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Tracking Of Maneuvering Target Using Kalman Based Estimators

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Abstract: Kalman filter is often used tool for stochastic state estimation of a noisy system that is described by linear system and linear measurement model. It uses all it gets to make an overall best estimate of a state, i.e., the values of the variables of interest. It does not matter how accurate or precise the information is. It does this by incorporating knowledge about the system dynamics, statistical descriptions about the system dynamics, statistical descriptions of the system noise, measurement noise, uncertainty in the dynamics model and any available information about the initial conditions of the variables of the interest. We discuss the estimation of maneuvering aircraft state vector (i.e., position, velocity, acceleration) using Kalman filter (KF) and its variants like Extended Kalman filter (EKF) and Unscented Kalman filter (UKF).The tracking of an aircraft is challenging and highly complex in non-linear filtering. The major challenge lies in keeping track of the aircraft, whose dynamics deviate due to its evasive maneuvering capability. The Kalman-based estimator is the best linear minimum mean squared error (MMSE) available today under Gaussian assumptions. But, for tracking a non-linear system, such as aircraft tracking, the EKF is used because of nonlinear nature in motion.
Keywords: Stochastic, system dynamics, system noise, measurement noise, maneuvering

I. INTRODUCTION

Radar receivers are usually, but not always, in the same location as the transmitter. Although the reflected radar signals captured by the receiving antenna are usually very weak, they can be strengthened by electronic amplifiers. More sophisticated methods of signal processing are also used in order to recover useful radar signals.

The weak absorption of radio waves by the medium through which it passes is what enables radar sets to detect objects at relatively long ranges—ranges at which other electromagnetic wavelengths, such as visible light, infrared light, and ultraviolet light, are too strongly attenuated. Such weather phenomena as fog, clouds, rain, falling snow, and sleet that block visible light are usually transparent to radio waves. Certain radio frequencies that are absorbed or scattered by water vapour, raindrops, or atmospheric gases (especially oxygen) are avoided in designing radars, except when their detection is intended.

However, the radio signals received by the receiver suffer from different types of noise. Clutter, which refers to radio frequency (RF) echoes returned from targets which are uninteresting to the radar operators. Shot noise is produced by electrons in transit across a discontinuity, which occurs in all detectors.

In order to design an optimal estimator, the major idea lies in minimizing the error in the estimate. The minimization of the mean squared error is obtained using the Least Squares Filtering as well as Recursive Least Squares Filtering, without considering the state dynamics are designed and then the performance is estimated using the error in the estimate. The Kalman based estimators, Kalman Filter, Extended Kalman Filter and the Unscented Kalman Filter are designed to have an optimal estimation. The necessities of adopting a new filter are discussed.

II. EXISTING SYSTEM

A. Adaptive Filtering

Adaptive systems are devices that adjust themselves to an ever-changing environment; the structure of an adaptive system changes in such a way that its performance improves through a continuing interaction with its surroundings. Its superior performance in non-stationary environments results from its ability to track slow variations in the statistics of the signals and to continually seek optimal designs.

The closed loop adaptive process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify filter transfer function to minimize the cost on the next iteration. The most common cost function is the mean square of the error signal.

B. Least Squares Filtering

If the observations consists of linear combinations of the parameters of interest, in the presence of additive errors (noise), then minimization of the sum of squares of the residuals in fitting the data namely, the least squares of the difference between the model and the observations which is also equivalent to maximization of the likelihood function of the parameters.

$$R = \sum_{k=1}^{n} (\hat{x}_k - z_k)^2$$

$$\hat{x}_k = a_0 + a_1(k-1)T_s + a_2((k-1) * T_s)^2 + \cdots$$

where

1) R is the square of the summation of all the residuals.
2) $\hat{x}_k$ is the best estimate polynomial of the filter
3) We sample n measurements of z_k.
4) $a_0, a_1, \dots, a_n$ are the coefficients of estimated polynomial.
5) T_s, is the sampling time interval.

The values of coefficients are calculated using the matrix multiplications. The coefficients for first order least squares filter can be obtained using the below equations

$$\begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} n & \sum_{k=1}^{n} (k-1)T_s \\ \sum_{k=1}^{n} (k-1)T_s & \sum_{k=1}^{n} ((k-1)T_s)^2 \end{bmatrix}^{-1} \times \begin{bmatrix} \sum_{k=1}^{n} x_k{}^* \\ \sum_{k=1}^{n} (k-1)T_s x_k{}^* \end{bmatrix}$$

C. Recursive Least Squares Filtering

Recursive least squares filtering also called as wiener filtering does not involve calculation of matrix inverses, further reducing the complexity. The simple nature of the calculations involved makes recursive least-squares filtering ideal for digital computer implementation.

The batch Least Squares (LS) estimate solution can be rewritten as

$$(estimate)_{k+1} = (estimate)_k + (weighting)_{k+1} * (residual)_{k+1}$$

where k is the time index, $(.)_k$ indicates the value at time k,

$$(residual)_{k+1} = (measurement)_{k+1} - (predicted\ measurement\ or\ e)_k$$

III. PROPOSED SYSTEM

A. Kalman Filter

The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone.

The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance—when some presumed conditions are met.

The state of the filter is represented by two variables:

1) $\boldsymbol{x_{k/k}}$, the a posteriori state estimate at time k given observations up to and including at time k;
2) $\boldsymbol{P_{k/k}}$, the a posteriori error covariance matrix (a measure of the estimated accuracy of the state estimate).

B. Extended Kalman Filter

The extended Kalman filter (EKF) is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance. The EKF which adapted techniques, namely multivariate Taylor Series expansions, from calculus to linearize about a working point became the working solution

The comparison for LMS, RLS and KF filters using 2nd order filter is given below

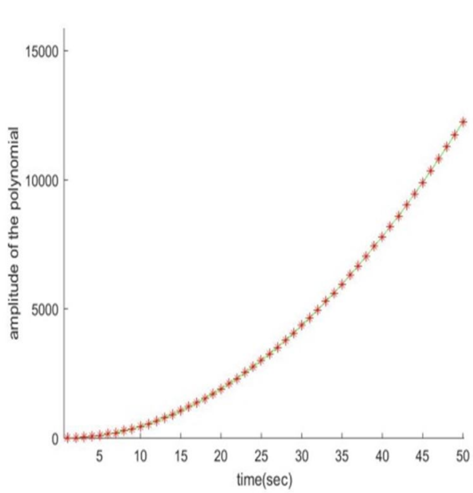

Fig 1. LMS 2^{nd} order output

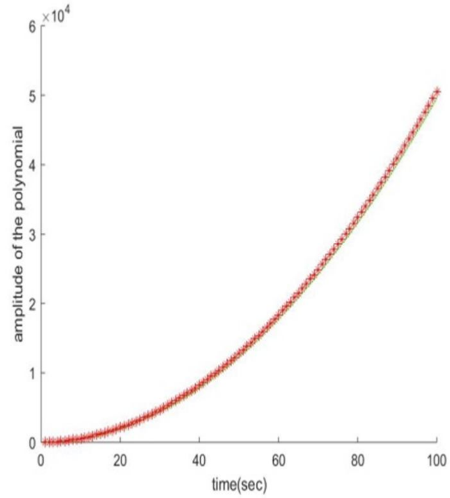

Fig 2. RLS 2^{nd} order output

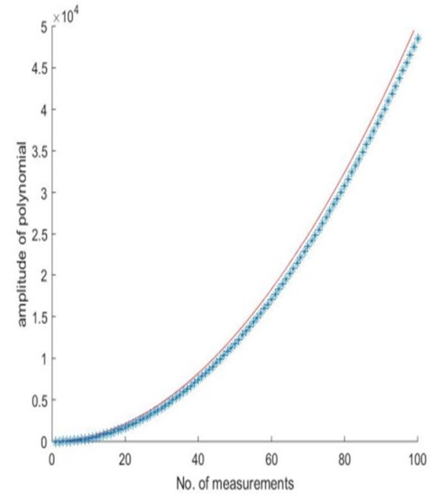

Fig 3. KF 2^{nd} order output

Table 1
Comparison of SNR values

Filter	SNR values
LMS	86.805
RLS	73.3807
KF	95.67

For a non-linear estimation the output for KF and EKF is shown below

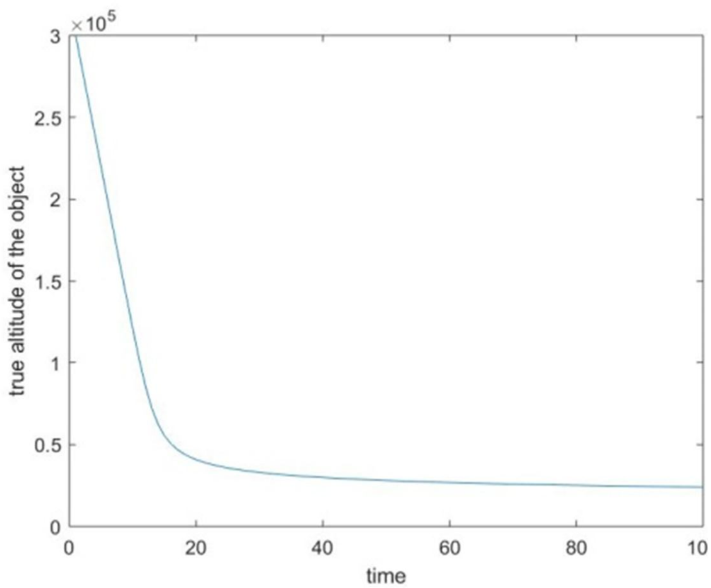

Fig 4. True altitude of the object

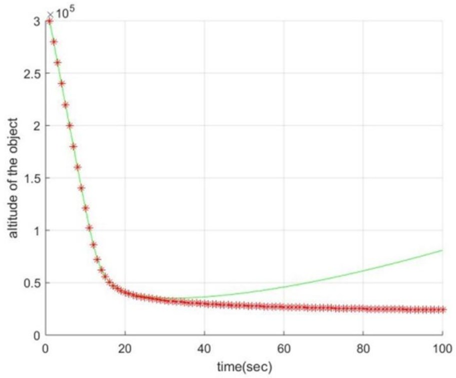

Fig 5. Altitude comparison using KF

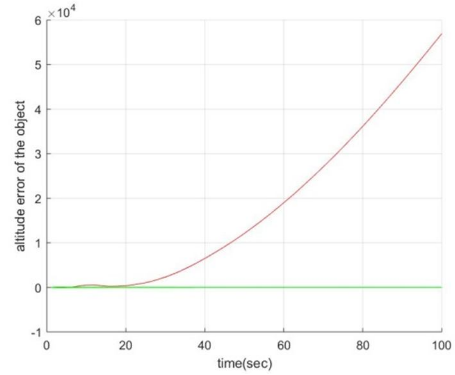

Fig 6. Absolute error calculating KF

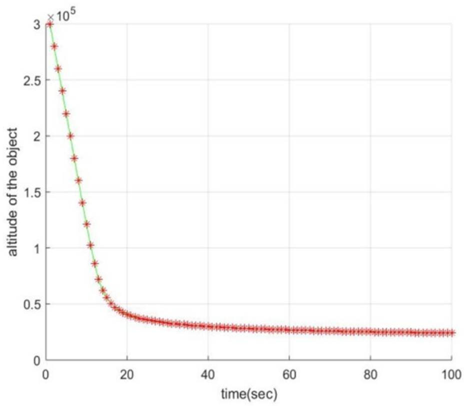

Fig 7. Altitude comparison using EKF

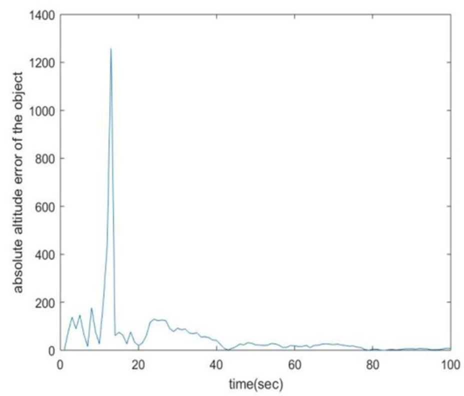

Fig 8. Absolute error calculating EKF

IV.CONCLUSION

From table 1 we can depict that KF gives the high signal to noise ratio than others.

Henceforth, the simulation results of different algorithms show that the Kalman filter gives optimal estimation of the noisy signal. So, the Kalman filter used for the radar tracking, but for military purposes the tracking involves non-linear dynamics of the target whose estimation is not optimal using the Kalman filter. So, for non-linear systems Extended Kalman Filter is proposed which provides an optimal estimation.

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