed. Then the elements of initial covariance diagonal matrix can be written as

$$p_{00}(2/2) = \frac{4 * \dot{x}^2(2/2)}{12}$$

$$p_{11}(2/2) = \frac{4 * \dot{y}^2(2/2)}{12}$$

$$p_{22}(2/2) = \frac{4 * R_x^2(2/2)}{12}$$

$$p_{33}(2/2) = \frac{4 * R_y^2(2/2)}{12} \qquad (32)$$

The target motion parameters are target's range, course, bearing and speed and these are calculated from the estimated state vector as follows.

$$R(k) = \sqrt{R_x^2(K) + R_y^2(K)}$$

$$B(k) = \tan^{-1}\left(\frac{R_x(k)}{R_y(k)}\right)$$

$$C(k) = \tan^{-1}\left(\frac{\dot{x}(k)}{\dot{y}(k)}\right)$$

$$B(k) = \sqrt{\dot{x}(k)^2 + \dot{y}(k)^2} \qquad (33)$$

The Kalman filter is implemented as follows. After receiving the second measurement, X(2/2) and P(2/2) are computed using equation (30) and (32) respectively. Using X(2/2), P(2/2) and H(2) are calculated. Then transient matrix, Kalman gain, correction in state vector and its covariance matrix are computed. Target motion parameters are calculated from the corrected state vector using equation (33) and the validity of the solution is found out using the corrected covariance matrix. After the receipt of the 3rd sample, transient matrix is computed and then the state vector and its covariance matrix are updated. Using Kalman gain, the state vector and its covariance matrix are corrected. In this way, the process is repeated for a simulation period of 30 minutes[9,10].

The size of the sliding window, in manoeuvre detection, is selected on the basis of the results of several geometries in Monte-Carlo simulation. If the window size is less than two, it is seen that the performance is drastically reduced and hence a 2-sample window is employed.

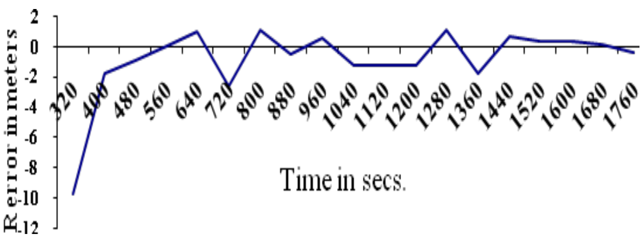
4. Simulation and Results

Let us consider active sonar with range scales and their corresponding measurement timings as 5 Km, 10 Km, 20 Km, 40 Km and 10 sec, 20 sec, 40 sec and 80 sec respectively. It means that if range is less than 5 km, then range and bearing measurements are available at 10 sec and so on. The time intervals based on these range scales are not considered in Kalman filter, as these are not exact. They are recalculated based on the range measurement considering that the sound velocity in water as 1500 m/sec. Let the maximum noise in the bearing and range measurements be 1 deg and 20 meters respectively.

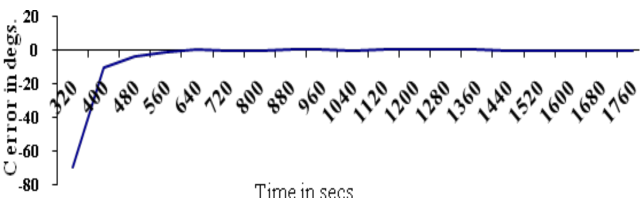
The algorithm is realized using Matlab on a pc platform. Let us consider a typical long-range scenario on sea. The observer is moving on 65 degrees course at a speed of 30 knots. The target is moving on 100 degrees course at a speed of 10 knots. The target is initially at zero degrees line of sight and at a range of 30 km. The positions of target and observer are updated at every second. However the measurements after corruption with noise available to the Kalman filter are according to range scales. Here the range is 30 km, so the time interval between the measurements is 80 seconds.

In general, the errors allowed in the estimated target motion parameters are 8% in the range, 3^o in the course and 3m/s in velocity estimates. The results of this scenario in Monte-Carlo Simulation with 100 runs are shown in Figure 1. In these figures and in the subsequent figures, R error, C error and S error denote the errors in range, course and speed estimates respectively. From the results, it is observed that the solution with the required accuracy is obtained from 6th sample (480 seconds) onwards. The theoretical value of the chi-square variable with 2 degrees of freedom at 90% confidence level is 4.61. Out of 100 Monte-Carlo runs, it is observed that the maximum value of d(u) is 1.6 and mostly it is around 0.3. So, when there is no target manoeuvre, the experimental value is matching with that of theoretical value.

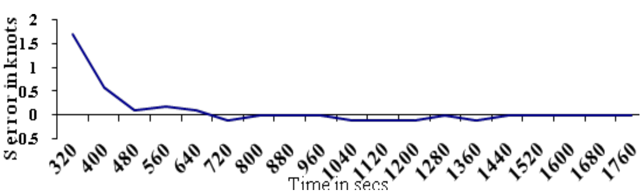
For the purpose of illustration, in the previous scenario, it is assumed that the target is changing its course from 100 to 180 degrees at 540 seconds. The target has completed the manoeuvre by 560 seconds, with turning rate of 3 degrees per second. The statistic threshold d(u) is changed to 0.4, 1, 6.7 at 7th (560 secs), 8th (640 secs) and 9th (720 secs) samples respectively. So the correction of state vector is commenced from 10th sample onwards. The statistic threshold d(u) is changed to 3.8, 0.9 at 10th and 11th samples respectively.



(a)

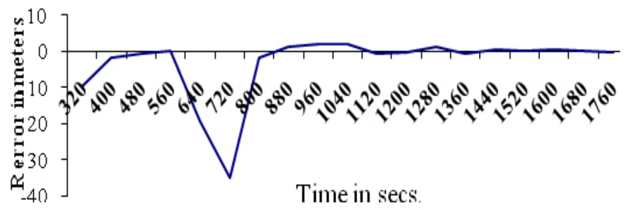


(b)

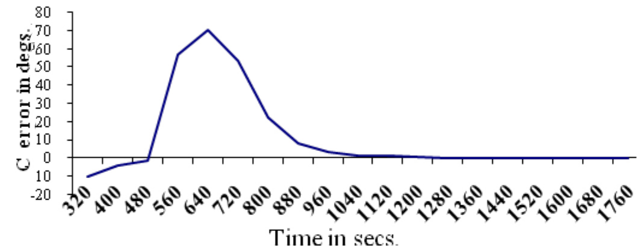


(c)

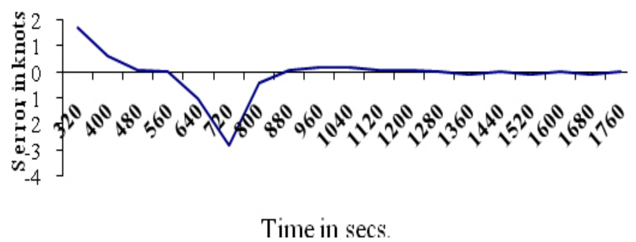
Figure 1. **(a)** Error in Range Estimate. **(b)** Error in Course Estimate. **(c)** Error in Speed Estimate.



(a)



(b)



(c)

Figure 2. **(a)** Error in Range Estimate. **(b)** Error in Course Estimate. **(c)** Error in Speed Estimate.

5. Limitations of Filter

It is seen that the filter is able to provide good results when the error in bearing measurement is less than 1.5^{o} rms.

6. Conclusion

The authors have attempted an approach to extend the algorithm for applications in air to the applications in underwater-viz. Tracking a maneuvering target using measurements from active sonar. The experiment shows that the algorithm is able to track the target and hence it can be used for underwater applications.

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