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Review Article

INVESTIGATION OF ADVANCED NON-LINEAR CONTROL AND ESTIMATION ALGORITHM FOR ROCKET BASED APPLICATIONS

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ABSTRACT

Online object tracking is an important task in radar and sonar signal processing as it is a challenging problem due to the presence of noise, and dynamic changes. A variety of stochastic algorithms for tracking targets have been proposed and implemented to reach these challenges. Approaches toward highly nonlinear applications are an advanced task. In this paper, we devote the effort to use the particle filtering with estimation of various states of a vehicle launched from an idealized spherical, airless, non-rotating earth to improve tracking efficiency. The simulation results show that the PF improved the tracking performance compared to the Kalman based filters (EKF, UKF) for the rocket launch application.

Keywords: Estimation, Kalman based filters, Particle filters, A priori information.

INTRODUCTION

In earlier days, many real-time applications have been carried on, but due to some unwanted errors and inefficient estimation techniques there existed a deviation in the results from its expected values. To avoid these, many mathematical models have been developed, but the one most acceptable is the state estimation models. This is one of the most powerful mathematical tools. This paper focuses on the use of a state estimation method for real-time monitoring and control of a system. The advantages of the state estimation as well as the challenges associated with adopting such a method in practice have been reviewed. This paper also deals with the estimation of the state vector of nonlinear system, assumes that the measurement errors, as well as the number of outliers that could occur within a given time window, are bounded. Nonlinear Filtering is certainly very important in estimation since most real-world problems are nonlinear. In this paper, we devote the effort to use the particle filtering (PF) with estimation of various states of a vehicle launched from earth to improve tracking efficiency. Estimation of vehicle states is done by PF, which focuses on controlling of any process modeling, obtained from a priori knowledge and updating it. The simulation results show that the PF improved the tracking performance compared to the Kalman based filters (EKF, UKF) for the rocket launch application.

From previous data of certain recognizable parameters such as physical laws or exploratory perceptions is one of the imperative practices for Engineers to control the procedure demonstrating.

A vast class of estimation issues is worried with finding an ideal gauge of an obscure parameter, when a straight capacity of this amount, undermined by clamor, is accessible for producing the gauge. Be that as it may, the class of estimation issues frequently experienced are those in which the obscure amount is describable by conditions which are not direct capacities. At that point, the hypothesis of Kalman channel [1,2], created to show ideal state assessments of straight frameworks, no longer yields an ideal gauge.

A problematic arrangement, to such nonlinear frameworks, is linearizing the nonlinear conditions around some ostensible esteem [3-5], with a supposition, an ostensible arrangement of the framework's nonlinear differential conditions must exist, and hence, it must give a decent estimate to the real conduct of the framework [6-12]. It gives great results if the contrast between the ostensible and real arrangement is depicted by an arrangement of straight differential conditions. By and by the ostensible conditions or ostensible direction may not be accessible from the earlier.

For exceptionally nonlinear application regions, show precisely the fundamental elements of a physical framework is a testing errand. Furthermore, it is vital to process information on-line as it arrives, both from the perspective of capacity expenses and in addition for fast adjustment to changing sign attributes. In this paper, following of very nonlinear issues are investigated, with an emphasis on molecule channels.

Nonlinear separating can be troublesome and complex; it is unquestionably not too comprehended as straight sifting. In any case, as a large portion of this present reality issues are nonlinear in nature, change of nonlinear models is required. Moreover, every single nonlinear framework is displayed by state space of limited measurement. Amplified Kalman channel, unscented separating, goes under nonlinear augmentations of the Kalman channel and these nonlinear estimation strategies have gotten to be across the board. In this paper, the nonlinear Kalman based sifting models and molecule separating models are assessed and executed on MATLAB, and the outcomes demonstrated that PF gives better likelihood of state estimation.

PF

PF, otherwise called consecutive Monte Carlo strategies (SMC), are complex model estimation systems in light of recreation. Molecule channels have imperative applications in all fields of science and designing, econometrics (the utilization of arithmetic and measurements to the investigation of monetary and money related data), tracking move targets, radar, and sonar flag preparing. The PF is a powerful answer for the test of non-straight, non-Gaussian following.

They are typically used to appraise Bayesian models and are the consecutive ("on-line") simple of Markov chain Monte Carlo (MCMC) clump strategies and are frequently like significance examining techniques. All around planned molecule channels can regularly be much speedier than MCMC. They are regularly a contrasting option to the extended Kalman channel (EKF) or unscented Kalman channel (UKF) with the favorable position that, with adequate examples, they approach the Bayesian ideal gauge, so they can be made more precise than either the EKF or UKF. Be that as it may, when the reenacted test is not adequately huge, they may experience the ill effects of test impoverishment. The methodologies can likewise be joined by utilizing a form of the Kalman channel as a proposition conveyance for the molecule channel.

Molecule channels are presently a standard method for doing non-direct, non-Gaussian separating. Molecule channel is a consecutive Monte Carlo strategy utilized for Bayesian sifting. Point mass, or particles, with relating weights are utilized to frame an estimation of a likelihood thickness work PDF). The particles are proliferated after some time by Monte Carlo reproduction to acquire new particles and weights (as a rule as new data are gotten), subsequently shaping a progression of PDF approximations after some time.

The primary target of molecule channel (PF) is to track a variable of enthusiasm as it advances after some time. In this strategy for estimation, the whole pdf is spoken to by a limited number of haphazardly chose tests. The premise of the technique is to build an example based representation of the whole pdf. Different duplicates (molecule) of the variable of intrigue are utilized, everyone connected with a weight that means the nature of that particular molecule. The weighted whole of the considerable number of particles gives the gauge of the variable of intrigue.

PF is a recursive model, works in two states: Forecast and updation. After every activity, every molecule is adjusted by existing model (expectation arrange), including the expansion of arbitrary commotion keeping in mind the end goal to recreate the impact of clamor on the variable of intrigue. At that point, every molecule's weight is re-assessed in light of the most recent tangible data accessible (overhaul stage). At times, the molecule with little weight is dispensed with, a procedure called resampling.

The PF method receives an alternate way to deal with Kalman based channels by examining various guessed states for the objective; these are the particles. It does not endeavor to demonstrate the conveyance utilizing a diagnostic shape. Rather, the instability (thus the dispersion) is spoken to utilizing the differing qualities of the arrangement of particles which basically speak to the conveyance. Every Particle is contrasted and the estimation and weighted in like manner [13,14]. Those particles with high weights are engendered, and those with low weights disposed of.

In this manner, the PF speaks to a track utilizing various weighted irregular specimens in the track space, from which it is anything but difficult to concentrate track gauges and measures of vulnerability. Ordinarily, a solitary track may be spoken to utilizing something like 250 particles.

The thought required in PF is to speak to the back thickness by an arrangement of irregular particles with related weights. And after that process a gauge in light of these examples and weights.

MODELING EXAMPLE FOR ROCKET LAUNCH

Consider the problem of estimating various states of a vehicle launched from an idealized spherical, airless, and non-rotating earth. The measured output is processed to give estimates of the vehicle's states which describe its trajectory.

The state estimation cannot be accurately explained by KF since nonlinearities are exhibited by forces that act on the vehicle. The most dominant force is aerodynamic drag which is a function of vehicle acceleration and has a substantial nonlinear variation in altitude. The gravitational force attracts the vehicle toward the center of the earth. The tracking radar should be able to track accurately the vehicle that is experiencing a set of complicated and highly nonlinear forces. These depend on the current position and velocity of the vehicle as well as on certain other characteristics which are not known a priori.

The topological depiction of parameters is shown in the Fig. 1.

The altitude above the earth's surface (h), distance of the vehicle downrange from the launch site (D), velocity with respect to an inertial base (v),
Flight path angle between velocity vector and vehicle fixed reference line (γ),
Aerodynamic drag (Dg),
Earth radius (R),
Elevation angle between radar site and vehicle (α),
Reference angle between launch site and vehicle (θ),
Reference angle between launch site and radar site (θ_R),
Slant-range distance from radar site to vehicle s–Disturbing force orthogonal to v is (Fn),
Vehicles thrust vector with respect to an inertial basis (T).

And r=h+R

State variable equations that define the vehicle's trajectory:

$$\dot{h} = v\sin\gamma \tag{1}$$

$$\dot{d} = \frac{R\, v\cos^3}{h+R} \tag{2}$$

$$\dot{v} = \frac{-k\sin\gamma}{(h+R)^2} + g\frac{T}{Wo}\frac{1}{1-\left(\frac{T}{Wo}\right)\frac{t}{ISP}} \tag{3}$$

$$\dot{\gamma} = \frac{D}{R} - \frac{k\cos\gamma}{v(h+R)2} + \frac{Fn}{v} \tag{4}$$

The development of the above equations takes the assumption that the propagation errors and the measurement errors were Random and these equations are modeled as a continuous non-linear system.

For the observation equations, the functions are,

$$h_1\left[x_N(t),t\right] = s = \sqrt{r^2 + R^2 - 2R\, r\cos(\theta_R - \theta)} \tag{5}$$

$$h_2\left[x_N(t),t\right] = \alpha = \arctan\left(\frac{\cos(\theta_R - \theta) - \frac{R}{r}}{\sin(\theta_R - \theta)}\right) \tag{6}$$

To estimate the states a non-linear filter is used which estimates their deviation from the normal trajectory or the current estimated trajectory. The nominal trajectory is given by the nominal state equations with the white process noise ignored.

The actual trajectory is the trajectories represented by the launch and boost it. In this study, it is simulated by the state equation which contains the process noise as would be expected in a realistic situation.

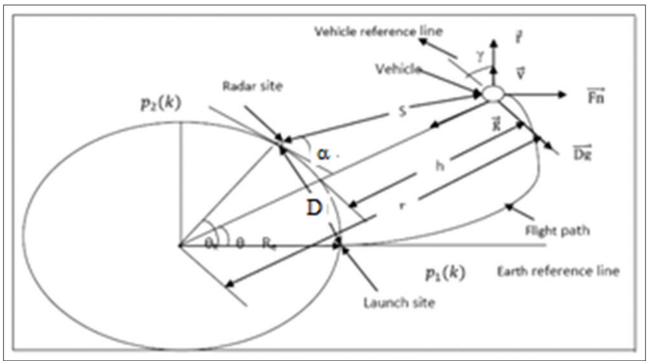

Fig. 1: Topological depiction of parameters

To linearize about the nominal state, we define a small error as the difference between the nominal state and the actual state.

The problem is to estimate the four parameters of vehicle's trajectory launched from the earth. The launch site and Trajectory of the launch vehicle are in a plane which contains a RADAR tracking station. The measurement model is located at 40 nautical miles from the launch site. The wind noise is assumed to be zero until 15 seconds and surface winds are assumed to be negligibly small up to 2500 feet for simulation purpose.

The trajectory is intended to achieve 80 miles of altitude with a suitable flight path angle (γ) to leave the satellite into a circular orbit. In the simulation process, it was assumed that in the absence of noise (it was assumed that until 10 seconds the vehicle will not be disturbed by any unknown forces) the initial estimated equations are same as the actual equations. After 10 seconds, the predictions are generated and updated more accurately by taking the noisy measurements into account. Furthermore, the bearing ($_\alpha$) measured by an observer is not computed for approximately 10 seconds, to prevent the computer from reaching an exponential overflow during the simulation process.

In the initialization, several constants, initial conditions, and standard deviations of measurement errors have been assumed as follows.
v_o=100 ft/second,
D_o=0 ft,
h_o=0 ft,
γ_o= 89.66°,
T/w_o=1.3,
R=20.89×10^6 ft,
g=32.17 ft/second^2,
D=40 n mi,
σ_v=0 ft/second,
σ_D=10 ft,
σ_h=100 ft,
σ_ϕ=0.001°,
σ_s=100 ft,
σ_α=0.01 rad.

FILTER MODEL FORMULATION

Step 1:
The state space model by means of propagation and measurement equations are given by Equation (5) and (7)

$$X_{k+1}=f\,(xk,\, uk,\, wk) \tag{7}$$

$$x^{a}_{k-1}=\begin{pmatrix} x_{k-1} \\ 0w \\ 0v \end{pmatrix} \tag{8}$$

$Z_k=h\,(x_k, v_k)$

Where,
x_k is state of the system, u_k is the input and (w^k) and (v_k) are independent white noise processes with known pdf.

Step 2:
Assuming that the pdf of the initial state $p(x_0)$ is known, randomly generate N initial particles on the basis of the pdf $p(x_0)$. These particles are denoted $I_0^+, i(i=1,2....,N)$. The parameter N is chosen by the user as trade-off between computational effort and estimation accuracy.

Step 3:
For k=1, 2,…, do the following.

i. Perform the time propagation step to obtain a priori particles $I_{k,i}^-$ using the known process equation and the known pdf of the process noise.

$$I_{k,i}^- = \int k-1(I_{k-1,i}^+, \omega_{k-1}^i)\; i=1\,...., N.$$

Where each ω_{k-1}^i noise vector is randomly generated on the basis of the known pdf of ω_{k-1}

ii. Compute the relative likelihood q_i of each $I_{k,i}^-$ particle conditioned on the measurement Z_k. This is done by evaluating the pdf $p(z_k / I_{k,i}^-)$ on the basis of the nonlinear measurement equation and the pdf of the measurement noise.
iii. Scale the relative likelihoods obtained in the previous step as follows.

$$q_i = \frac{q_i}{\sum_{j=1}^{N} q_j}$$

Now the sum of all the likelihoods is equal to one.

iv. Generate a set of posteriori particles $I_{k,i}^+$ on the basis of the relative likelihoods q_i. This is called the resampling step.
v. Now that we have a set of particles, $I_{k,i}^+$ that are distributed according to the pdf $p(x_k/z_k)$ we can compute any desired statistical measure of this pdf. We are interested in computing the mean and the covariance.

RESULTS

Figs. 2-5 plots the estimated mean squared error values of the parameters Altitude, Distance, velocity, and path angle, respectively.

Figs. 6-9 plots the comparison between true and estimated parameters of altitude, distance, velocity, and path angle, respectively.

Figs. 10-13 plot the comparison of true and estimated parameters of EKF and UKF for altitude, distance, velocity, and path angle, respectively.

CONCLUSIONS

In this paper, the performance of idealized rocket launch has been analyzed and presented using estimation approaches for state space models with nonlinear measurements using PF. Montecarlo simulations are carried out for Kalman based, and PF approaches in the noisy environment. The PF maintains multiple hypotheses about the state of the tracked objects by representing the state space by a set of weighted samples. In general, the more samples and richer target representation, the better the chances of tracking in cluttered and noisy environments. A PF has been shown to provide more accuracy than the classical Kalman based approaches. It was shown from the simulation result that, the

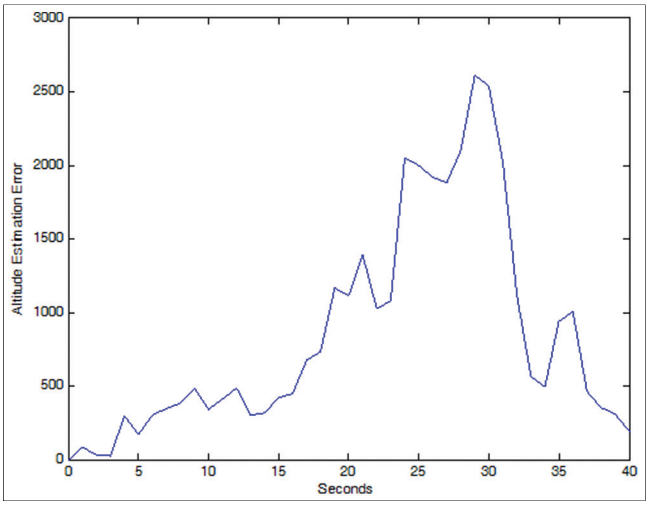

Fig. 2: Altitude estimation error

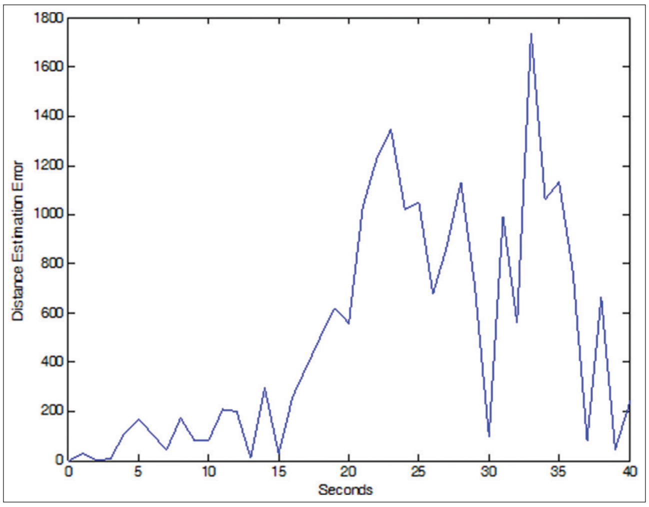

Fig. 3: Distance estimation error

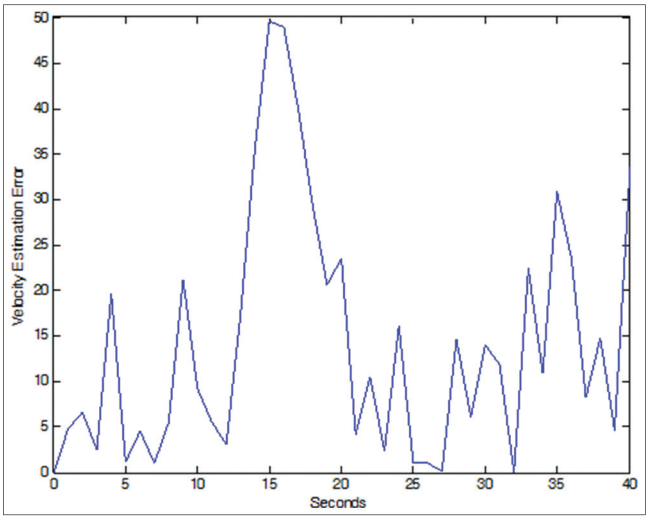

Fig. 4: Velocity estimation error

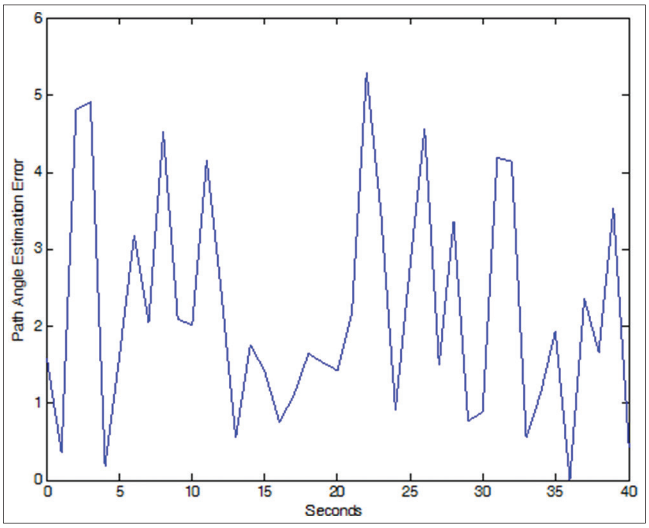

Fig. 5: Path angle estimation error

four parameters of the launch vehicle converges earlier in PF approach when compared to the conventional Kalman based approaches.

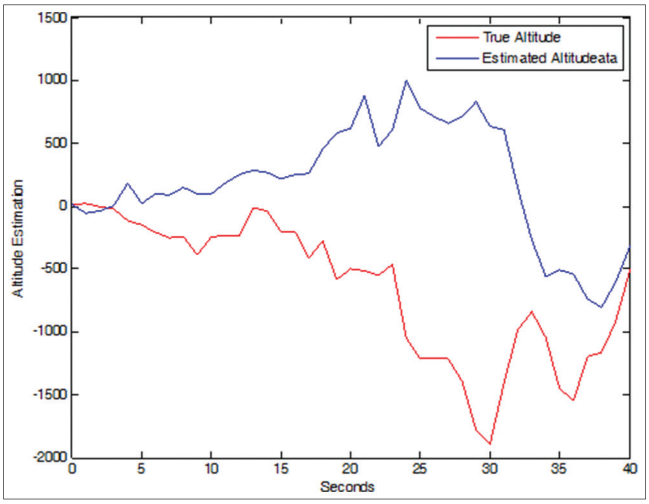

Fig. 6: True and estimated altitude estimation

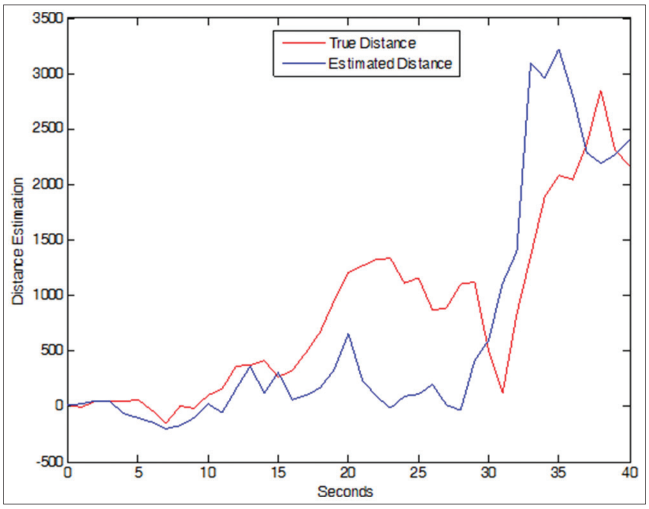

Fig. 7: True and estimated distance

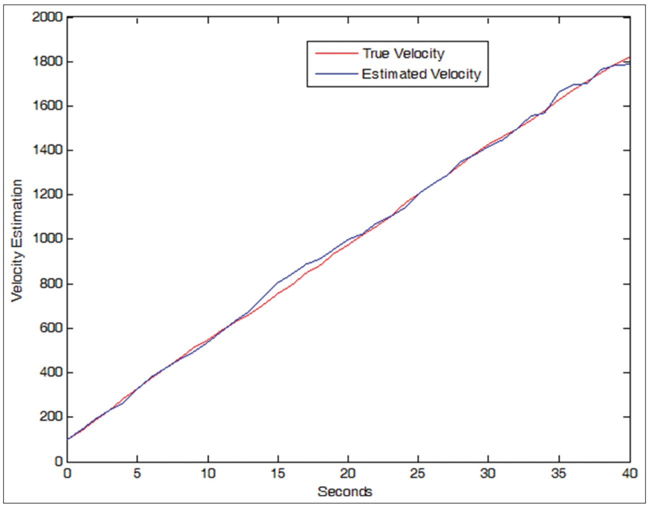

Fig. 8: True and estimated velocity

PF provides better performance for highly nonlinear and noisy environment. However, it increases the computational complexity. Hence, for further development, this paper proposes the following improvements:

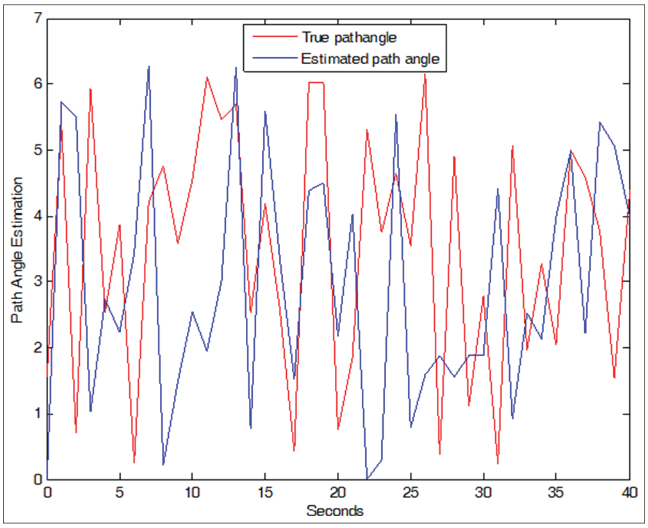

Fig. 9: True and estimated path angle

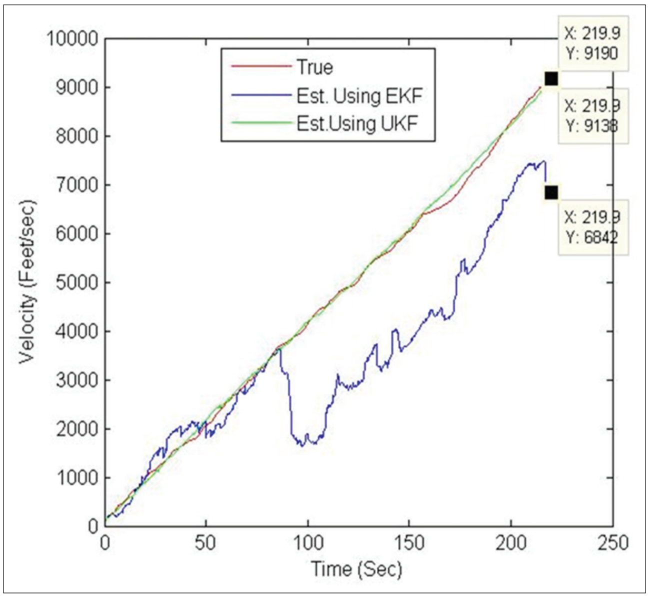

Fig. 12: Velocity estimation using EKF and UKF

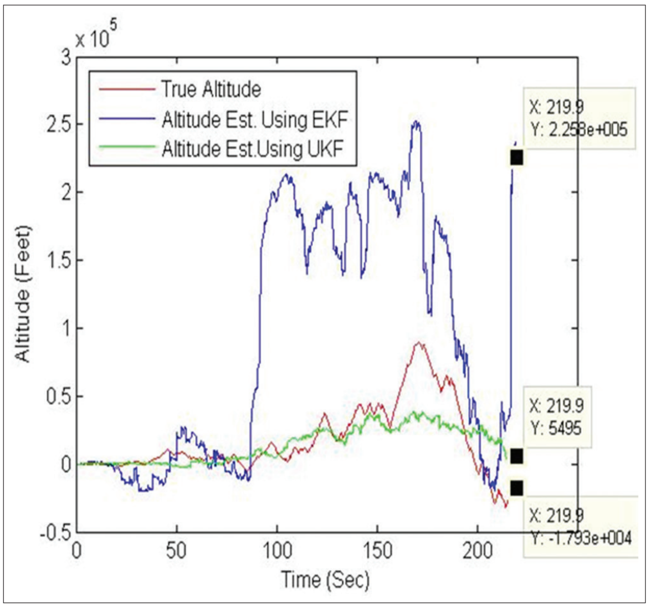

Fig. 10: Altitude estimation using EKF and UKF

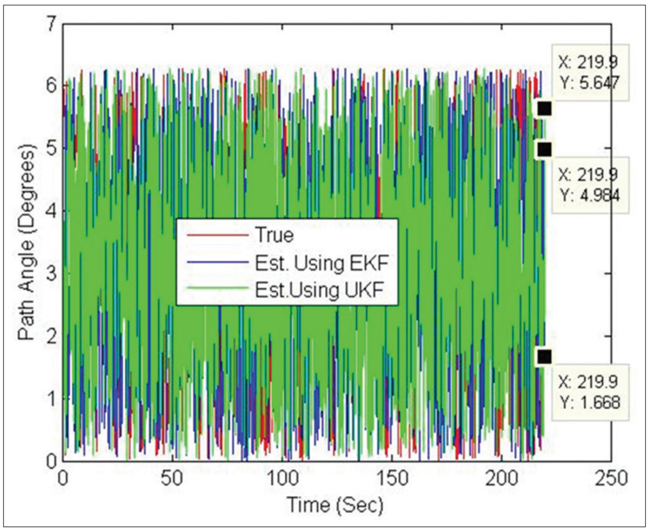

Fig. 13: Pathangle estimation using EKF and UKF

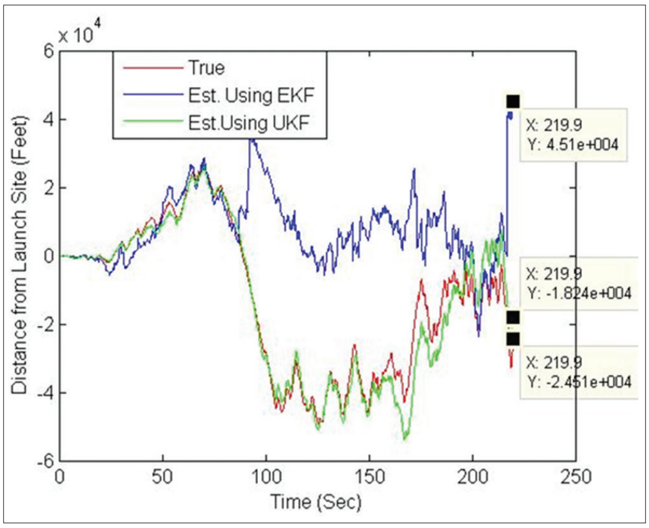

Fig. 11: Distance estimation using EKF and UKF

- PF can be associated with unscented Kalman filter not only to improve the performance but to reduce the complexity.
- It can further be enhanced by processing multiple filters.

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