Particle Swarm optimization Based Tuning of Extended Kalman Filter for Manoeuvring Target Tracking

RAVI KUMAR JATOTH, T. KISHORE KUMAR

Abstract—- **Kalman filter is a well known adaptive filtering Algorithm, widely used for target tracking applications. When the system model and measurements are non linear, variation of Kalman filter like extended Kalman filter (EKF) is used. For obtaining reliable estimate of the target state, filter has to be tuned before the operation (off line).Tuning an EKF is the process of estimation of the noise covariance matrices from process data. In practical applications, due to unavailable measurements of the process noise and high dimensionality of the problem tuning of the filter is left for engineering intuition. In this paper, tuning of the EKF is investigated using Particle Swarm Optimization (PSO). The simulation results show the superiority of the PSO tuned EKF over the conventional EKF**

Keywords— **Adaptive Filter; Extended Kalman Filter; Noise Covariances; Tuning; Particle Swarm Optimisation, Manoeuvring target tracking.**

I. Introduction

IN many tracking applications Kalman Filter (KF) is used to estimate the velocity, position and acceleration of a manoeuvring target from noisy radar measurements at high data rates. When the process is to be estimated and measurement model is nonlinear, EKF is used in which, the process is approximated to first order term of the Taylor's expansion for calculating the mean and covariance of the random process [1]. The Kalman filter demands priori information about the noise covariances from the user [2]. Initial process and measurement noise covariances play an important role in convergence of the filter. If the noise covariances are not chosen properly it may leads towards degradation of the filter performance [3]. A few techniques for determining the process and measurement noise covariances for various applications have been discussed in the literature [4], [5] and widely used tuning method is least squares approach.

Particle Swarm Optimization (PSO) is population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling in searching for food [6]. PSO exploits a population of individuals to probe promising regions of the search space. In the context, the population is called a swarm and the individuals are called particles. Each particle moves with an adaptable velocity within the search space, and retains in its memory the best position it ever encountered. In the global variant of PSO the best position ever attained by all individuals of swarms is communicated to all the particles.

The bistatic range and range rate based tracking is considered here for target tracking where a number of Radar receivers measures bistatic range (transmitter-target-receiver distance) and bistatic Doppler (bistatic range rate divided by the wave- length, at the frequency of the radar operation). If bistatic range and range rates are used for tracking then we can use wide band antennas in which we can perform signal processing at baseband frequencies [7].

This paper implements PSO based tuned EKF, in which process noise and measurement covariances are tuned based on biologically inspired evolutionary computing tool.

Organization of this paper is as follows. The problem description presented in Section II. In Section III, the Extended Kalman Filtering algorithm and the New PSO Tuned Extended Kalman Filter are discussed. The manoeuvring target tracking modeling equations and CRLB bounds are derived in section IV. In Section V, simulations results are presented to compare the algorithm with an extended Kalman filter for maneuvering target tracking. Conclusions are presented in Section IV.

II. Problem description.

In this paper target tracking environment is taken as shown in figure1. The transmitter is placed at High altitude and receivers are placed at different places which is called bistatic radar environment. If bistatic range and range rate are used to extract the information about target trajectories then we can use wide band antennas for tracking which facilitates signal processing at low frequencies. Because of the current day technologies cheaper and low power receivers are available, so

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we can deploy number of receivers which gives accurate information about the target.

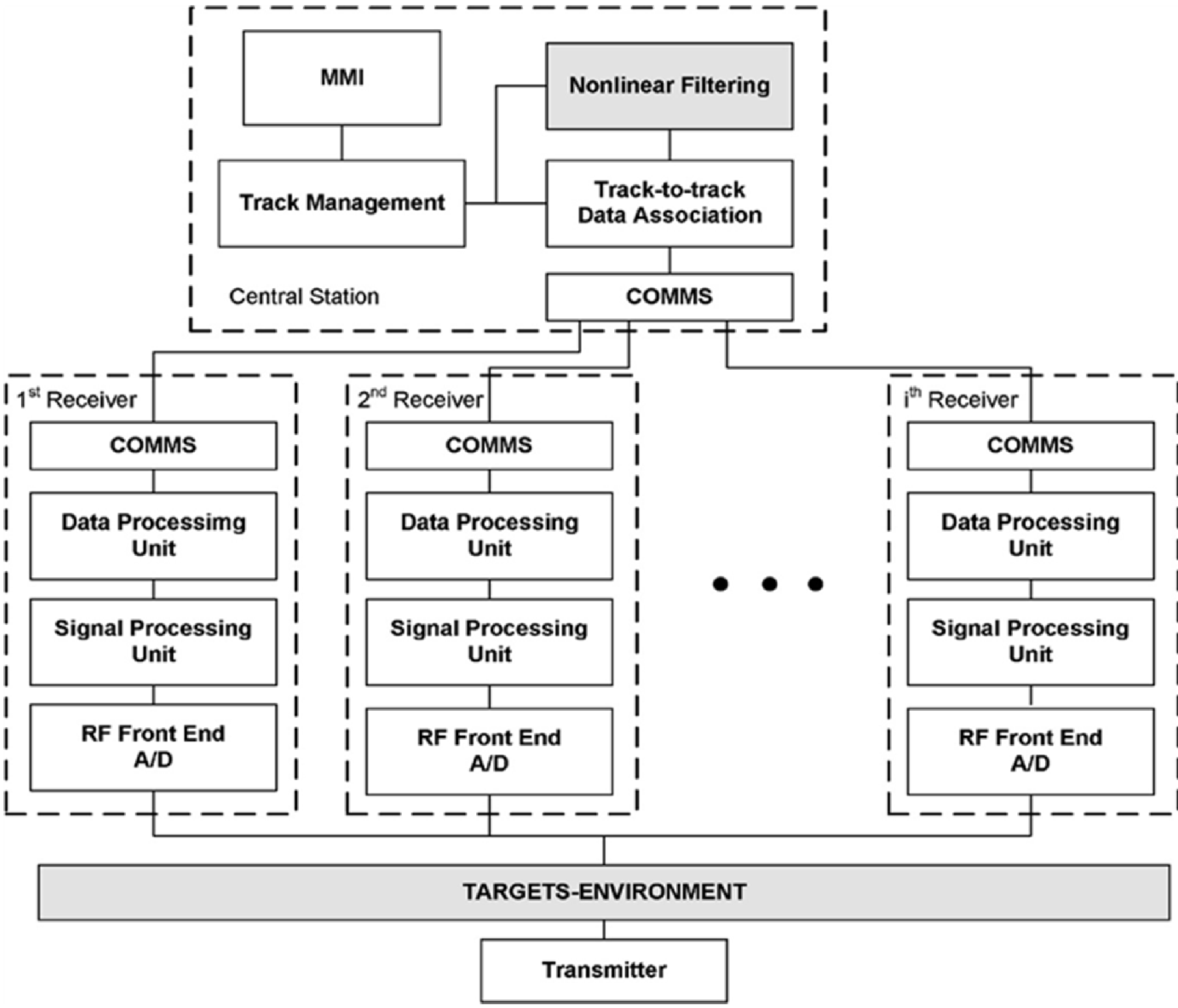

Figure 1: Target Environment

The state equation for the target motion could be approximated with a linear equation of the form

$$X_{k+1} = F_k x_k + G w_k \text{ .... (1)}$$

Where x_k is the state vector that contains state variables at time k, F_k is state transition matrix, which relate system state k to k+1 time in the absence of forcing function and $w_k \sim N(0, Q_k)$ which is assumed as zero mean white Gaussian noise with covariance Q_k (called process noise covariance). G is the noise forcing matrix.

The measurement model of the system can be written as

$$z_k = H_k x_k + v_k \text{ .... (2)}$$

Where z_k measurement vector, H_k is measurement matrix and $v_k \sim (0, R_k)$ which is assumed as zero mean white Gaussian noise with covariance R_k (called measurement noise covariance). Both noises are assumed to be uncorrelated. The measurement equation above relates the state x_k to the measurement z_k..

In practice of Initial estimate of the process is x_0^- and initial estimation of the error covariance matrix is P_0^-. The priori estimation error is given by

$$e_k^- = x_k - x_k^- \text{ .... (3)}$$

Error covariance matrix is given by

$$P_0^- = E[e_k e_k^T] \text{ .... (4)}$$

The EKF algorithm starts with calculation of Kalman Gain which is given by

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \text{ .... (5)}$$

The next step is to update the position using the new measurement which is given by

$$\hat{x}_k = x_k^- + K_k (z_k - Hx_k^-) \text{ ....(6)}$$

From (6) we can say that based on the Kalman gain or the correction factor the estimated accuracy depends which in turn depends on initial noise covariance matrices. Selecting optimum parameters of these values gives optimum performance of the filter.

Trial and error approach to obtain these tuning parameters is tedious process and doesn't guarantee the accuracy of estimation in Mean Square Error (MSE) sense. Choosing optimum Parameters of noise covariance matrices, "i.e." is tuning the filter is a challenging task for Kalman filter designer.

In this paper another approach of tuning the Kalman filter based on the particle swarm intelligence is proposed.

III. Filter Tuning

Tuning of the filter is referred as estimation of the noise covariance matrices [8]. It has been shown previously that the performance of an EKF process depends largely on the accuracy of the knowledge of process covariance matrix and measurement noise covariance matrix. Incorrect apriori knowledge of noise covariances may lead to performance degradation and it can even lead to practical divergence. Hence, intelligent method of estimation of these matrices becomes very important for online deployment. Measurements can be performed before the operation of the filter under various noise conditions and measurement noise covariances can be obtained off line.

In literature it has been reported a pioneering work on adaptive estimation of noise covariance matrices and for Kalman filtering algorithm, based on correlation-innovations method that can provide asymptotically normal, unbiased and consistent estimates[9]. The other algorithm is based on the assumption that noise statistics is stationary and the model under consideration is a time invariant one. Later several research works have been reported in the same direction, employing many classical approaches.

The hardware implementation problems, however, demand certain other factors such as process and noise covariances. In practice, owing to the complex background and other inherent factors, the maneuverability of target has a larger randomness, and the acceleration is an important parameter reflected maneuverability of target, hence, when we design the Maneuvering target tracking *(MTT)* adaptive filter, it becomes an important problem of MTT that how to correctly estimate acceleration of target and reasonably adjust its covariance so as to that they can timely reflect the variety of maneuvering acceleration.

A few techniques for determining the process and measurement noise covariances for various applications have been discussed in the literature [10].

The innovations process can be used to adapt the covariances on-line. The drawback of the method is that it utilizes initial, and often unavailable, estimate of the covariance matrices, the output innovations, and the process model to estimate the model's accuracy, as represented by the process noise statistics.

A. Conventional Extended Kalman Filter

Most processes in real life are unfortunately not linear, and therefore needs to be linearized before they can be estimated by means of a Kalman filter. The extended Kalman filter (EKF) solves this problem by calculating the Jacobian of *f* and *h* around the estimated state, which in turn yields a trajectory of the model function centred on this state.

The extended Kalman filter extends the scope of Kalman filter to nonlinear optimal filtering problems by forming a Gaussian approximation to the joint distribution of state x and measurements z using a Taylor series based transformation. Extended Kalman filters is presented, which are based on linear and quadratic approximations to the transformation.

Let us assume that our process has a state vector $x \varepsilon \Re^n$, but that the process is now governed by the *non-linear* stochastic difference equation

$$x_k = f(x_{k-1}, u_k, w_{k-1}) \text{ ....(7)}$$

With a measurement that is

$$z_k = h(x_k, v_k) \text{ .... (8)}$$

In this case the non-linear function in the difference equation above relates the state at the previous time step to the state at the current time step. It includes as parameters, any driving function u_k and the zero-mean process noise w_k. The non-linear function h course one does not know the individual values of the noise w_k and v_k at each time step. However, one can approximate the state and measurement vector without them as

$$\tilde{x} = f(\hat{x}_{k-1}, u_k, 0) \text{ ....(9)}$$

and

$$z_k = h(\tilde{x}_k, 0) \text{ ....(10)}$$

Where $\hat{x}_k$ is some *aposteriori* estimate of the state (from a previous time step *k*). Here the function h is linearized over a nominal trajectory and the algorithm is applied as shown below in figure2.

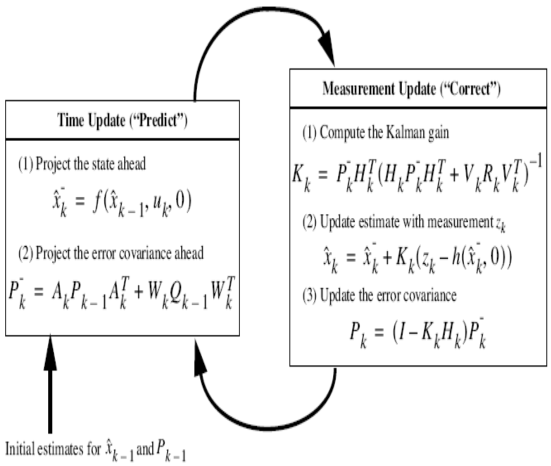

Figure2: EKF Algorithm

B Particle Swarm Optimization.

The particle swarm algorithm is an adaptive algorithm based on a social-psychological metaphor; a population of individuals adapts by returning stochastically toward previously successful regions in the search space, and is influenced by the successes of their topological neighbors [11].

The Swarm of particles indicates estimates of multiple parameters involved in the problem. We can begin with initializing a random swarm of particles. During each iteration fitness of the particle is evaluated with the help of fitness function (Mean Square Error in our problem).

The algorithm progressively replaces most fit parameters of each particle i.e. *pbest*, the best position of the particle itself.

There exist another best position *gbest* which is the global best i.e. the best position in the swarm. Each particle has the influence of these two bests in their trajectories. The parameters of each particle are updated with the following equations.

Velocity updation

$$v_i(t+1) = w.v_i(t) + c_1.rand.(pbest(t) - x(t)) +$$

$$c_2.rand.(gbest(t) - x_i(t)) \quad \ldots\ldots (11)$$

Position updation

$$P_{t+1} = P_t + v_{t+1} \ldots\ldots\ldots\ldots\ldots\ldots \quad (12)$$

Where

p- instantaneous position of the particle
v- instantaneous velocity of the particle
Pbest-positional best of the particle
gbest-global best position of the swarm of particles
W – Inertial weight factor
C1, C2 – acceleration coefficients

The trajectory of the particle is dependent on three factors: its previous position, pbest and gbest. Greater the strain of the particle in searching food, smaller is the acceleration coefficients. The inertial weight factor w signifies the importance of the particle's previous position in further search.

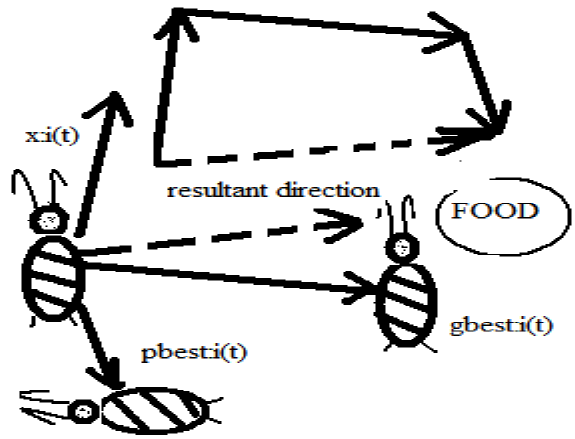

Fig.3 Trajectory of particle after velocity updation

Thus each particle tend to move towards *gbest* to reach food early. If *gbest* has less number of values then the particles will reach the food early. The algorithm comes to an end when all the particles converge at that gbest i.e. food position. In our problem i.e. attaining minimum possible value for *MSE.*

The trajectory of each particle is influenced in a direction determined by the previous velocity and the location of *gbest* and *pibesti*. The two acceleration coefficients combined form what is analogous to the step size of an adaptive algorithm. Small acceleration coefficients tend to give a better search with slower convergence, while larger coefficients give a lesser search and faster convergence. The random *ei* vectors provide the randomness of the step between *gbest* and *pbesti*. The inertia weight controls the influence of the previous velocity. A single particle update is graphically illustrated in two dimensions in Figure 4. The new particle coordinates can lie anywhere within the bounded region, depending upon the weights and random components associated with each vector.

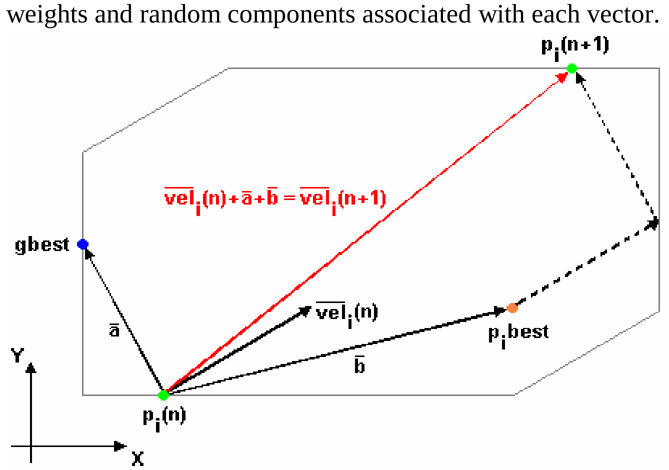

Figure.4: Resultant direction of particles.

As new *gbests* are encountered during the update process, all other particles begin to swarm toward the new *gbest*, continuing to search along the way. The search regions continue to constrict as new *pbestis* are encountered. The algorithm is terminated when all of the particles in the swarm have converged to *gbest* or a suitable minimum error condition is met.

The block diagram of PSO can be shown like this:

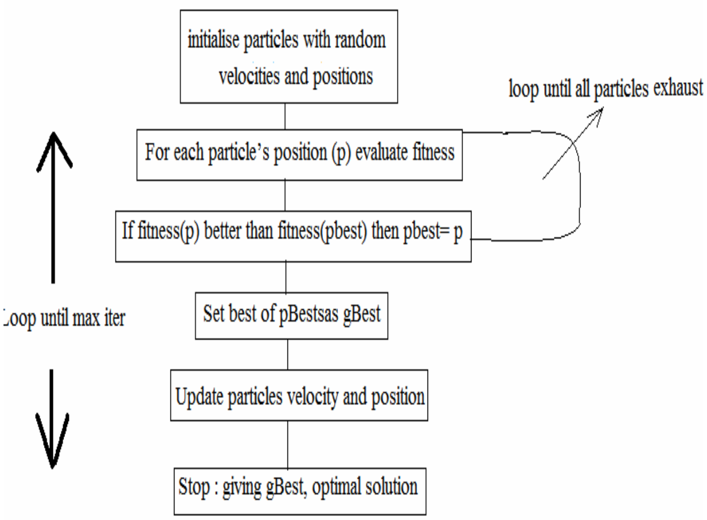

Fig.5 Block Diagram of PSO

C. Applying PSO in Filter Tuning

We refer to filter tuning as a process of obtaining parameters of a filter such as values of matrices *Q* and *R* for EKF that give the best filter performance in Mean Square Error (MSE) sense. Typically this kind of problems of designing a filter with optimal tuning parameters was left up to engineering intuition, and trial and error method that do not guarantee best filter performance due to large number of parameters to be tuned. A straightforward way of tackling this problem is to employ global optimization method that minimizes function of MSE position error with respect to filter parameters. There are several issues associated with such an approach. First, each time we need a value of MSE during global optimization procedure we have to run EKF on all available data. This requires a significant computational time since for example in order to find a global minimum of a smooth function of 5 parameters; we need to compute the function value many times.

One of the practical solutions to these issues is to estimate approximate functional relation between tuning parameters and the MSE criterion of optimization in a deterministic way and then apply nonlinear global optimization method to find optimal parameters which correspond to minimum of MSE.

Here in this problem we are tracking the target under different conditions such as nearly constant velocity, nearly constant acceleration and nearly constant turn. Therefore we have three power spectral densities of the corresponding continuous process noise, two parameters of measurement noise standard deviations (range and range rate) . So, a total of five parameters have to be optimized. Taking the extreme worst cases of these five parameters, we proceed according to the Particle Swarm Optimization.

IV. Mathematical Modeling Of Target Tracking Using Bistatic and Range Rate Measurements.

Real Target Motion could be described by a large number of models, mixed in unknown ways [12-17]. At this section, three motion models nearly constant velocity, nearly constant acceleration, and constant turn are described. Basic problem is to estimate the target kinematic state (position and velocity) from noise corrupted measurements. Since the output of the filtering algorithm is required to be Cartesian position and velocity, the target kinematic state can be described by the state vector defined in discrete time as

$$x_k = [x_k, y_k, z_k, v_{xk}, v_{yk}, v_{zk}]^T \quad \text{............. (13)}$$

where T denotes matrix transpose, x_k, y_k and z_k are the Cartesian target coordinates at time index k and v_{x_k}, v_{y_k} ,and v_{z_k} are their respective derivatives (velocities). It is well known that if a derivative, such as range-rate, is measured, better performance can typically be obtained if an acceleration state is included in the filter In this case, acceleration is added to the state vector, which becomes

$$x_k = [x_k, y_k, z_k, v_{xk}, v_{yk}, v_{zk}, a_{xk}, a_{yk}, a_{zk}]^T \quad \text{...... (14)}$$

Where a_{x_k}, a_{y_k} and a_{z_k} are the target accelerations.

For extracting three dimensional positions four wide band radars are used by employing triangulation method. Each radar-sensor measures bistatic range and bistatic Doppler. These measurements, after being processed locally (at each receiver) and transformed to bistatic range and bistatic velocity (forming bistatic tracks), are sent to the central station where they form the measurement vector of the central station filtering algorithm. The measurement vector is given by

$$z_k = [r_1 \quad r_2 \quad r_3 \quad r_4 \quad v_{r_1} \quad v_{r_2} \quad v_{r_3} \quad v_{r_4}]^T \quad \text{..... } (15)$$

Where r_i and v_{r_i} are the bistatic range and bistatic range-rate, respectively, measured by the ith receiver.

Taking as the origin the coordinate frame the transmitter, the relationship of each measurement with filter state vector is described via the non linear measurement model,

$$z_k = h(x_k) + v_k \quad \text{........................... (16)}$$

Mathematical Modeling

The target motion with constant velocity in state space model can represented as

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ z_{k+1} \\ v_{x_{k+1}} \\ v_{y_{k+1}} \\ v_{z_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & t_k & 0 & 0 \\ 0 & 1 & 0 & 0 & t_k & 0 \\ 0 & 0 & 1 & 0 & 0 & t_k \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ z_k \\ v_{x_k} \\ v_{y_k} \\ v_{z_k} \end{bmatrix} + \begin{bmatrix} t_k & 0 & 0 \\ 0 & t_k & 0 \\ 0 & 0 & t_k \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} w_x & w_y & w_z \end{bmatrix}$$

………………(17)

Where Tk is the observation time. The process noise covariance matrix

$$Q = E[w_k w_k^T] = \int_0^T G\sigma^2 G^T dt$$

$$= q_1 \begin{bmatrix} t_k^3/3 * I_{3*3} & t_k^2/2 * I_{3*3} \\ t_k^2/2 * I_{3*3} & t_k * I_{3*3} \end{bmatrix}$$ …………….(18)

Where q1 is the level of power spectral density of continuous process noise.

Nearly constant acceleration (NCA) model for manoeuvring target flight segment is is given by

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ z_{k+1} \\ v_{x_{k+1}} \\ v_{y_{k+1}} \\ v_{z_{k+1}} \\ a_{x_{k+1}} \\ a_{y_{k+1}} \\ a_{z_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & t_k & 0 & 0 & t_k^2/2 & 0 & 0 \\ 0 & 1 & 0 & 0 & t_k & 0 & 0 & t_k^2/2 & 0 \\ 0 & 0 & 1 & 0 & 0 & t_k & 0 & 0 & t_k^2/2 \\ 0 & 0 & 0 & 1 & 0 & 0 & t_k & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & t_k & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & t_k \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ z_k \\ v_{x_k} \\ v_{y_k} \\ v_{z_k} \\ a_{x_k} \\ a_{y_k} \\ a_{z_k} \end{bmatrix} + \begin{bmatrix} t_k^2/2 & 0 & 0 \\ 0 & t_k^2/2 & 0 \\ 0 & 0 & t_k^2/2 \\ t_k & 0 & 0 \\ 0 & t_k & 0 \\ 0 & 0 & t_k \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} w_x & w_y & w_z \end{bmatrix}$$

……………….(19)

The process noise covariance is

$$Q_k = q_2 \begin{bmatrix} t_k^5/20 * I_{3*3} & t_k^4/8 * I_{3*3} & t_k^3/6 * I_{3*3} \\ t_k^4/8 * I_{3*3} & t_k^3/3 * I_{3*3} & t_k^2/2 * I_{3*3} \\ t_k^3/6 * I_{3*3} & t_k^2/2 * I_{3*3} & t_k * I_{3*3} \end{bmatrix}$$ ....(20)

Where q2 is the level of power spectral density of corresponding continuous noise.

A three dimensional nearly constant speed turn (NCT) manoeuvring flight segment is written as [10]

$$x_{k+1} = Fx_k + Gw_k$$ ……… (20)

$$F_k = \begin{bmatrix} I_{3*3} & \sin(w_k t_k)/w_k I_{3*3} & (1-\cos(w_k t_k))/w_k^2 I_{3*3} \\ 0_{3*3} & \cos(w_k t_k) I_{3*3} & \sin(w_k t_k)/w_k I_{3*3} \\ 0_{3*3} & -w_k \sin(w_k t_k) I_{3*3} & \cos(w_k t_k) I_{3*3} \end{bmatrix}$$

The process noise covariance is

$$Q = E[w_k w_k^T] = \int_0^T G\sigma^2 G^T dt$$

$$Q_k = q_3 \begin{bmatrix} A_k I_{3*3} & B_k I_{3*3} & C_k I_{3*3} \\ B_k I_{3*3} & D_k I_{3*3} & E_k I_{3*3} \\ C_k I_{3*3} & E_k I_{3*3} & F_k I_{3*3} \end{bmatrix}$$ …..(21)

Where

$$A_k = \frac{6\omega_k t_k - 8\sin \omega_k t_k + \sin 2\omega_k t_k}{4\omega_k^5}$$

$$B_k = \frac{2\sin^4(\omega_k t_k / 2)}{\omega_k^4}$$

$$C_k = \frac{-2\omega_k t_k + 4\sin \omega_k t_k - \sin 2\omega_k t_k}{4\omega_k^3}$$

$$D_k = \frac{2\omega_k t_k - \sin 2\omega_k t_k}{4\omega_k^3}$$

$$E_k = \frac{\sin^2 \omega_k t_k}{2\omega_k^2}$$

$$F_k = \frac{2\omega_k t_k + \sin 2\omega_k t_k}{4\omega_k}$$

V. CRAMER-RAO LOWER BOUND DERIVATION

The optimal solution to the problem formulated cannot be derived analytically, even for the case of a single dynamic model, since the measurement equation is non linear. In the absence of optimal analytic solution, one has to resort to approximate solutions. However, the existence of a lower bound of performance would help the assessment of the level of approximation introduced by a particular algorithm. The bound will be derived under the assumption that process noise is zero and the model history is known [18-19].

The general framework for derivation of CRLB of an unbiased estimator for non linear discrete time is described. The CRLB for an unbiased estimator of the target state vector is given by the inverse of Fisher Information Matrix (FIM).Thus the error covariance matrix P_k is bounded from below as follows :

$$\mathbf{P}_k = E\{(\hat{\mathbf{x}}_k - \mathbf{x}_k)(\hat{\mathbf{x}}_k - \mathbf{x}_k)^{\mathrm{T}}\} \geqslant \mathbf{J}_k^{-1},$$ ……..(22)

Where J_k in the Fisher Information matrix defined as

$$\mathbf{J}_k = E\{[\nabla_{x_k} \log p(\mathbf{x}_k, \mathbf{Z}_k)][\nabla_{x_k} \log p(\mathbf{x}_k, \mathbf{Z}_k)]^{\mathrm{T}}\},$$ ………… (23)

Where ∇_{x_k} being the gradient operator with respect to x_k, and E{.} the expectation operator. The CRLBs of the state vector components are calculated as the diagonal elements of the inverse information matrix

$$\mathrm{CRLB}\{[\hat{\mathbf{x}}_k]_j\} = [\mathbf{J}_k^{-1}]_{jj}. \quad \text{……….(24)}$$

Information matrix can be calculated using the following recursion

$$\mathbf{J}_{k+1} = [\mathbf{Q}_k + \mathbf{F}_k \mathbf{J}_k^{-1} \mathbf{F}_k^{\mathrm{T}}]^{-1} + E\{\mathbf{H}_{k+1} \mathbf{R}_k^{-1} \mathbf{H}_{k+1}\}, \quad \text{...(25)}$$

and the initial value of this matrix is taken as

$$\mathbf{J}_0 = \mathbf{P}_{0|0}^{-1}. \quad \text{……(26)}$$

V. Simulation Results

The signal bandwidth was assumed to be 10MHz, concerning the target simulated motion, its initial position Firstly, as far as multistatic radar deployment is concerned, the transmitter is placed in [0, 0, 0m], while the four receivers are assumed to be at: (i) [31500, 0, -700 m]; (ii) [3500, -200 m]; (iii) [38500, 0, -500 m] and (iv) [35000, -3500, -300 m]. It should be underlined that the topology of the whole system affects directly the system performance since the multistatic radar resembles a large distributed antenna. As a consequence, the more distributed the elements-receivers the better the performance (tracking accuracy) obtained. The radar frequency of operation was selected to be at the lower is

$$[x_0 \quad y_0 \quad z_0] = [25000m \quad 4000m \quad 1000]$$

moving with nearly constant velocity system model with an initial velocity

$$[v_{x_0} \quad v_{y_0} \quad v_{z_0}] = [0m/s \quad -83.3m/s \quad 0m/s]$$

for the first 50s.

For the next 50 s the target makes a motion with nearly constant acceleration with initial acceleration of approximately 1 g

$$[a_{x_1} \quad a_{y1} \quad a_{z1}] = [-10m/s^2 \quad 0m/s^2 \quad 0m/s^2]$$

It turns right for 25 s with initial acceleration being the acceleration of the last segment of motion and a nearly constant turn rate of 6^0/s, thus changing its heading by more than 150^0. The maximum acceleration obtained during this phase is approximately 6g.

Finally, the target resumes a nearly constant velocity motion, with the velocity it had attained at the end of the previous phase.

The bistatic range measurement error deviation, the bistatic range-rate measurement error, process noise level of power spectral densities during constant velocity, constant acceleration, constant turn are tuned according to the PSO. Here the fitness function is a function of the RMS errors in the 3 directions. In order to make the performance analysis more realistic, the parameters ranges are taken between the extremes. Finally, the sampling interval t_k was assumed to be 1s (which means that the number of measurements is the same as time in seconds), while the detection and false alarm probabilities of radar equal to 1 and 0, respectively. The magnitude of the acceleration is divided by g (g = 9.8 m|s^2).

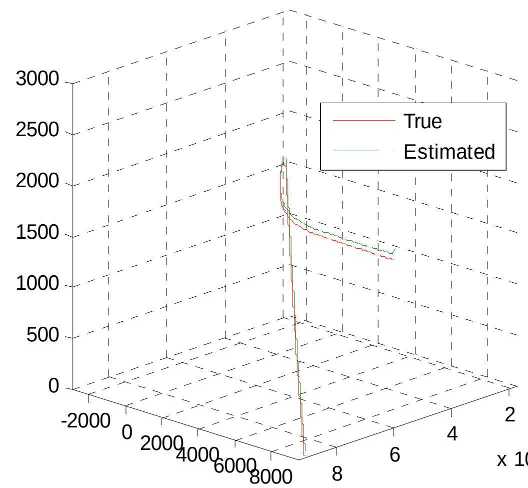

Figure 6: Simulated target motion in three dimensions

Figure 6 shows that the PSO tuned filter accurately tracks the true motion. The projections of tracking on different planes are shown for further information.

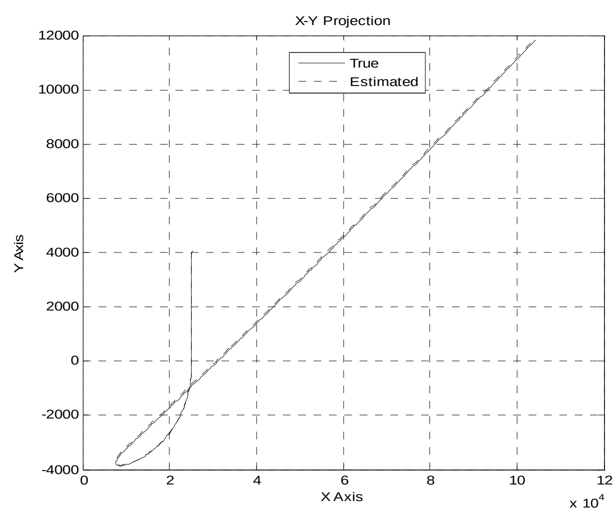

Figure7: Simulated target motion in X-Y plane projections.

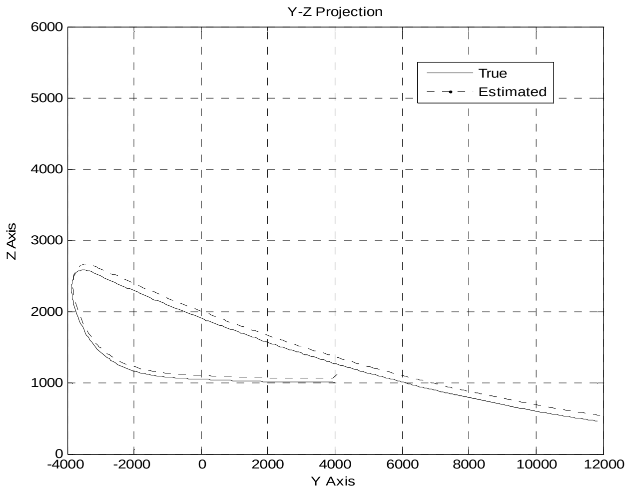

Figure8: Simulated target motion in Y-Z plane projections.

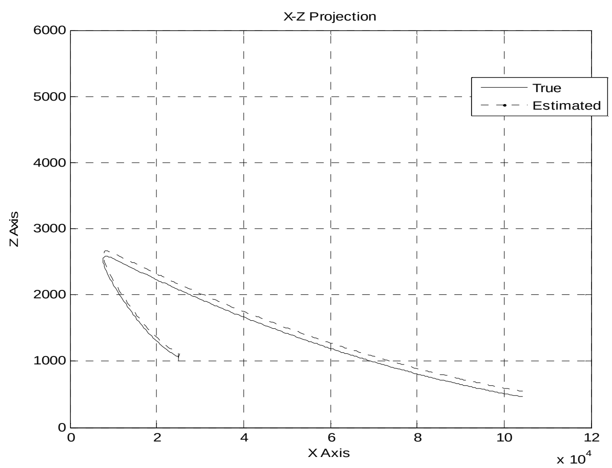

Figure9: Simulated target motion in X-Z plane projections.

Figures 7-9 are projections drawn on X-Y, Y-Z, and X-Z respectively. From these results also we can say that in all maneuvering motions filter tracking original position of the vehicle.

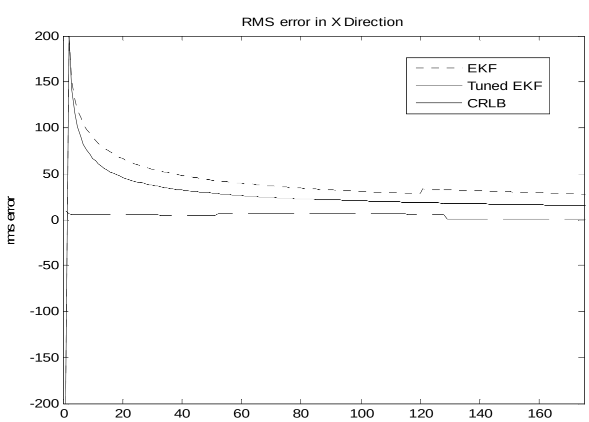

Figure 10: RMSE in X-Direction.

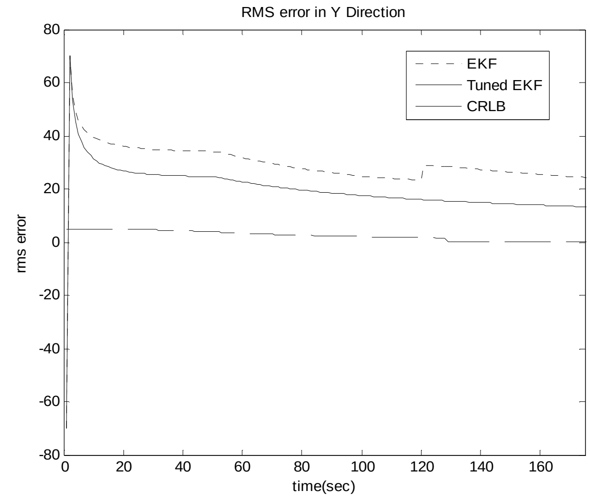

Figure 11: RMSE in Y-Direction.

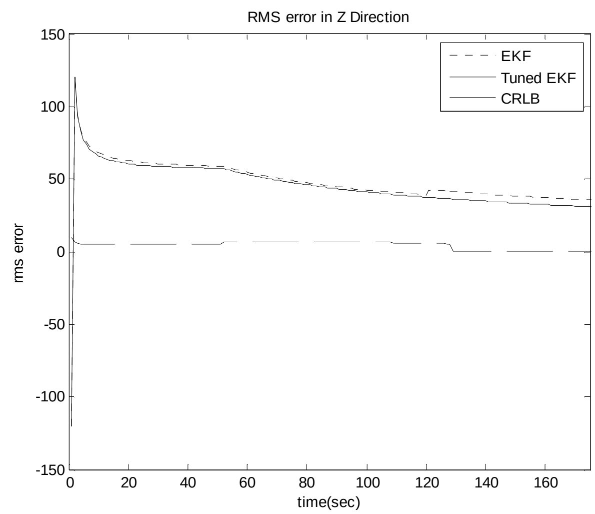

Figure 12: RMSE in Z-Direction.

When the RMS errors are compared in the 3 directions with the conventional EKF, it has observed that the PSO tuned EKF is outperforming the conventional EKF.

VI. CONCLUSION.

The work presented tuning Procedure for EKF and a comparison of two nonlinear filtering algorithms EKF and PSO Tuned EKF for maneuvering target tracking and their application to a multistatic radar system. The Cramer–Rao lower bound for the problem of maneuvering target tracking using multiple bistatic range and bistatic velocity measurements with switching dynamic models was firstly derived. The theoretical bound is conservative, being derived under the assumption that model history is known.

RMSE	Conventional EKF (meters)	Tuned EKF (meters)
RMSE in X-direction	200	150
RMSE in Y-direction	68	44
RMSE in Z-direction	110	105

Motivated by the idea of the EKF and the advantages of the new developed PSO tuned EKF, we have presented a new approach for estimating state in nonlinear system. Given its performance and implementation advantages in the example, we conclude that the new filter should be preferred over EKF and be efficient in many nonlinear filtering applications.

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