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EFFECTIVE RADAR TRACKING USING ADAPTIVE KALMAN FILTER

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ABSTRACT

Radar trailing plays an important role inside the space of early warning and detection system, whose preciseness is closely connected with filtering rule. With the event of noise jam technology in sign, linear filtering becomes extra and harder to satisfy the strain of measuring device trailing, whereas nonlinear filtering can solve problems like non-Gaussian noises. There exist several nonlinear filtering algorithms at the current, and   their characteristic of linear and nonlinear data filters are totally different, we tend to discover that KF is easy to implement and has been wide used.Therefore, we'll simulate and show the performance of the Kalman data filter (KF) . One of the problems with the Kalman filter is that they will not sturdy against modeling uncertainties. The Kalman filter algorithmic rule is that the optimum filter for a system whereas not uncertainties. The performance of a Kalman filter is additionally significantly degraded if the actual system model does not match the model thereon the Kalman filter was based, thus needed a advance version of Kalman filter , This filter is thought as Adjustive/Adaptive Kalman Filter (AKF).

KEYWORDS: KF, AKF, Radar trailing, Linear Filtering, Nonlinear Filtering.

INTRODUCTION

Radar is associate instrument that radiates non corpuscular radiation among the world, that detects and locates of objects. Today, it's wide used for speed estimation, imaging, and lots of various functions. The principle of measuring instrument operates likes to undulation reflection. If any wave sound incident on the issue , it will be reflected and detected, this undulation reflective is termed echo. If sound speed is assumed, we'll estimate the gap and direction of the objects. measuring instrument systems unit of measurement composed of a transmitter that radiates attractive force waves of a particular undulation and a receiver that detects the echo came back from the target. exclusively somewhat portion of the transmitted energy is re-radiated back to the measuring instrument. These echoes will processed by the measuring instrument receiver to extract target data like (range, speed, direction, position and others

Modern measuring instrument typically processes data with digital computers. Exploitation parameter estimation techniques, we are going to estimate voluminous motion parameters just like the explicit location of the target, velocity, and acceleration basing on the measuring instrument measurements and generate a spread of knowledge relating to the target just like the expected position and also the present and also successive state of the target. the procedure is as shown in Figure one.
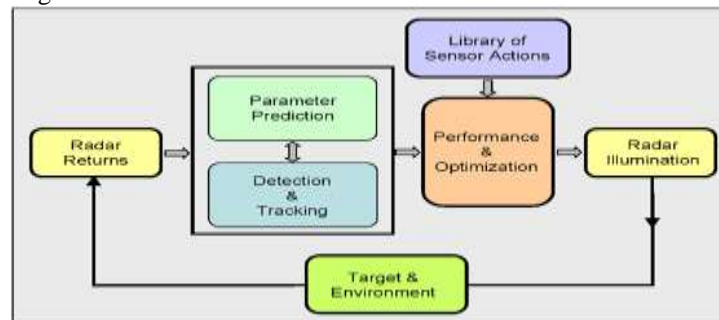

Figure. 1: Block diagram of the Radar system for target detection, tracking

KALMAN FILTER
The Kalman filter may well be a tool which will estimate the variables of an oversized vary of processes. In mathematical terms we would say that a Kalman filter estimates the states of a linear system. The Kalman filter not solely works well in observe, but it's in theory attractive as a results of it'll be shown that of all possible filters, it is the one that minimizes the variance of the estimation error. Kalman filter is associate unvarying operation that uses a collection of equations and consecutive info inputs to quickly estimate verity value ,position,velocity etc of the object being measured, once the measured values contain unexpected or random error, uncertainty or variation.

Therefore the Kalman filter consists of two steps:
1.   The prediction
2.   The correction

In the first step the state is foreseen with the dynamic model. among the second step, it's corrected with the observation model, so as that the error variance of the estimator is reduced. throughout this sense it's associate best estimator. This procedure is continual for each time step, with the step of the previous time step as initial value. that the Kalman filter is termed a recursive filter.

Three main equation or calculation that need to be done:
1)   We need to calculate the Kalman gain and these three calculation are iterative,they have to over & over again estimate and zoom in to actual estimate value. Each time calculate the Kalman gain sometimes called gain.
2)   We have to calculate current estimate, each time updates this estimate so that it is the current estimate as going to be recalculated.
3)   Finally we have to calculate error in this estimate.
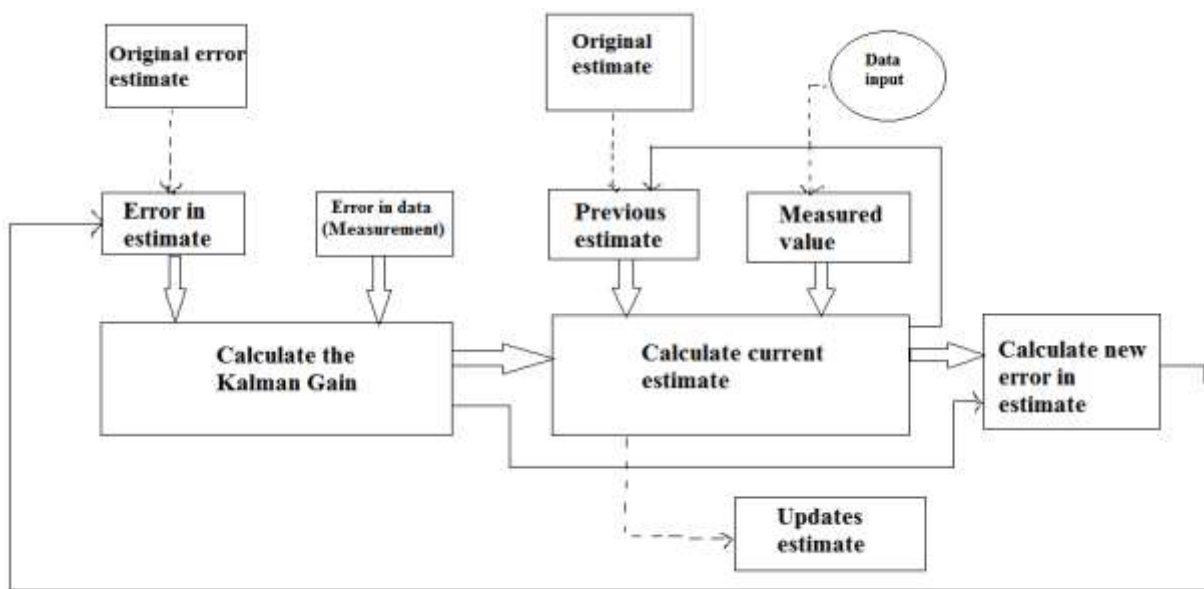

Figure 3 : Flowchart of Kalman filter

What do we need to calculate Kalman gain two things are need one we need to error in estimate this is the previous error and some cases it is the original error, we always try to consider original error estimate.each time we need to calculate error in estimate and the estimate comes back in error in estimate block and with help of this we calculate the value of Kalman gain.We also need error in data input because we going to regular data inputs here to that continue data inputs comes in.both this data inputs, error in estimate and error in data (measurement) feed in to Kalman gain. Secondary the Kalman gain feeds then in to the calculation of the current estimate . currents estimate is again depends upon the previous estimate and measured value. So the measured value previous estimate some times the original estimate and the Kalman gain decided how much weight put on the new measure value and the previous estimate. What is the error in estimate we need to current estimate and we need to know Kalman gain based upon the current estimate and again come up and new error in the estimate feed in to error in estimate again

calculate gain again current estimate and calculate new error in estimate. This process is continuously done so many times.

Step 1: Build a model
The system is described by a linear random distinction equation:

$$x_{k+1} = Ax_k + Bw_k$$
$$y_k = Cx_k + v_k$$

➢ Any x_{k+1} is a linear combination of its previous value plus a control signal w_k and a process noise.
➢ The entities A, B and C are in general matrices related to the states. In many cases, we can assume they are numeric value and constant.
➢ W_k is the process noise and v_k is the measurement noise, both are considered to be Gaussian.

Step 2: Start process:
TIME UPDATES EQUATIONS

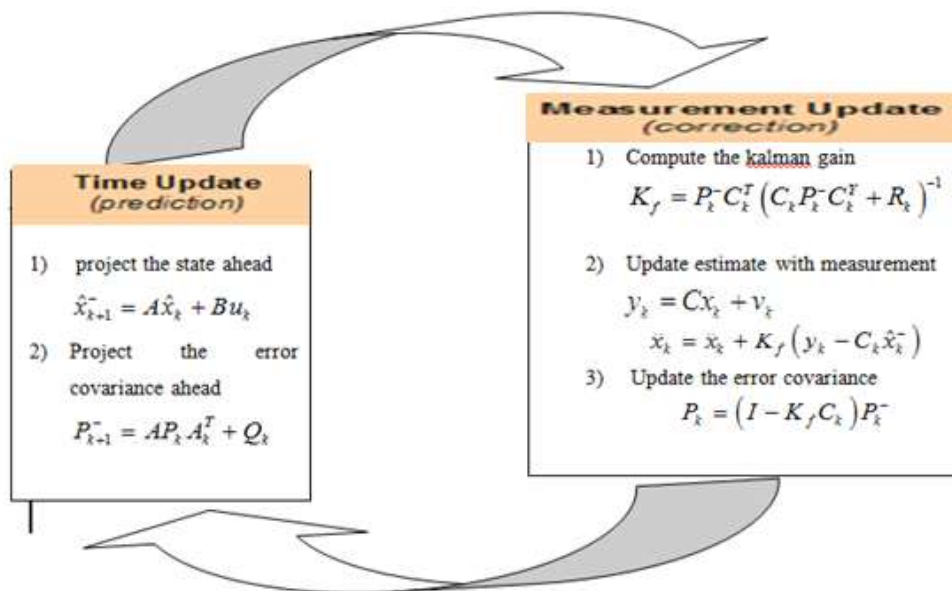$$\hat{x}_{k+1}^- = A\hat{x}_k + Bu_k$$

$$P_{k+1}^- = AP_k A_k^T + Q_k$$

MEASUREMENTS UPDATE EQUATIONS

$$K_f = P_k^- C_k^T \left(C_k P_k^- C_k^Y + R_k \right)^{-1}$$

$$\hat{x}_k = \hat{x}_k + K_f \left(y_k - C_k \hat{x}_k^- \right)$$

$$P_k = \left(I - K_f C_k \right) P_k^-$$

Step 3: Iterate:

ADAPTIVE KALMAN FILTER
Facts:

1) For any matrix X, Y with appropriate dimensions, for any positive constant μ, we have

$$X^T Y + Y^T X \le \mu X^T X + \frac{1}{\mu} Y^T Y$$

2) Let $A \in \mathfrak{R}^{n \times n}, H \in \mathfrak{R}^{n \times 1}, E \in \mathfrak{R}^{j \times n}$, and $Q = Q^T \in \mathfrak{R}^{n \times n}$, be given matrix. If there exists a scalar $\varepsilon > 0$ such that $\frac{1}{\varepsilon} - E \Sigma E^T > 0$, and

$$A \Sigma A^T + A \Sigma E^T \left(\frac{1}{\varepsilon} - E \Sigma E^T \right)^{-1} E \Sigma A^T + \frac{1}{\varepsilon} H H^T + Q = 0$$

then there exists a real matrix $\Sigma = \Sigma^T \ge 0$ such that

$$(A + H F_k E) \Sigma (A + H F_k E)^T + Q \le 0$$, for all F_k satisfying $F_k^T F_K \le I$.

We use a AKF to estimate the state $x_k \in \mathfrak{R}^n$ of a discrete time uncertain controlled system. The system is described by a linear stochastic difference equation as follows,

$$x_{k+1} = (A + \Delta A_k) x_k + (A_d + \Delta A_k^d) x_{k-d} + B w_k \qquad (0.1)$$

$$y = (C + \Delta C_k) x_k + v_k \qquad (0.2)$$

where $x_k \in \mathfrak{R}^n$ is the system state, $y_k \in \mathfrak{R}^m$ is the measured output, $w_k \in \mathfrak{R}^q$ is the process noise, $v_k \in \mathfrak{R}^p$ is the measurement noise. In the following v_k and w_k will be regarded as zero mean, uncorrelated white noise sequence with covariance R_k and Q_k.

$$v_k = N(0, R_k) \qquad (0.3)$$

$$w_k = N(0, Q_k) \qquad (0.4)$$

The matrix $A \in \mathfrak{R}^{n \times n}$ and $\Delta A_k \in \mathfrak{R}^{n \times n}$ in the difference equation (0.1) is the dynamics matrix and time-varying uncertainty which relates the sate at time step k to the sate at time step $k+1$. The matrix $B \in \mathfrak{R}^{n \times 1}$ called noise

matrix. The matrix $C \in \Re^{m \times m}$ and $\Delta C_k \in \Re^{n \times n}$ in the measurement equation (0.2) relates the state measurement y.

The matrix $A_d \in \Re^{p \times p}$ and ΔA_k^d in the difference equation (0.1) is the delayed matrix and time varying delayed matrix. In this chapter a critical issue concerns the uncertainty model with time delay used. Earlier we already discussed If the uncertain model used does not give an accurate representation of the true uncertainty in the problem but rather over bounds the true uncertainty then this will lead to an overlay conservative robust filter with a correspondingly poor performance, therefore in order to obtain good results from AKF we are assumed the uncertainty matrix in the following structure.

$$
\begin{bmatrix} \Delta A_k \\ \Delta C_k \\ \Delta A_k^d \end{bmatrix} = \begin{bmatrix} H_1 \\ H_2 \\ H_3 \end{bmatrix} F_k E. \tag{0.5}
$$

where, $F_K \in \Re^{I \times J}$ is an unknown real time varying matrix and H_1, H_2, H_3 and E are known real constant matrices of appropriate dimensions that specify how the elements of A, A_d and C are affected by uncertainty in F_k.

Our objective is to design KF in the form of an equation(0.6), and determine a gain matrix which minimize the mean square of the error e_k,

$$
\hat{x}_{k+1} = A_f \hat{x}_k + K_f \left[y_k - \left(C + \Delta C_{ek} \right) \hat{x}_k \right] \tag{0.6}
$$

$$
\Delta A_{ek} = \varepsilon_k A S_k E^T \left(I - \varepsilon E S_k E^T \right) E \tag{0.7}
$$

$$
\Delta C_{ek} = \varepsilon_k C S_k E^T \left(I - \varepsilon E S_k E^T \right) E \tag{0.8}
$$

$$
K_f = \left(A Q_k C^T + \varepsilon_k H_1 H_2^T \right) \left(C Q_k C^T + R_{\varepsilon k} \right)^{-1} \tag{3.9}
$$

$$
A_f = \left[A + \varepsilon_k A \Sigma_{11,k} E^T \left(I - \varepsilon_k E \Sigma_{11,k} E^T \right)^{-1} E \right] \\
- K_f \left[C + \varepsilon_k C \Sigma_{11,k} E^T \left(I - \varepsilon_k E \Sigma_{11,k} E^T \right)^{-1} E \right] \tag{3.10}
$$

The matrix $A_f \in \Re^{j \times j}$ in the KF equation(0.6), the matrix $K_f \in \Re^{P \times 1}$ in the KF equation (0.6) is the KG matrix which relates the estimated state $\hat{x}_k$. Note that the matrix $A_f \ \& \ K_f$ both are time varying matrices to be determined in order that the estimation error $e_k = x_k - \hat{x}_k$ is guaranteed to be smaller than a certain bound for all

uncertainty   matrices,   i.e.,   the   estimation   error   dynamics   satisfies   equation
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$$\mathrm{E}\left(\left(x_k - \hat{x}_k\right)\left(x_k - \hat{x}_k\right)^T\right) \le S_k$$
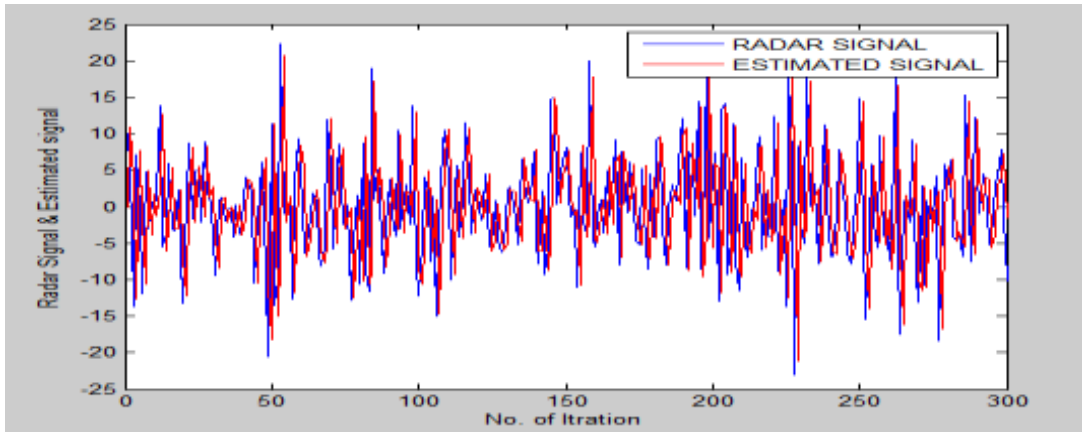
(3.11)

RESULTS AND DISCUSSION

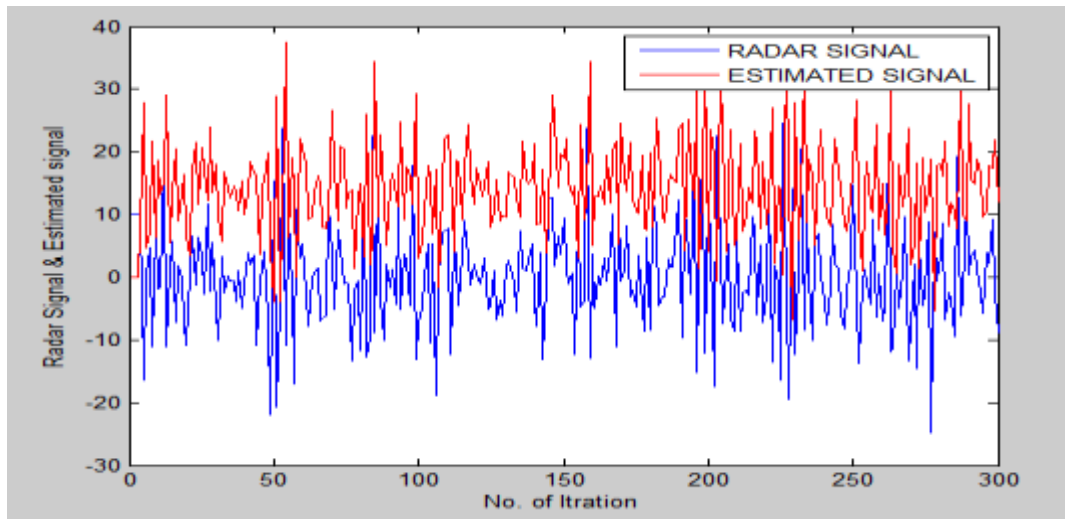*Figure 5 : Radar signal & estimated signal if delay & uncertainty are not present*

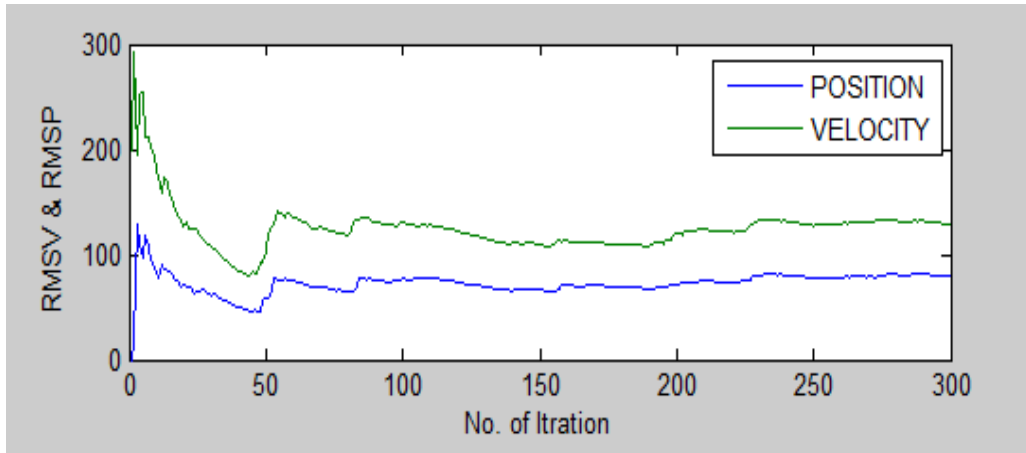*Figure 6: Radar signal & estimated signal if delay & uncertainty are present*

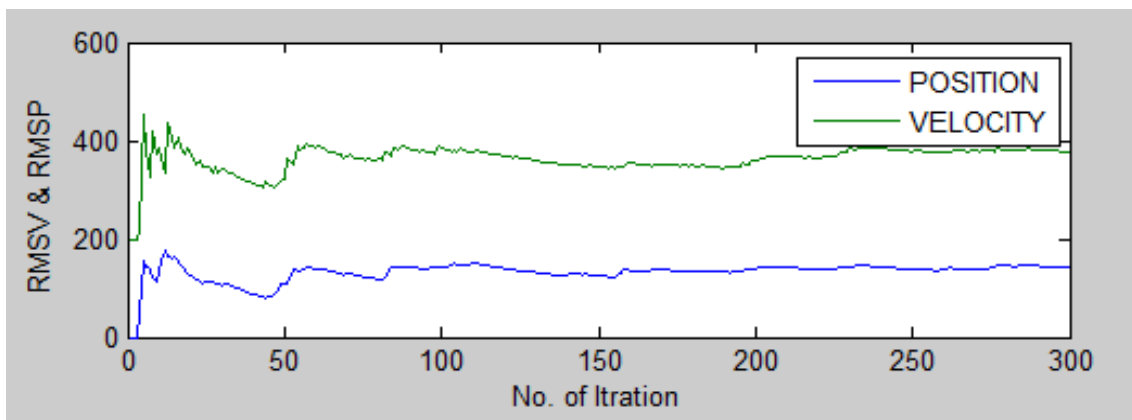*Figure 7: Plot between RMSV & RMSP if Delay & uncertainty is not present*

Figure 8: Plot between RMSV & RMSP if Delay & uncertainty are present
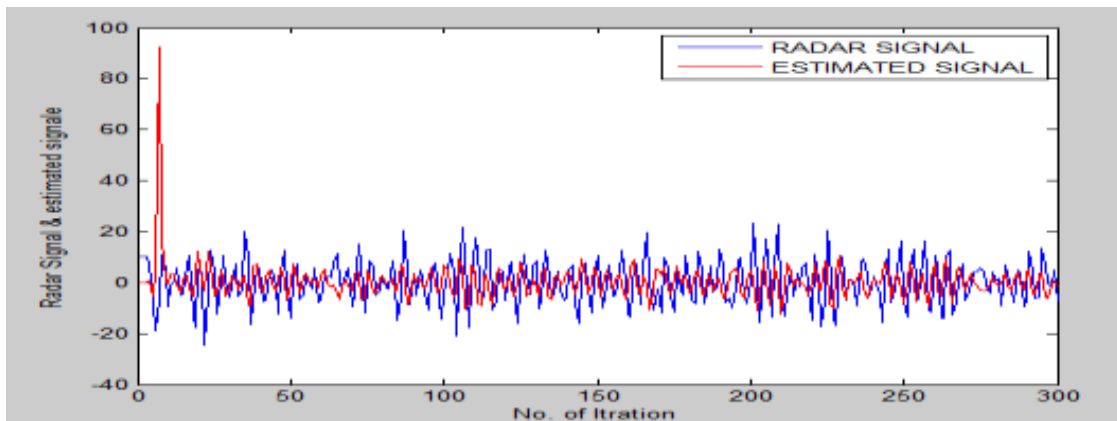
ADAPTIVE KALMAN FILTER RESULT

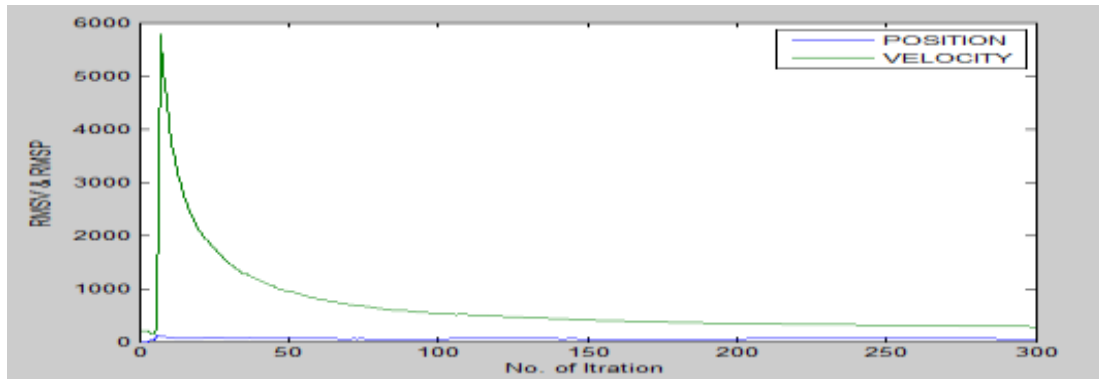*Figure 9: Plot Between Radar signal & estimated signal*

Figure 10 : Plot between RMSV & RMSP

CONCLUSION

From the simulation results it may be concluded that In kalman filter, we plot the output in form of Radar signal and estimated signal here we calculate the estimated value on the basis of actual position and measurement value. So it is clear that the estimated value is not near to actual value under noisy condition because kalman filter is more perfect in linear system where position of object not changes frequently but Radar system in non linear therefore we can say that Kalman filter is not efficient in radar tracking.So we are using Adaptive kalman filter for tracking purpose.

In Kalman Filter Result the first result shows Resultant Radar signal & estimated signal if delay & uncertainty is not present in that condition Kalman filter track Radar target very efficiently and estimated signal overlap the Resultant Radar signal. In second result , Resultant Radar signal & estimated signal if delay & uncertainty are present so in that condition Radar signal & estimated signal are not overlap so we can say that Kalman filter not efficiently track when delay & uncertainty are present. In third result Plot between RMSV & RMSP i) Delay & uncertainty is not present   ii) Delay & uncertainty is present.

Second part of the result using Adaptive Kalman filter for radar tracking first we Plot a graph between Radar signal & estimated signal using AKF here Radar signal & estimated signal are exactly overlap .The number of iterations are increase the resultant output is very close to the true value of the Radar signal and second part we Plot between RMSV & RMSP using AKF, here it is clear that at starting point estimated velocity of the object is not linear but as we increase the number of iteration the resultant RMSV & RMSP are linear. So we conclude that Kalman filter is efficient where delay & uncertainty is not present in the system but some system where delay & uncertainty are present like Radar tracking AKF is very useful.

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