Efficient RADAR tracking using Adaptive Kalman Filter

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Abstract— Radar tracking plays a crucial role within the space of early warning and detection system, whose preciseness is closely connected with filtering rule. There are various nonlinear filtering algorithms at the present, owning their explicit characteristics. Through the analyses of linear and nonlinear information filters, we discover that KF is simple to implement and has been wide used. Therefore, we'll simulate and show the performance of the Kalman information filter (KF). One of the issues with the Kalman filter is that they'll not strong against modeling uncertainties. The Kalman filter algorithm is that the optimum filter for a system while not uncertainties. The performance of a Kalman filter is also considerably degraded if the particular system model doesn't match the model on that the Kalman filter was primarily based, therefore required an advance version of Kalman filter , This filter is known as Adaptive Kalman Filter (AKF). Kalman filter (KF) is mostly applicable for linear system i.e. where speed are linear but Radar movements are nonlinear and they cannot easily track with linear system and estimation in Radar system is also not easy, so we can say that Kalman filter is not efficient where delay or uncertainties are present ,So we required a new filter they work efficiently in those condition , we use Adaptive Kalman filter (AKF).

Key words: Kalman filter, Adaptive Kalman filter, linear filter, nonlinear filter

I. INTRODUCTION

Radar is an instrument that radiates non particulate radiation within the area that detects and locates of objects. Today, it's wide used for speed estimation, imaging, and plenty of different functions. The principle of measuring device operates likes to undulation reflection. If any wave sound incident on the thing, it'll be mirrored and detected, this undulation reflective is termed echo. If sound speed is thought, we will estimate the gap and direction of the objects. Measuring device systems area unit composed of a transmitter that radiates magnetic attraction waves of a selected wave shape and a receiver that detects the echo came back from the target. Solely a little portion of the transmitted energy is re-radiated back to the measuring device. These echoes can process by the measuring device receiver to extract target info like (range, speed, direction, position and others). The vary to the target is evaluated from the traveling time of the wave. The direction of the target is set by the arrival angle of the echoed wave.

A. Radar Tracking and System Model:

Modern measuring device typically processes information with digital computers. Exploitation parameter estimation techniques, we'll estimate a lot of motion parameters just like the specific location of the target, velocity, and acceleration basing on the radar measurements and generate a variety of information relating to the target like the expected position and additionally this and additionally consecutive state of the target. the procedure is as shown in Figure one.

Radar target tracking algorithm relies on the premise of target motion model, it's necessary to make sure the objectives of non-stop smooth track, however also got to reach quick tracking of maneuvering turn. But in the actual engineering, theoretical model and also the actual movement typically includes a huge distinction, meanwhile, there are some radar measure error data. Therefore, a way to estimate the unknown parameters from observed data, to correct filter gain, to achieve the aim of quick and correct maneuvering target tracking by adaptive Kalman filter, is incredibly necessary

The role of the Adaptive Kalman Filter (AKF) is to require this familiar state (i.e. position, heading, speed and presumably acceleration) of the target and predict the new state of the target at the time of the foremost recent radiolocation measure.

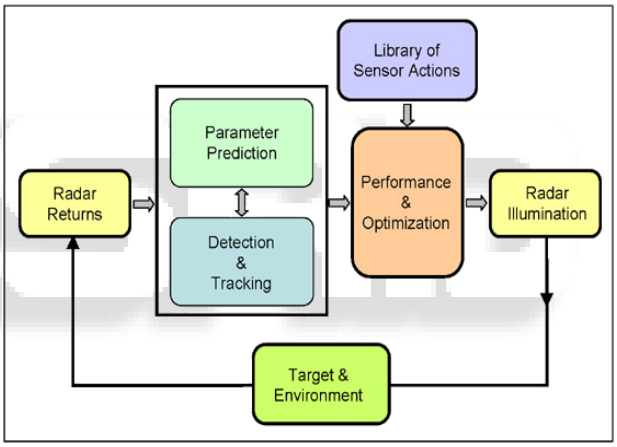

Fig. 1: Block diagram of the Radar system for target detection, tracking, classification

In creating this prediction, it additionally updates its estimate of its own uncertainty (i.e. errors) during this prediction. It then forms a weighted average of this prediction of state and also the latest measure of state, taking account of the familiar measure errors of the radiolocation and its own uncertainty within the target motion models. Finally, it updates its estimate of its uncertainty of the state estimate. A key assumption within the arithmetic of the Kalman filter is that measure equations (i.e. the connection between the radio location measurements and also the target state) and also the state equations (i.e. the equations for predicting a future state supported this state) area unit linear.

II. KALMAN FILTER

The Kalman filter could be a tool that may estimate the variables of a large vary of processes. In mathematical terms we might say that a Kalman filter estimates the states of a linear system. The Kalman filter not only works well in observe, however it's theoretically attractive as a result of it will be shown that of all possible filters, it's the one that minimizes the variance of the estimation error. Kalman filter

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is an iterative operation that uses a set of equations and consecutive information inputs to quickly estimate verity value, position, velocity etc. of the object being measured, once the measured values contain unpredicted or random error, uncertainty or variation.

Therefore the Kalman filter consists of 2 steps:

1) The prediction
2) The correction

In the opening move the state is predicted with the dynamic model. Within the second step, it's corrected with the observation model, in order that the error covariance of the estimator is reduced. During this sense it's a best estimator. This procedure is continual for every time step, with the step of the previous time step as initial value. So the Kalman filter is termed a recursive filter.

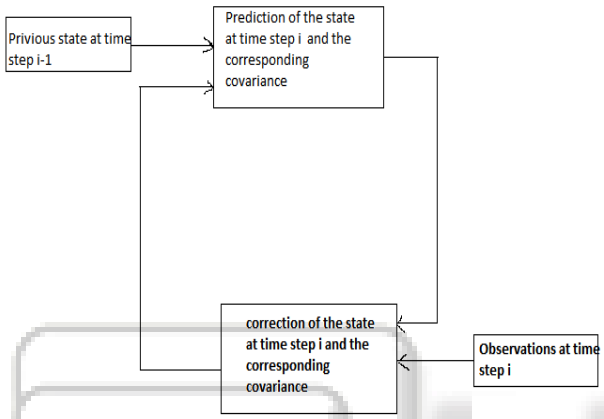


Fig. 2: Circuit of the Kalman filter

A. *Dynamic and Observation Model*

The dynamic model describes the modification of the state vector over time. Linear dynamics model describes relation between the state and the next state, and the observation

$$\begin{aligned}\mathbf{x}_{t+1} &= A\mathbf{x}_t + \mathbf{w}_t, \quad \mathbf{w}_t \sim W_t = N(\mathbf{0}, Q)\\ \mathbf{y}_t &= C\mathbf{x}_t + \mathbf{v}_t, \quad \mathbf{v}_t \sim V_t = N(\mathbf{0}, R)\end{aligned}$$

1) Example (If Process Has Time- Step δ):

$$A = \begin{pmatrix} 1 & \delta & \frac{1}{2}\delta^2 \\ 0 & 1 & \delta \\ 0 & 0 & 1 \end{pmatrix}, \quad C = \begin{pmatrix} 1 & 0 & 0 \end{pmatrix}$$

2) Normal Distributions:

- Let X0 be a normal distribution of the initial state X0.
- Then, every Xt is a normal distribution of hidden state xt. Recursive definition:

$$X_{t+1} = AX_t + W_t$$

And every Yt is a normal distribution of observation yt. Definition:

$$Y_t = CX_t + V_t$$

Goal of filtering: compute conditional distribution

$$(X_t \mid Y_0 = \mathbf{y}_0, \ldots, Y_t = \mathbf{y}_t)$$

Because Xt's and Yt's are normal distributions:
is also a normal distribution.

Normal distribution is fully specified by mean and covariance

We denote:

$$\begin{aligned}X_{t|s} &= (X_t \mid Y_0 = \mathbf{y}_0, \ldots, Y_s = \mathbf{y}_s)\\ &= N(\mathrm{E}(X_t \mid Y_0 = \mathbf{y}_0, \ldots, Y_s = \mathbf{y}_s), \mathrm{Var}(X_t \mid Y_0 = \mathbf{y}_0, \ldots, Y_s = \mathbf{y}_s))\\ &= N(\hat{\mathbf{x}}_{t|s}, P_{t|s})\end{aligned}$$

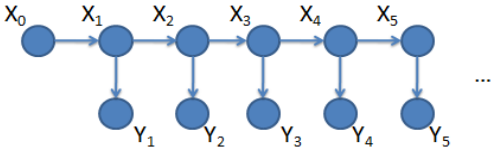
Problem reduces to computing xt|t and Pt|t

B. *Recursive Update of State*

Kalman filtering algorithm:

Time update: from Xt|t, compute a priori distrubution Xt+1|t

Measurement update: from Xt+1|t (and given yt+1), compute a posteriori distribution Xt+1|t+1



C. *Time Update*

From $X_{t|t}$, compute a priori distribution $X_{t+1|t}$:

$$\begin{aligned}X_{t+1|t} &= AX_{t|t} + W_t\\ &= N(\mathrm{E}(AX_{t|t} + W_t), \mathrm{Var}(AX_{t|t} + W_t))\\ &= N(A\,\mathrm{E}(X_{t|t}) + \mathrm{E}(W_t), A\,\mathrm{Var}(X_{t|t})A^T + \mathrm{Var}(W_t))\\ &= N(A\hat{\mathbf{x}}_{t|t}, AP_{t|t}A^T + Q)\end{aligned}$$

So,

$$\begin{aligned}\hat{\mathbf{x}}_{t+1|t} &= A\,\hat{\mathbf{x}}_{t|t}\\ P_{t+1|t} &= AP_{t|t}A^T + Q\end{aligned}$$

1) Measurement Update

- From $X_{t+1|t}$ (and given y_{t+1}), compute $X_{t+1|t+1}$.

2) Compute a priori distribution of the observation $Y_{t+1|t}$ from $X_{t+1|t}$:

$$\begin{aligned}Y_{t+1|t} &= CX_{t+1|t} + V_{t+1}\\ &= N(\mathrm{E}(CX_{t+1|t} + V_{t+1}), \mathrm{Var}(CX_{t+1|t} + V_{t+1}))\\ &= N(C\,\mathrm{E}(X_{t+1|t}) + \mathrm{E}(V_{t+1}), C\,\mathrm{Var}(X_{t+1|t})C^T + \mathrm{Var}(V_{t+1}))\\ &= N(C\hat{\mathbf{x}}_{t+1|t}, CP_{t+1|t}C^T + R)\end{aligned}$$

$$(X_t \mid Y_0 = \mathbf{y}_0, \ldots, Y_t = \mathbf{y}_t)$$

3) Look at joint distribution of $X_{t+1|t}$ and $Y_{t+1|t}$:

Where,

$$\begin{aligned}\mathrm{Cov}(Y_{t+1}, X_{t+1|t}) &= \mathrm{Cov}(CX_{t+1|t} + V_{t+1}, X_{t+1|t})\\ &= C\,\mathrm{Cov}(X_{t+1|t}, X_{t+1|t}) + \mathrm{Cov}(V_{t+1}, X_{t+1|t})\\ &= C\,\mathrm{Var}(X_{t+1|t})\\ &= CP_{t+1|t}\end{aligned}$$

- Recall from undergrad that if

$$(Z_1, Z_2) = N\left(\begin{pmatrix}\mu_1\\ \mu_2\end{pmatrix}, \begin{pmatrix}\Sigma_{11} & \Sigma_{12}\\ \Sigma_{21} & \Sigma_{22}\end{pmatrix}\right)$$

Then

$$(Z_1 \mid Z_2 = \mathbf{z}_2) = N(\mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(\mathbf{z}_2 - \mu_2), \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})$$

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4) Compute $X_{t+1|t+1} = (X_{t+1|t}|Y_{t+1|t} = y_{t+1})$:

$$X_{t+1|t+1} = \left(X_{t+1|t} \mid Y_{t+1|t} = \mathbf{y}_{t+1}\right)$$
$$= N\left(\hat{\mathbf{x}}_{t+1|t} + P_{t+1|t}C^T\left(CP_{t+1|t}C^T + R\right)^{-1}\left(\mathbf{y}_{t+1} - C\hat{\mathbf{x}}_{t+1|t}\right),\right.$$
$$\left. P_{t+1|t} - P_{t+1|t}C^T\left(CP_{t+1|t}C^T + R\right)^{-1}CP_{t+1|t}\right)$$

– Often written in terms of Kalman gain matrix:

$$K_{t+1} = P_{t+1|t}C^T\left(CP_{t+1|t}C^T + R\right)^{-1}$$
$$\hat{\mathbf{x}}_{t+1|t+1} = \hat{\mathbf{x}}_{t+1|t} + K_{t+1}\left(\mathbf{y}_{t+1} - C\hat{\mathbf{x}}_{t+1|t}\right)$$
$$P_{t+1|t+1} = P_{t+1|t} - K_{t+1}CP_{t+1|t}$$

Model

$$\mathbf{x}_{t+1} = A\mathbf{x}_t + \mathbf{w}_t, \quad \mathbf{w}_t \sim W_t = N(\mathbf{0}, Q)$$
$$\mathbf{y}_t = C\mathbf{x}_t + \mathbf{v}_t, \quad \mathbf{v}_t \sim V_t = N(\mathbf{0}, R)$$

Algorithm

– **Time update:**

$$\hat{\mathbf{x}}_{t+1|t} = A\hat{\mathbf{x}}_{t|t}$$
$$P_{t+1|t} = AP_{t|t}A^T + Q$$

– **Measurement update:**

$$K_{t+1} = P_{t+1|t}C^T\left(CP_{t+1|t}C^T + R\right)^{-1}$$
$$\hat{\mathbf{x}}_{t+1|t+1} = \hat{\mathbf{x}}_{t+1|t} + K_{t+1}\left(\mathbf{y}_{t+1} - C\hat{\mathbf{x}}_{t+1|t}\right)$$
$$P_{t+1|t+1} = P_{t+1|t} - K_{t+1}CP_{t+1|t}$$

III. ADAPTIVE TRACKING STRATEGY

The initial value of P isn't necessary, are converged in Iteration. In real-time radar echo following, the difficulty of using Kalman filter lies in:

1) the estimation of target status. sometimes measuring instrument can't offer rate data, the speed / acceleration data of target should be calculated by position data, random measuring errors can cause massive fluctuations within the position data, that seriously affect the velocity/ acceleration estimation.
2) confirm the magnitude of noise. Observation noise v isn't only regarding the preciseness of radar detection, however also relevant with the distance from the radar station. Input uncertainty w reflects the accuracy of input u , it's an excellent relationship with target status. once target is Maneuvering to show, there's clearly lagging of input estimation, at an equivalent time, the uncertainty can greatly increase. during this paper, adaptive Kalman filter is proposed. Target status is estimated exploitation the dynamic limited memory prediction of measuring points Observation noise R is corrected in keeping with the newest measured data and radar performance parameters.

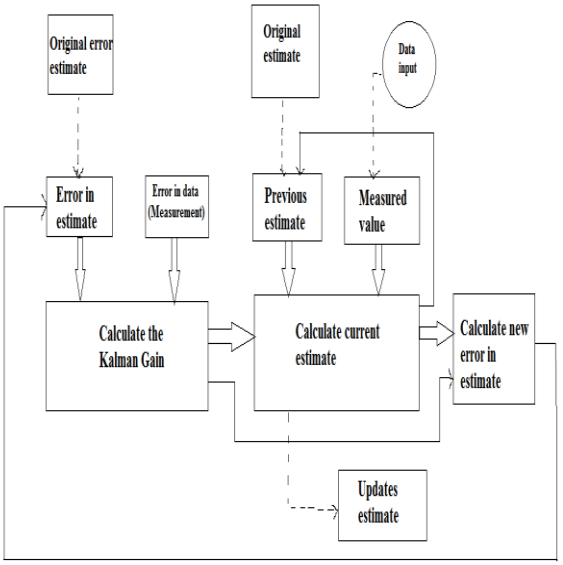

Fig. 3: Flowchart of Kalman filter

IV. THE SIMULATION RESULT

A. Kalman Filter Result

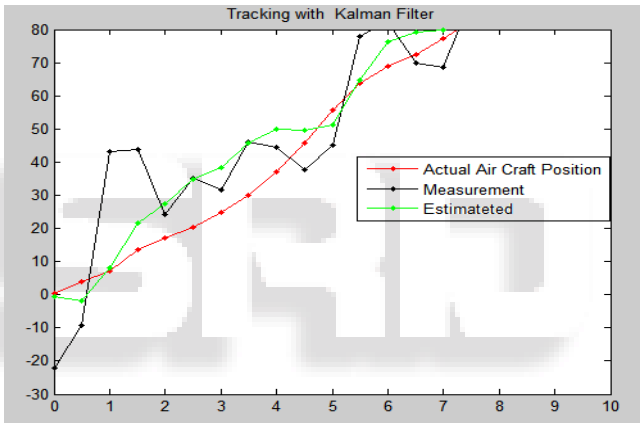

Fig. 4: Tracking with Kalmn filter

B. Adaptive Kalman Filter Result

1) If Radar Signal Noise = 0.1

RADAR Signal Model: Model 1

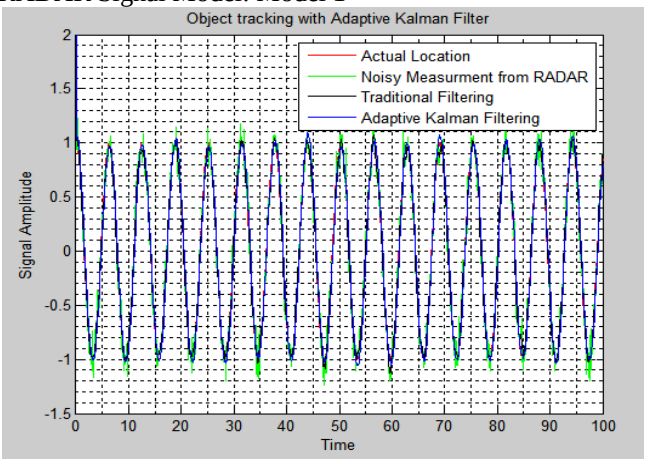

Fig. 5: Signal amplitude Vs time for Radar signal noise=0.1

There are following result obtainded:

RADAR Signal Noise is : 1.000000e-001

RMSE between Actual and Estimated Location: 0.007374

RMSE between Actual and Estimated Velocity: 0.010147

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RMSE between Actual and Estimated Acceleration: 0.018015

2) If Radar signal noise = 0.5

RADAR Signal Model: Model 1

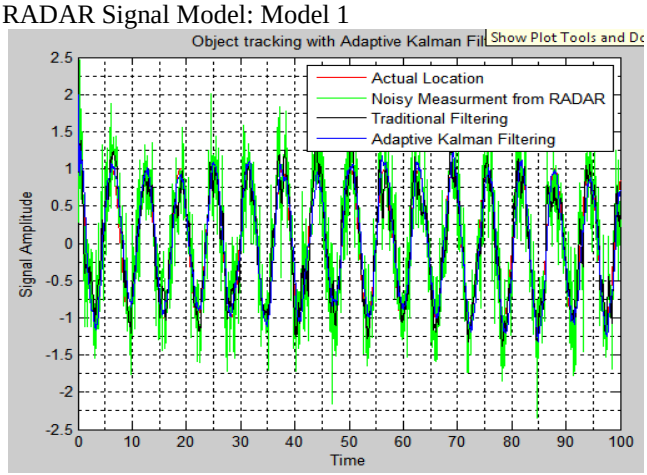

Fig. 6: Signal amplitude Vs time for Radar signal noise=0.5

There are following result obtained:

RADAR Signal Noise is: 5.000000e-001

RMSE between Actual and Estimated Location: 0.033228

RMSE between Actual and Estimated Velocity: 0.032677

RMSE between Actual and Estimated Acceleration: 0.245778

3) If Radar Signal Noise = 1

RADAR Signal Model: Model 1

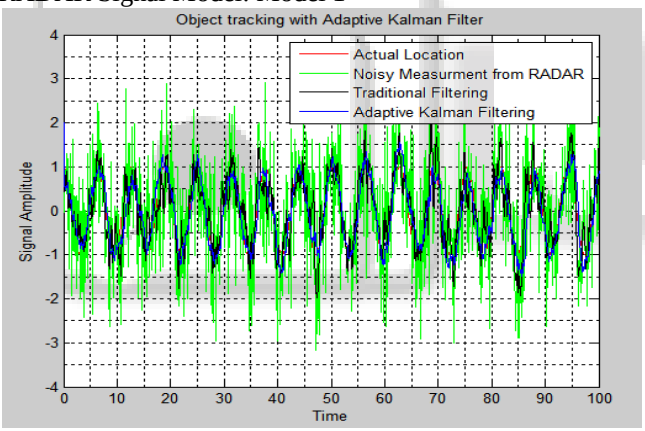

Fig. 7: Signal amplitude Vs time for Radar signal noise= 1.0

There are following result obtainded:

RADAR Signal Noise is: 5.000000e-001

RMSE between Actual and Estimated Location: 0.033228

RMSE between Actual and Estimated Velocity: 0.032677

RMSE between Actual and Estimated Acceleration: 0.245778

S.no.	Radar signal noise	RMSE between actual & estimated location	RMSE between actual & estimated Velocity	RMSE between actual & estimated Acceleration
1	0.1	0.00735952	0.0098336	0.0190978
2	0.2	0.00846708	0.0125987	0.0476574
3	0.3	0.015444	0.0152757	0.087348
4	0.4	0.0160283	0.0220997	0.165149
5	0.5	0.0278602	0.031841	0.25944
6	0.6	0.0336339	0.0418628	0.369704
7	0.7	0.0378387	0.0441383	0.441525
8	0.8	0.0547948	0.0498114	0.661682
9	0.9	0.0683993	0.0679987	0.83032
10	1	0.109895	0.0927538	0.950828

Table 1: RMSE between Actual & Estimated Location, Velocity & Acceleration in Various Radar Signal Noise Value

V. CONCLUSION

From the simulation results it may be concluded that In kalman filter, we plot the output in form of actual position, measurement and estimated value 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 nonlinear therefore we can say that Kalman filter is not efficient in radar tracking. So we are using Adaptive kalman filter for tracking purpose.

Adaptive Kalman filter is developed to track object location using radar signals. there are two non-linear radar signal models are developed to simulate non-linear behavior of radar.the Adaptive kalman filter is developed to find the object location from the noisy measurement of radar signal.

Two Radar noise models are developed, where we can change noise level in radar signal and contest the robustness of Adaptive kalman filter to noise. The noise can be changed by changing sigma. The RMSE measures the difference between the actual location and estimated location of object using Adaptive kalman filter. The traditional filtering is averaging filter used to reduce noise effect in measurement, and also maintain signal mean same as previous. The graphs show that the Adaptive kalman filter is able to estimate the location of object more efficiently than the traditional filtering methods.

VI. FUTURE SCOPE

- Dynamic method with proverbial management input
- Non-linear dynamic method with multiple delay
- Kalman smoothing: compute optimum estimate of state XT given all knowledge y1, …, yT, with T > t (not real-time).

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