ADVANCED FUSION TECHNIQUES FOR HIGH ACCURACY NAVIGATION

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Abstract

Navigation accuracy requirements for long duration, multiphase missions are very stringent when compared to short duration space missions. All inertial navigation systems suffer from integration of sensor drift which results in large errors over time. For integration of data from various systems efficient, accurate and robust state estimation are considered a key technology in all segments of space systems. For future missions, techniques such as data assimilation, sensor data fusion, data fusion from various satellite systems etc. are used which require advanced filtering techniques for estimation of navigation states. Presently EKF is widely used for data fusion. The design of data fusion of INS system and GPS for a typical launch vehicle is carried out using EKF and UKF. The performance of EKF and UKF for this particular application is studied and the pros and cons are brought out through this paper.

Key Words: Data Fusion, Unscented Kalman filter, INS, GPS

1. Introduction

Inertial Navigation System is usually the primary source of navigation data because of its reliability, autonomy and short term accuracy. Though INS is autonomous and provides good short-term accuracy, its usage as a stand-alone navigation system is limited due to the time-dependent growth of the inertial sensor errors. This is a major disadvantage of using the INS alone for long duration. The accuracy of the INS is highly dependent on the sensor quality, navigation system mechanization and dynamics of the flight vehicle. The navigation accuracy provided by standalone INS cannot meet the high accuracy navigation requirements for applications in multiphase missions. Inertial navigation, blended with other navigation aids Global Positioning System (GPS) in particular, has gained significance due to enhanced navigation accuracy. Kalman Filter is an extremely effective and versatile procedure for combining data from various systems.

In INS/GPS integration, the data fusion algorithm involves properly handling of nonlinear models. Therefore the nonlinear filtering methods have been commonly applied in the INS/GPS integration to estimate the state vector. The most popular and commonly used method is the Extended Kalman Filter (EKF) which approximates the nonlinear state and measurement equations using the first order Taylor series expansion.

EKF simply linearize all nonlinear transformations and substitute Jacobian matrices for the linear transformations in the Kalman filter equations, but these procedures are accompanied by some shortcomings: linearized approximation can be extremely poor in cases when error propagation can't be well approximated by a linear function, linearization can be applied only if the Jacobian matrices exist or in some situations calculation of Jacobian matrices is a very difficult and error prone process.

Recently emerged nonlinear filters such as Particle Filter (PF), Unscented Kalman Filter (UKF), Mixture Particle filter (MPF), Gaussian Sum Filter (GSF) etc can also be used for efficient data fusion.

In this paper section 2 deals with the system model, section 3&4 presents EKF and UKF modelling for this application. Simulation results are shown in section 5 and conclusions are provided in section 6.

2. System Model

A 12 state model with 6 measurements is considered. The states being the position error, velocity error, accelerometer bias error, and computational frame misalignment. So the state vector is as given below

$$X = [\Delta x, \Delta y, \Delta z, \Delta\dot{x}, \Delta\dot{y}, \Delta\dot{z}, bx, by, bz, mx, my, mz]$$

The feed forward integration of the GPS and INS is shown in Figure 1:

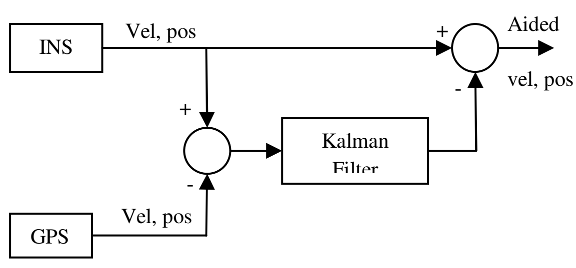

Figure 1: Block Schematic of GPS aided INS

The algebraic combination of the errors of the INS and GPS (i.e. error in position and velocity) are taken as the measurements. The state space model considered in this study is as given below:

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$$\dot{X} = \begin{bmatrix} 0 & I & 0 & 0 \\ 0 & 0 & C_b^i & Accl \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} X + \begin{bmatrix} 0_{3x1} \\ f_g \\ 0_{3x1} \\ 0_{3x1} \end{bmatrix} + w \tag{2.1}$$

$$Z = \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & I & 0 & 0 \end{bmatrix} X + v \tag{2.2}$$

Where

0: Null matrix of dimension 3x3

I: Identity matrix of dimension 3x3

C_b^i: Body to ECI transformation matrix 3x3

Accl: acceleration components in ECI frame 3x3

f_g: gravity effect which is nonlinear 3x1

0_{3x1}: Null matrix of dimension 3x1

The above state space model is discretized with a sampling period of 0.5 sec and is used for applying Kalman filter.

3. Extended Kalman Filter

The linearized Kalman filter works on a state space model which is obtained by linearizing the non-linear model around a nominal trajectory of the states. In some situations the nominal state trajectories may not be found explicitly. Instead we can use the states estimated by the filter to linearize the non-linear model and then the states are estimated based on the linearized model. This method of state estimation is known as Extended Kalman Filtering technique. A brief flow diagram of EKF algorithm is shown in figure 2. The stepwise procedure involved in applying Extended Kalman Filter is given below:

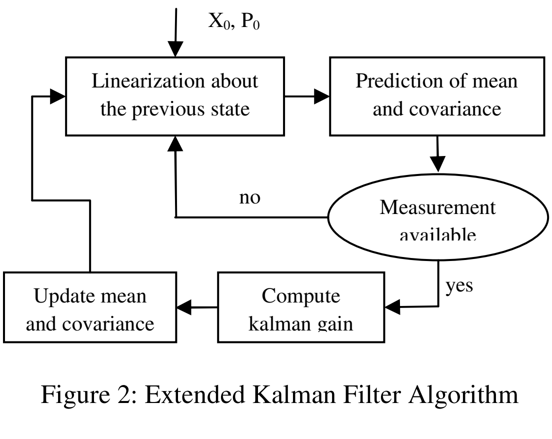

Figure 2: Extended Kalman Filter Algorithm

Plant Model:

$$X_k = \phi_{k-1} X_{k-1} + w_{k-1} \tag{3.1}$$

$w_k \sim (0,Q)$ is WGN: Process Noise

Measurement Equation:

$$Z_k = HX_k + v_k \tag{3.2}$$

$v_k \sim (0,R)$ is WGN : Measurement Noise

Initialization:

X_0 $\quad$ P_0: *Covariance of* X_0

Time Update:

$$X_{k/k-1} = \phi_{k-1} X_{k-1/k-1} \tag{3.3}$$

$$P_{k/k-1} = \phi_{k-1} P_{k-1/k-1} \phi_{k-1}^T + Q \tag{3.4}$$

k/k-1: prediction at k given k-1

k-1/k-1 : estimate at k-1 given k-1

Measurement at instant k:

Z_k

Predicted Measurement:

$$Z_{k/k-1} = HX_{k/k-1} \tag{3.5}$$

Computation of Kalman Gain:

$$K_k = P_{k/k-1} H^T [HP_{k/k-1} H^T + R]^{-1} \tag{3.6}$$

Measurement Update:

$$X_{k/k} = X_{k/k-1} + K_k [Z_k - Z_{k/k-1}] \tag{3.7}$$

$$P_{k/k} = [I - K_k H] P_{k/k-1} \tag{3.8}$$

4. Unscented Kalman Filter

The extended kalman filter works on the principle that a linearized transformations of means and covariances is approximately equal to the true non-linear transformation, this approximation is unsatisfactory if the effect of non-linearity is high[1]. In Unscented Kalman filter, unscented transformation is used to propagate the means and covariances. The Unscented transformation is based on the intution that it is easier to approximate a probability distribution than it is to approximate an arbitrary nonlinear function [2]. A set of 2n+1 (where n is the order of the system) sigma points are chosen such that their mean and covariance is equal to mean and covariance of the states. These sigma points are then propagated to the next step by using the nonlinear plant model from which the predicted mean and covariance of the next state is calculated. A brief flow diagram of EKF algorithm is shown in figure 3. The stepwise procedure involved in applying Unscented Kalman filter is given below:

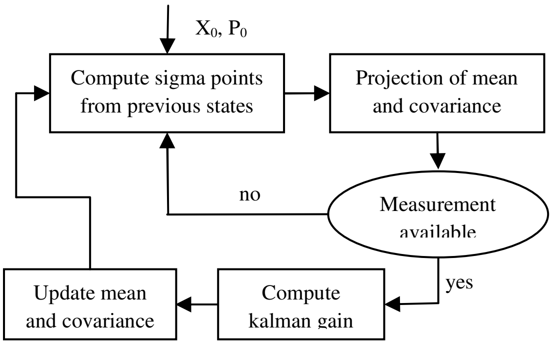

Figure 3: Unscented Kalman Filter Algorithm

Plant Model:

$$X_k = f(X_{k-1}) + w_{k-1} \quad (4.1)$$

w_k ~ (0,Q) is WGN : Process Noise

Measurement Equation:

$$Z_k = h(X_k) + v_k \quad (4.2)$$

v_k ~ (0,R) is WGN : Measurement Noise

Initialization:

$$X_0 \qquad P_0: Covariance\ of\ X_0$$

r : *unscented transformation parameter*

$$W_0 = \frac{r}{n+r} \qquad W_i = \frac{1}{2(n+r)}\ ,\ i=1,2,\ldots 2n$$

W_i : weights for mean and covariance in unscented transformation

Time Update:

Step1: Calculation of sigma points (2n+1)

$$\chi_{k-1,0} = X_{k-1} \quad (4.3)$$

$$\chi_{k-1,i} = X_{k-1} + (\sqrt{(n+r)P_{k-1}})_i \quad (4.4)$$

$$\chi_{k-1,i+n} = X_{k-1} - (\sqrt{(n+r)P_{k-1}})_i \quad (4.5)$$

where $(\sqrt{(n+r)P_{k-1}})_i$ represents i[th] column of the matrix

Step2: Projection of sigma points using the plant model

$$\chi_{k/k-1,i} = f(\chi_{k-1,i})\ ,i=0,1,2,\ldots,2n \quad (4.6)$$

Step3: Calculation of mean and covariance of the new state from the projected sigma points

$$X_{k/k-1} = \sum_0^{2n} W_i \chi_{k/k-1,i} \quad (4.7)$$

$$P_{k/k-1} = \sum_0^{2n} W_i [\chi_{k/k-1,i} - X_{k/k-1}][\chi_{k/k-1,i} - X_{k/k-1}]^T + Q \quad (4.8)$$

Measurement at instant k:

$$Z_k$$

Predicted measurement at instant k:

Step1: Calculation of measurement sigma points using measurement equation

$$\zeta_{k,i} = h(\chi_{k/k-1,i})\ ,i=0,1,2,\ \ldots\ ,2n \quad (4.9)$$

Step2: Prediction of the measurement from the sigma points

$$\hat{Z}_k = \sum_0^{2n} W_i \zeta_{k,i} \quad (4.10)$$

Computation of Kalman Gain:

Step1: Computation of measurement covariance

$$P_{zz} = \sum_0^{2n} W_i [\zeta_{k,i} - \hat{Z}_k][\zeta_{k,i} - \hat{Z}_k]^T + R \quad (4.11)$$

Step2: Computation of cross-correlation between predicted states and measurement

$$P_{xz} = \sum_0^{2n} W_i [\chi_{k/k-1,i} - X_{k/k-1}][\zeta_{k,i} - \hat{Z}_k]^T \quad (4.12)$$

Step3: Kalman gain calculation

$$K_k = P_{xz} * P_{zz}^{-1} \quad (4.13)$$

Measurement Update:

$$X_k = X_{k/k-1} + K_k [Z_k - \hat{Z}_k] \quad (4.14)$$

$$P_k = P_{k/k-1} - K_k P_{zz} K_k^T \quad (4.15)$$

5. Simulation Results

Simulations were run with both EKF and UKF taking different noise conditions in GPS and INS data in navigation phase. Some of the simulation results are shown below:

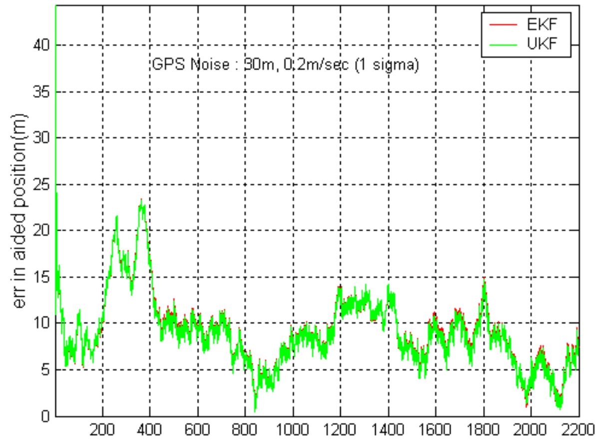

Figure 4: Aided position error with noise in GPS and INS data

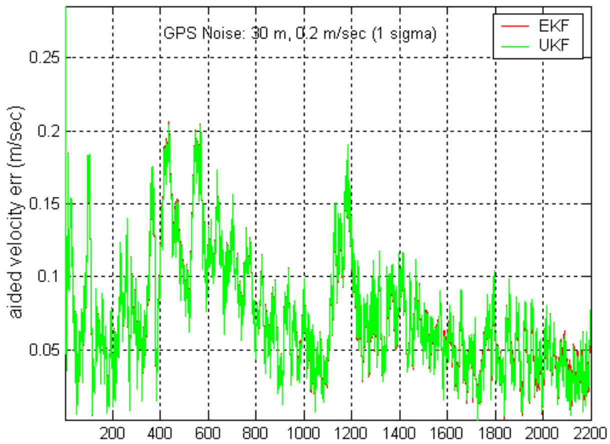

Figure 5: Aided velocity error with noise in GPS and INS data

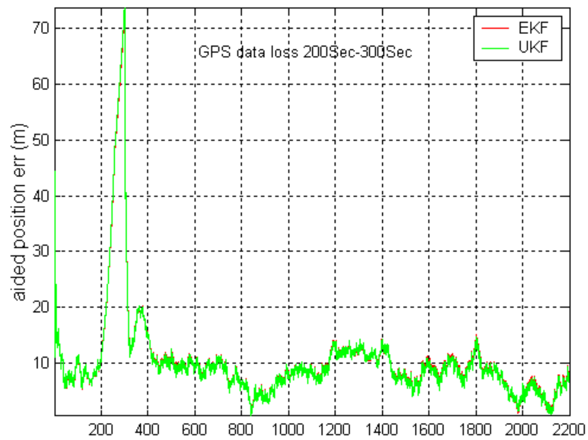

Figure 6: aided position error with loss in GPS data

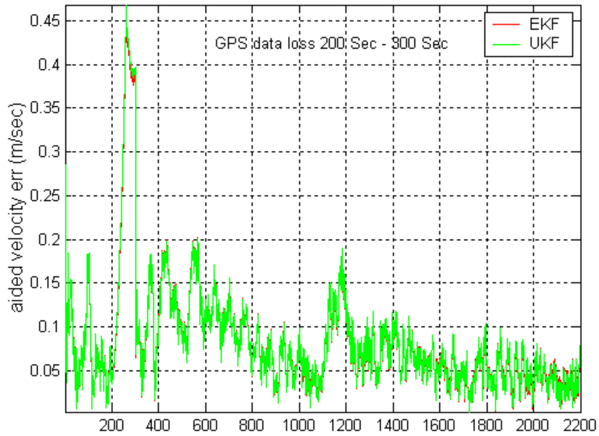

Figure 7: Aided velocity error with loss in GPS data

Figure 8: Aided position error with burst of noise in GPS data

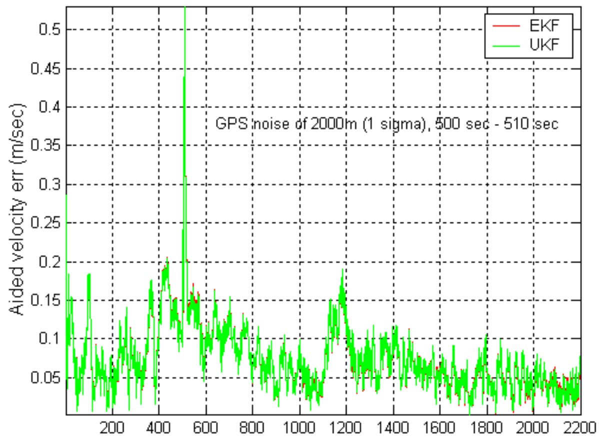

Figure 9: Aided velocity error with burst of noise in GPS data

6. Conclusion

Design tradeoff is carried out for GPS/INS integration using EKF & UKF. It is observed that both EKF and UKF are performing well for normal flight regime. The mean in the error of aided position and velocity is less in the case of UKF when compared to that of EKF, but this difference is not significant if medium errors are simulated in Ins. This is due to the fact that nonlinearity in the system model is not very high. So UKF is more advantageous in cases where the system nonlinearity is high. The advantage of UKF is very clearly seen when large initial errors are simulated in the INS. The UKF has shown improved performance during the initial alignment phase.

From the study it is evident that adopting UKF for the initial alignment phase and then switching to EKF for the regular flight phase is an efficient strategy for GPS/INS integration.

7. References

1. Simon, D., "Optimal State Estimation", John Wiley & Sons, New Jersy, 2006.
2. Julier, S., Uhlmann, J., and Durrant Whyte, H., "A new method for the nonlinear transformation of means and covariances in filters and estimators", IEEE transactions on Automatic Control, 45(3), pp. 477-482, march 2002.
3. Haidong Hu, Xianlin Huang, and Zhuoyue Song, "A novel algorithm for SINS/CNS/GPS integrated navigation system", IEEE Conf. on Decision and Control, 2009, pp. 1471-1475
4. Wei Gao, Bo Xu, Hongjun Sun, and Fei Yu, " Application of nonlinear filter for SINS initial alignment", Proc. IEEE Int. Conf. on Mechatronics and Automation, 2006, pp. 2259-2263.
5. Fanming Liu, Yan Li, Yingfa Zhang, and Huijan Hou, "Application of Kalman Filter algorithm in gravity aided navigation system", Proc. IEEE Int. Conf. on Mechatronics and Automation, 2011, pp. 2322-2326.