Implementation and performance evolution of Kalman Filters for Target Tracking using Bistatic Range and Range Rate Measurements

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ABSTRACT
Multisensor target tracking is finding many applications these days, due to its advantages like accurate target tracking and cheaper in cost. Range and range rate measurements from sensor often used for tracking target. In estimating target location in central station, Kalman filter and its extensions (like extended Kalman Filter) are generally preferred, because if we go to the Multilateration process we will get more error even though it may takes less time for calculation. Extended Kalman filter is of two step algorithm prediction and updation. In updating the current state, the Kalman gain or correction factor plays a vital role in convergence of the filter. Kalman gain intern depends upon the initialization of process noise and measurement noise covariance matrices which is called tuning of filter. The process which is going to be estimated is unobservable to the tracker.

Keywords: *Target tracking, Extended Kalman filter, Multilateration, Range Rate measurement, Process noise Covariance, Measurement noise co variance matrices*

1. INTRODUCTION

A target is of anything whose position is interest to us. A target tracking is a process in which we have to locate the position of the moving target from the obtained measurements from the many numbers of sensors. The goal of a tracking system is to process the measurements obtained from the target and use them to estimate, its current state, such as the position and velocity of the object. The main objective of Radar Systems is to track the target. Tracking is a fundamental necessity and widely used for both military applications and in civilian cases.

Previously the radar systems were constructed with separate transmitters and receivers to avoid the transmitter and receiver switching and to use the continuous waves this type of system is nothing but the monostatic radar system. Due to economical and operational efficiency, monostatic radar has dominated, after the invention of duplexers and pulsed transmission. In multi Static systems, there is only one transmitter and many receivers will present and number of radar receivers measure bistatic range i.e. transmitter–target–receiver distance and bistatic Doppler (bistatic range-rate divided by the wavelength at the frequency of the radar operation). The motivation for the separate trackers is to develop a multi-sensor, joint-tracking system that employs radar sensors.

There are various kinds of bistatic radars are being proposed by taking the radio-electronic background noise from radio/TV station transmitters, mobile phones, wireless PC, etc. where characteristics like target's Doppler and angle of arrival are measured [1]. The main technology of the future is to design and use of low-cost sensor networks in order to replace large aperture antennas. Various receivers can be deployed over a large area has the advantage of demanding a huge effort to neutralize the rid and each node can be easily replaced with a minimal cost [2]

The multistatic radar system, consists of single transmitter, placed in a high altitude site, at least four receivers (radar sensors) distributed in a lower altitude area and a central station processing unit. The multiple sensors, single tracking system as shown in figure1: The transmitter emits a FMCW signal which is reflected by the natural environment and the targets inside the radar surveillance area. Measurement processing generally includes a form of thresholding (measurement detection) process.

Information loss during the thresholding has to be taken care and in very low SNR scenarios, thresholding might not be used, which leads to Track before Detect algorithms with high computation cost. Detections originate not only from targets being tracked, but also from thermal noise as well as from various objects such as terrain; clouds and these unwanted measurements are usually termed clutter. Target trackers (TT) are widely used in air defence, ground target tracking, and missile defence.

Target tracking have two portions: Data association algorithm section and estimation and prediction section. Data association is the process to match a measurement to a landmark .Gating is a technique for eliminating unlikely measurement-to-track pairings and the purpose of gating is to reduce computational expense by eliminating from consideration measurements which are far from the predicted measurement location Data association algorithms deal with situations where there are measurements of uncertain origin. The signal after data association algorithms passed to filtering section in central station

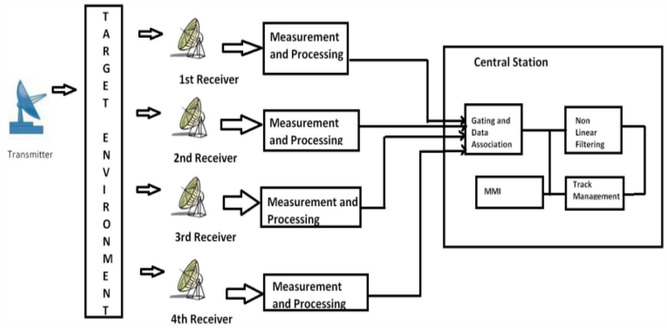


Figure1: Multiple sensor Tracking

2. PROBLEM FORMULATION

The problem is to estimate the target kinematic state (position and velocity) from noise corrupted measurements. Target tracking is basically a modeled based and they assume that the target motion and its observations can be represented by some known mathematical models accurately. The most commonly used such models are those known as state-space models, in the following form.

$$x_{k+1} = f(x_k) + w_k \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (1)$$

where x_k, is the target state, at the discrete time t_k which are indexed by k ,w_k is process noise sequences, respectively in all the three directions that is in x,y and z directions, zero mean Gaussian with covariance Q_k which is nothing but $w_k \approx N(0, Q_k)$

The measurement model for every system can be written as

$$z_k = h(x_k) + v_k \quad \ldots\ldots\ldots(2)$$

Where z_k is measurement vector, and $v_k \approx N(0, R_k)$ which is assumed as zero mean white Gaussian noise with covariance R_k is called measurement noise covariance.

The range and range rate equations which are obtained are non-linear equations and are not easy to solve directly for calculating the exact point of target in the range using the range and range rate equations and so it can be solved using the technique called as the Multilateration. The points which are obtained based on this model will give more error in the calculation process. And so the next stage is applying moving average filter to the obtained points and then going to the Multilateration process. If we apply in this way for the moving average filter as the window length is go on increasing it will take more time to calculate the exact point in the range and range rate measurements of target. Of course if we apply a filter it will give less error compared to the crude process that is Multilateration. But even in this process it is having an error like, in the error adding direction the moving average filter is not able to give the exact results and the target estimation path is totally deviating from its original path.

Then the next stage is applying the Kalman filter to the obtained measurements but in Kalman filter it is having a problem like we are applying on the non linear equations in cases with high measurement noise in bearing, the probability distributions may also be highly non-Gaussian in (x, y). So moving to the next stage that is the Extended Kalman filter in this process it will linearize the non linear equations and so the computational complexity decreases and we can get the accurate output in less time. Coming to the calculation of initial points Multilateration process is more helpful and through those initial points we can apply both the filters to the obtained measurements.

3. MATHEMATICAL MODELING

3.1 Constant velocity Model.

The target motion model is second order kinetic model i,e constant velocity model with position and velocity components in each of the three coordinates x,y and z.

$$X_k = \begin{bmatrix} x_k, & y_k, & z_k, & v_{x_k}, & v_{y_k}, & v_{z_k} \end{bmatrix}^T \ldots(3)$$

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ z_{k+1} \\ v_{x_{k+1}} \\ v_{y_{k+1}} \\ v_{z_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & T_K & 0 & 0 \\ 0 & 1 & 0 & 0 & T_K & 0 \\ 0 & 0 & 1 & 0 & 0 & T_K \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} x_k \\ y_k \\ z_k \\ v_{x_k} \\ v_{y_k} \\ v_{z_k} \end{bmatrix} + \begin{bmatrix} T_k^2/2 & 0 & 0 \\ 0 & T_k^2/2 & 0 \\ 0 & 0 & T_k^2/2 \\ T_k & 0 & 0 \\ 0 & T_k & 0 \\ 0 & 0 & T_k \end{bmatrix} \times \begin{bmatrix} w_x \\ w_y \\ w_z \end{bmatrix} \ldots(4)$$

Where T_k = sampling interval, w_x = level of covariance in X-directional noise, w_y = level of covariance in Y-directional noise, w_z = level of covariance in Z-directional noise

The variation in velocity is modeled as zero mean white noise accelerations. The process noise intensity in each coordinate is assumed to be small which accounts for air turbulence, slow turns and small linear acceleration.

The process noise covariance for this model can be given by

$$Q_k = E[w_k, w_k^T] =$$

$$\begin{bmatrix} q_x*T_k^5/20 & 0 & 0 & q_x*T_k^4/8 & 0 & 0 \\ 0 & q_y*T_k^5/20 & 0 & 0 & q_y*T_k^4/8 & 0 \\ 0 & 0 & q_z*T_k^5/20 & 0 & 0 & q_z*T_k^4/8 \\ q_x*T_k^4/8 & 0 & 0 & q_x*T_k^3/3 & 0 & 0 \\ 0 & q_y*T_k^4/8 & 0 & 0 & q_y*T_k^3/3 & 0 \\ 0 & 0 & q_z*T_k^4/8 & 0 & 0 & q_z*T_k^3/3 \end{bmatrix} (5)$$

3.2 Nearly constant velocity model

The target motion model is first order kinematics model, position and velocity in all the three direction. In this model the velocity itself is treated as an error in all the three co-ordinates x, y and z.

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ z_{k+1} \\ v_{x_{k+1}} \\ v_{y_{k+1}} \\ v_{z_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & T_K & 0 & 0 \\ 0 & 1 & 0 & 0 & T_K & 0 \\ 0 & 0 & 1 & 0 & 0 & T_K \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} x_k \\ y_k \\ z_k \\ v_{x_k} \\ v_{y_k} \\ v_{z_k} \end{bmatrix} + \begin{bmatrix} T_k & 0 & 0 \\ 0 & T_k & 0 \\ 0 & 0 & T_k \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} w_x \\ w_y \\ w_z \end{bmatrix} \quad (6)$$

The variation in velocity is modeled as zero mean white noise velocities. The process noise intensity in each coordinate is assumed to be small which accounts for air turbulence, slow turns and small linear velocity. The process noise covariance matrix for this model can be given by

$$Q_k = E[w_k, w_k^T] =$$

$$\begin{bmatrix} q_x*T_k^3/3 & 0 & 0 & q_x*T_k^2/2 & 0 & 0 \\ 0 & q_y*T_k^3/3 & 0 & 0 & q_y*T_k^2/2 & 0 \\ 0 & 0 & q_z*T_k^3/3 & 0 & 0 & q_z*T_k^2/2 \\ q_x*T_k^2/2 & 0 & 0 & q_x*T_k & 0 & 0 \\ 0 & q_y*T_k^2/2 & 0 & 0 & q_y*T_k & 0 \\ 0 & 0 & q_z*T_k^2/2 & 0 & 0 & q_z*T_k \end{bmatrix} (7)$$

3.3 Measurement Model.

As mentioned, each radar-sensor measures bi-static range and bi-static Doppler. These measurements, processed locally (at each receiver) and transformed to bi-static range and bi-static velocity (forming bi-static tracks), are sent to the central station.

$$z_k = \left[r_1 r_2 r_3 r_4 v_{r_1} v_{r_2} v_{r_3} v_{r_4} \right]^T \quad ...(8)$$

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

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

$$Z_k = h(x_k) + v_k = \begin{bmatrix} h_r(x_k) \\ h_{v_r}(x_k) \end{bmatrix} + v_k \quad ...(9)$$

where v_k is the measurement noise assumed to be zero-mean Gaussian with covariance matrix

$$R_k = diag\left\{ \sigma_{r_1}^2 \sigma_{r_2}^2 \sigma_{r_3}^2 \sigma_{r_4}^2 \sigma_{v_{r_1}}^2 \sigma_{v_{r_2}}^2 \sigma_{v_{r_3}}^2 \sigma_{v_{r_4}}^2 \right\} \quad ...(10)$$

with σ_{r_i} and $\sigma_{v_{r_i}}$ being the range and range-rate error standard deviations, respectively, that is $v_k \sim N(0,R_k)$ $(E\{w_k w_k^T\} = 0)$ and

$$h_r(x_k) = \left[h_r^1(x_k) h_r^2(x_k) h_r^3(x_k) h_r^4(x_k) \right]^T \quad ...(11)$$

$$h_{v_r}(x_k) = \left[h_{v_r}^1(x_k) h_{v_r}^2(x_k) h_{v_r}^3(x_k) h_{v_r}^4(x_k) \right]^T \quad ...(12)$$

The range of i^{th} receiver is given by

$$h_r^i(x_k) = r_i = \sqrt{x_k^2 + y_k^2 + z_k^2} + \sqrt{(x_k - x_{r_i})^2 + (y_k - y_{r_i})^2 + (z_k - z_{r_i})^2} \quad ...(13)$$

The range rate measurement can be given by

$$h_{v_r}^i(x_k) = v_{r_i} = \frac{x_k v_{x_k} + y_k v_{y_k} + z_k v_{z_k}}{\sqrt{x_k^2 + y_k^2 + z_k^2}} + \frac{(x_k - x_{r_i}) v_{x_k} + (y_k - y_{r_i}) v_{y_k} + (z_k - z_{r_i}) v_{z_k}}{\sqrt{(x_k - x_{r_i})^2 + (y_k - y_{r_i})^2 + (z_k - z_{r_i})^2}} \quad ...(14)$$

Where $(x_{r_i}, y_{r_i}, z_{r_i})$ are the Cartesian coordinates of the i^{th} receiver.

4. MULTILATERATION

In this section we consider the problem of determining the target's absolute position based on distance or range measurements from the four bistatic receivers. We will consider the dynamic case in which the target position changes over time and the detection times are partially over lapping. We can implement this concept in both the two dimension and three dimension as we are dealing with the three dimension we will directly move to the three dimension co-ordinates calculation.

If we denote the unknown location of the target as (x,y,z), and the i-th sensors location as (X_i, Y_i, Z_i) and range estimate as r_i then the following set of equations hold true assuming no range error To determine the distance from the sensor to a target

$$r_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} \quad ...(15)$$

However, all real measurements have some degree of error, so we add an error term to the range estimate to account for any errors between the actual range and the estimated range, which gives Δ_{r_i} Ignoring the error term for the moment, squaring both sides, and writing in vector notation for n independent range estimates gives

$$\begin{bmatrix} (x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2 \\ (x_2 - x)^2 + (y_2 - y)^2 + (z_2 - z)^2 \\ (x_3 - x)^2 + (y_3 - y)^2 + (z_3 - z)^2 \\ \vdots \\ (x_n - x)^2 + (y_n - y)^2 + (z_n - z)^2 \end{bmatrix} = \begin{bmatrix} r_1^2 \\ r_2^2 \\ r_3^2 \\ \vdots \\ r_n^2 \end{bmatrix} \quad ...(16)$$

Expand the elements which are present in the left side then linearize the equations by subtracting the bottom row from each of the remaining rows (which eliminates all unknown square terms), moving all remaining square terms to the right hand side and factoring the unknown variables resulting in

$$2\begin{bmatrix} (x_n - x_1) & (y_n - y_1) & (z_n - z_1) \\ (x_n - x_2) & (y_n - y_2) & (z_n - z_2) \\ \vdots & \vdots & \vdots \\ (x_n - x_{n-1}) & (y_n - y_{n-1}) & (z_n - z_{n-1}) \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} r_1^2 - r_n^2 - x_1^2 + x_n^2 - y_1^2 + y_n^2 - z_1^2 + z_n^2 \\ r_2^2 - r_n^2 - x_2^2 + x_n^2 - y_2^2 + y_n^2 - z_2^2 + z_n^2 \\ \vdots \\ r_{n-1}^2 - r_n^2 - x_{n-1}^2 + x_n^2 - y_{n-1}^2 + y_n^2 - z_{n-1}^2 + z_n^2 \end{bmatrix} \quad (17)$$

For an exactly determined solution where precisely four independent sensors report estimated ranges, we can write

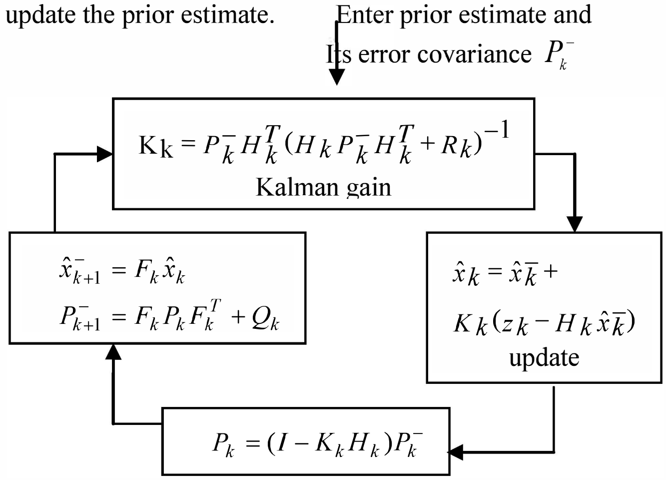
$$2\begin{bmatrix} (x_4 - x_1) & (y_4 - y_1) & (z_4 - z_1) \\ (x_4 - x_2) & (y_4 - y_2) & (z_4 - z_2) \\ (x_4 - x_3) & (y_4 - y_3) & (z_4 - z_3) \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} r_1^2 - r_4^2 - x_1^2 + x_4^2 - y_1^2 + y_4^2 - z_1^2 + z_4^2 \\ r_2^2 - r_4^2 - x_2^2 + x_4^2 - y_2^2 + y_4^2 - z_2^2 + z_4^2 \\ r_3^2 - r_4^2 - x_3^2 + x_4^2 - y_3^2 + y_4^2 - z_3^2 + z_4^2 \end{bmatrix} \quad (18)$$

which can be easily solvable as a system of three unknowns with three equations.

5. Kalman filter

Kalman proposed a recursive solution of the discrete-time linear filtering problem. Kalman Filter (KF) is a recursive, linear, optimal, real-time sequential data processing algorithm used to estimate states of a dynamic system in a noisy environment. Kalman algorithm is given below

In deriving the equations for the Kalman filter, we begin with the goal of finding an equation that computes an *a posteriori* state estimate x_k as a linear combination of an *a priori* estimate $\hat{x}_k^-$ and a weighted difference between an actual measurement z_k .From that calculate the Kalman gain and the update the prior estimate.



In this paper the prior estimate $\hat{x}_k^-$ is taken from the points obtained using the Multilateration process and the covariance Matrices are taken from the section 3.1 for constant velocity and from 3.2 for nearly constant velocity model

6.EXTENDED KALMAN FILTER

When the system has non linear equations and if non linear function f_k and h_k in (1) are sufficiently differential the variation of KF i,e Extended Kalman filter may be used. In EKF f_k and h_k are linearised about the estimated trajectory.

The recursive estimation equations for the extended Kalman filter can be written as the following five steps algorithm.

- Initialize state vector and state covariance matrix

  $\hat{x}_{k/k-1}, P_{k/k-1}$ ...(1)

- Compute Kalman gain matrix from state covariance and estimated measurement covariance

  $$K_k = P_{k|k-1}H_k^T(H_k P_{k|k-1}H_k^T + R_k)^{-1} \quad \text{... (2)}$$

- update state vector by using Kalman Gain in step 1 with Multiplying prediction error vector

  $$x_{k|k} = x_{k|k-1} + K_k(z_k - h(\hat{x}_{k|k-1})) \quad \text{... (3)}$$

  where the Kalman gain K_k is determined by

- Update error covariance

  $$P_{k|k} = (I - K_k H_k)P_{k|k-1}(I - K_k H_k)^T + K_k R_k K_k^T \text{ ...(4)}$$

- Predict new state vector and state covariance matrix:

  $$\hat{X}_{k|k-1} = f(\hat{X}_{k-1|k-1}) \quad \text{...(5)}$$

  $$P_{k|k-1} = F_{k-1}P_{k-1|k-1}F_{k-1}^T + Q_{k-1} \quad \text{...(6)}$$

F_{k-1} and H_k are the Jacobian matrices of the system equation and measurement equation.

7. Simulations and Results

Two types of motion have been simulated (NCV, CV) with maximum acceleration 10 m/s^2 (approximately 6 g, where g is the gravity acceleration assumed to be 9.81 m/s^2). Firstly, as far as multi static 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) [35000, -3500, -200 m];
(iii) [38500, 0, -500 m]
(iv) [35000, -3500, -300 m].

The radar frequency of operation was selected to beat the lower band of UHF (438MHz). The signal bandwidth was assumed to be 10 MHz. The trajectory under consideration is a target flying in the 3-D (x-y-z plane) starting with an initial position $[x_0, y_0, z_0]$ = [25000m, 4000m, -1000m] moving with constant velocity system model with an initial velocity $[v_{x0}, v_{y0}, v_{z0}]$ = [0 m/s, -83.3 m/s, 100 m/s] for 100s.

Finally, the target resumes a constant velocity motion, with the velocity it had attained. The sampling interval T_k was assumed to be 1 s which means that the number of measurements is the same as time in seconds. The data generated using the noise covariances as shown in table below in case of actual and worst cases.

	With minimum noise	With medium noise	With worst noise
W_{m/sec^2}	0.1	1	1.257

Table1: Co variances used in Data generation

Where $W_{m/sec}^2$ includes w_x,w_y and w_z as the error is equal in all directions for both the CV and NCV models.

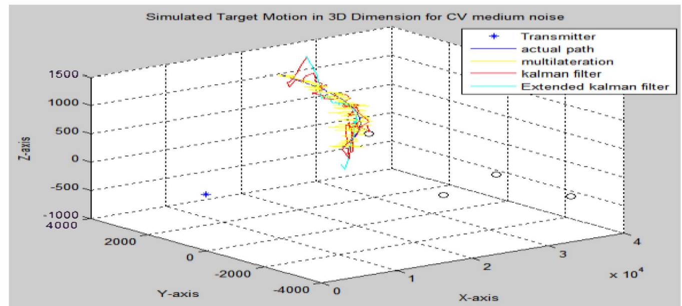


Figure 3: True and estimated trajectories in medium noise for CV

Figure 3 gives filtering results with Multilateration Kalman filter and Extended Kalman filter in medium noise for CV

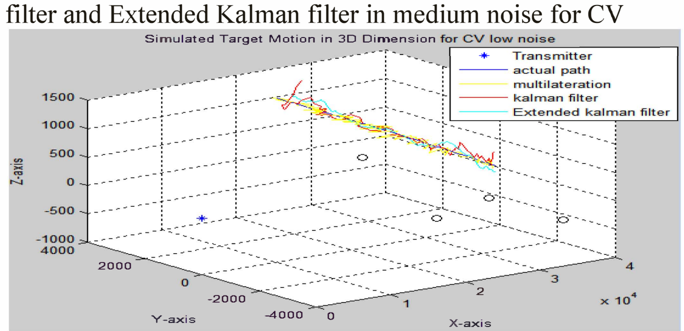


Figure 4: True and estimated trajectories in medium noise for CV

Figure 4 gives filtering results with Multilateration Kalman filter and Extended Kalman filter in low noise for CV

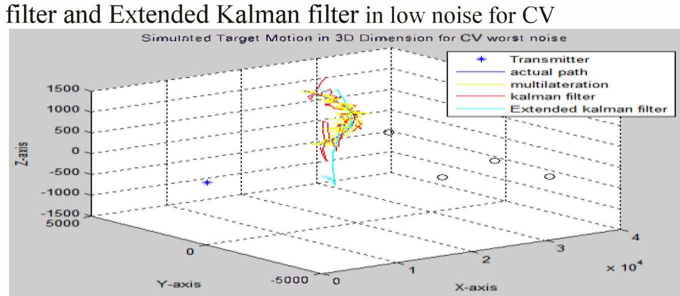


Figure 5: True and estimated trajectories in medium noise for CV

Figure 5 gives filtering results with Multilateration Kalman filter and Extended Kalman filter in worst noise for CV

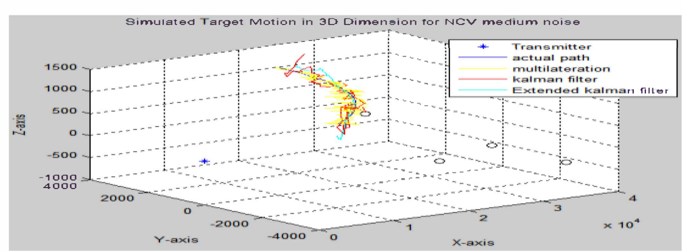


Figure 6: True and estimated trajectories in medium noise for NCV

Figure 6 gives filtering results with Multilateration Kalman filter and Extended Kalman filter in medium noise for NCV

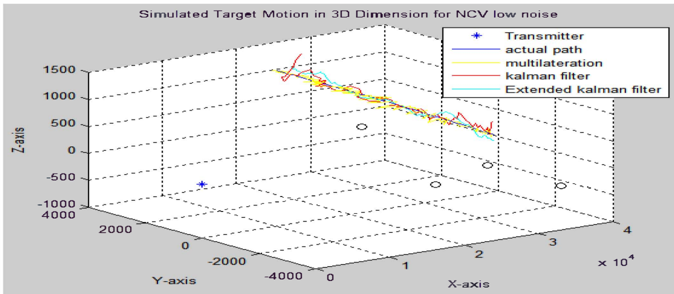


Figure 7: True and estimated trajectories in low noise for NCV

Figure 7 gives filtering results with Multilateration Kalman filter and Extended Kalman filter in low noise for NCV

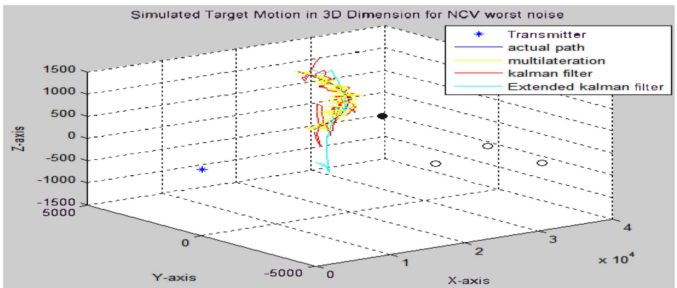


Figure 8: True and estimated trajectories in worst noise for NCV

Figure 8 gives filtering results with Multilateration Kalman filter and Extended Kalman filter in worst noise for NCV

RMSE for Trajectory (CV medium noise) in (m)	RMSE in X direction	RMSE in Y direction	RMSE in Z direction
Multilateration	814.3054	814.3054	814.3054
Kalman filter	518.9386	130.1882	120.3703
Extended Kalman filter	365.9418	97.4251	134.1129

Table 2. RMSE in X,Y and Z in three types of filtering in CV

RMSE for Trajectory (CV low noise) in (m)	RMSE in X direction	RMSE in Y direction	RMSE in Z direction
Multilateration	866.7759	866.7759	866.7759
Kalman filter	533.5174	127.6189	89.2014
Extended Kalman filter	341.4703	90.3468	70.8218

Table 3. RMSE in X,Y and Z in three types of filtering in CV

RMSE for Trajectory (CV worst noise) in (m)	RMSE in X direction	RMSE in Y direction	RMSE in Z direction
Multilateration	711.5454	711.5454	711.5454
Kalman filter	485.1850	129.7865	138.4240
Extended Kalman filter	375.4411	108.3810	292.0858

Table 4. RMSE in X,Y and Z in three types of filtering in CV

RMSE for Trajectory(NCV medium noise) in (m)	RMSE in X direction	RMSE in Y direction	RMSE in Z direction
Multilateration	808.1105	808.1105	808.1105
Kalman filter	512.1745	126.7189	122.6046
Extended Kalman filter	368.1115	93.3359	127.4227

Table 5. RMSE in X,Y and Z in three types of filtering in N CV

RMSE for Trajectory (NCV low noise) in (m)	RMSE in X direction	RMSE in Y direction	RMSE in Z direction
Multilateration	866.7759	866.7759	866.7759
Kalman filter	533.5127	127.6189	89.2014
Extended Kalman filter	341.4703	90.6956	70.8217

Table 6. RMSE in X,Y and Z in three types of filtering in N CV

RMSE for Trajectory (NCV worst noise) in (m)	RMSE in X direction	RMSE in Y direction	RMSE in Z direction
Multilateration	704.2037	704.2037	704.2037
Kalman filter	478.1970	126.4845	137.8188
Extended Kalman filter	374.1424	102.4684	255.2048

Table 7. RMSE in X,Y and Z in three types of filtering in N CV

Tables 2-7 shows the RMSE obtained for all the trajectories in all the directions that is in X, Y and Z directions for both the CV and NCV.

8. CONCLUSION

The paper presented a performance evolution of Kalman filters for target tracking using bistatic range and range rate measurements in various ways of changes occurring in noise. On comparing the results (plots and the tables) given above the extended kalman filter gives more precise values than the Kalman filter and Multilateration. When the noise is less the extended Kalman filter is giving more and more precise values in all the directions same as in the case of the medium noise. In the worst noise condition the EKF is having more error in z direction except that in remaining all conditions EKF is more suitable. Either the motion of the target is modeled using the constant velocity or nearly constant velocity the EKF is more preferable compared to the Kalman filter and Multilateration

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