ISSN 2176-5480

22nd International Congress of Mechanical Engineering (COBEM 2013)
November 3-7, 2013, Ribeirão Preto, SP, Brazil

AN APPROACH TO THE FUSION SENSOR FOR AERIAL PLATFORMS

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Abstract. *A navigation system INS/GPS (Inertial Navigation System / Global Positioning System) for unmanned aerial systems has been designed. This system uses the fusion data of an INS based in measurements from low-cost MEMS inertial sensor and a GPS receiver. By fusing the INS data with GPS data, the drift error of INS is compensated with the GPS's measurements. The fusion data has been implemented using the architecture "loosely coupled" and two algorithms of fusion: Extended Kalman Filter (EKF) and Unscented Kalman filter (UKF). The algorithms have been evaluated by means of simulation test using real data of inertial sensor ADIS16407. The simulation result demonstrates that the navigation system INS/GPS has the potential use in guidance application and control for aerial platforms or land vehicles.*

Keywords: *Data Fusion,Inertial Navigation,Extended Kalman Filter,Unscented Kalman Filter,Global Positioning System.*

1. INTRODUCTION

Inertial Navigation System (INS) (Woodman, 2007; Farrell, 2008; Titterton and Weston, 2004) is a self-contained navigation technique which aims to estimate the states of position, velocity and orientation of a vehicle by measuring the acceleration and angular velocity. In general, The INS is classified as dead reckoning systems that does not require external sources for its operation and has been studied for commercial and military applications. The major advantage of this type of navigation is the high rate; typically 100 times per second, also using MEMs inertial sensors (micro-electromechanical systems) its size and price are ideal for civil unmanned vehicles (Valavanis *et al.*, 2008). However, the main disadvantage of an INS system is that the error variance or drift error of the navigation state increases primarily due to sensor noise and errors in sensor calibration and alignment (Grewal *et al.*, 2007). On the other hand, The Global Positioning System (GPS) can provide a vehicle position with accuracy in the order of 5 meters. The main drawbacks of a GPS are: low data rate: (typically 1 Hz) and that the satellite signals can be blocked by obstacles.

Multisensor Data Fusion is the process of combing information from a number of different sources to provide a robust and complete description of an environment or process of interest (Whyte and Henderson, 2008). For navigation case, data fusion techniques allow correcting the error variance or cumulative error of INS in conjunction with a GPS. In addition, the INS would continue to provide position estimates at times when GPS signals are not available.

The purpose of the present paper is to design a navigation system INS / GPS low cost and light weight.This system combines the data from the INS with GPS data. The fusion data is implemented using an Extended Kalman Filter (EKF) and Unscented Kalman filter (UKF). The Fig. 1 shows the architecture "loosely coupled" implemented. The algorithms are evaluated using simulation test with real data of Inertial Measurement Unit (IMU) ADIS16407.

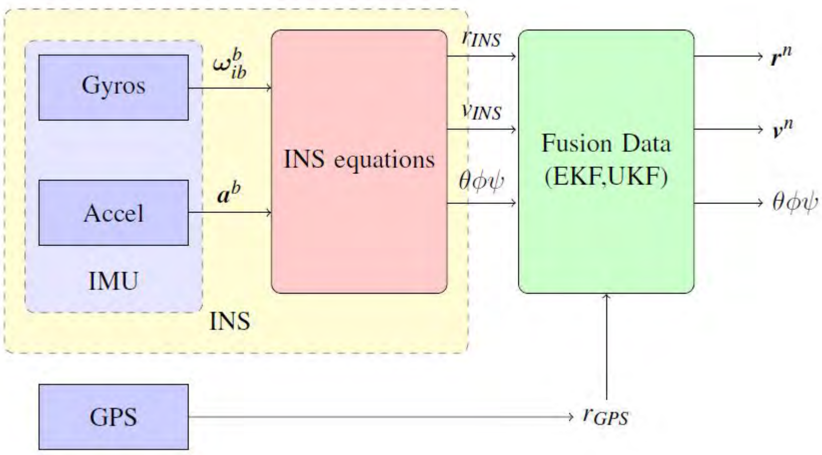

Figure 1. INS/GPS Navigation Systems

The designed navigation system was intended to be use mainly in guidance and control applications of aerial platforms,

ISSN 2176-5480

where its operating range is less than 5 km for civilian use.

2. DESCRIPTION OF INERTIAL NAVIGATION SYSTEM

The INS navigation system is composed of two distinguished parts. The Inertial Measurement Unit (IMU) that hosts the accelerometers and gyroscopes and navigation equations,see Fig. 1. The navigation equations represent the system dynamics model denoted by differential equations. This block is performed in two steps: first, the rotation matrix of direction cosines (DCM) is calculated by from gyro measurements. Then, the matrix of direction cosines is used for solving the differential equations relating accelerations in the vehicle frame or body frame to the navigation NED (North,East,Down) coordinate system (Skog, 2005).

2.1 INS equations

The continuous-time navigation equations in the NED frame are (Shin, 2001; Bortz, 1971)

$$\begin{bmatrix} \dot{\mathbf{r}}^{\mathbf{n}} \\ \dot{\mathbf{v}}^{\mathbf{n}} \\ \dot{\mathbf{R}}^{\mathbf{n}}_{\mathbf{b}} \end{bmatrix} = \begin{bmatrix} \mathbf{v}^{\mathbf{n}} \\ \mathbf{R}^{\mathbf{n}}_{\mathbf{b}}\mathbf{a}^{\mathbf{b}} + \mathbf{g}^{\mathbf{n}} \\ \mathbf{R}^{\mathbf{n}}_{\mathbf{b}}(\mathbf{\Omega}^{\mathbf{b}}_{\mathbf{ib}}) \end{bmatrix} \tag{1}$$

Where, $\mathbf{r}^{\mathbf{n}} = \begin{bmatrix} r_N & r_E & r_D \end{bmatrix}^T$ and $\mathbf{v}^{\mathbf{n}} = \begin{bmatrix} v_N & v_E & v_D \end{bmatrix}^T$ are the position and the velocity vectors of a vehicle in a navigation frame NED, respectively, $\mathbf{a}^{\mathbf{b}} = \begin{bmatrix} a_x & a_y & a_z \end{bmatrix}^T$ is the acceleration vector measurement by the IMU , $\mathbf{g}^{\mathbf{n}}$ is the gravity vector in the navigation frame, $\mathbf{R}^{\mathbf{n}}_{\mathbf{b}}$ is the direction cosine matrix (DCM) from a body frame to a navigation frame NED,the matrix $\mathbf{\Omega}^{\mathbf{b}}_{\mathbf{ib}}$ is the skew symmetric matrix representations formed from the elements of the angular rates of the body (vehicle) measurement by the IMU $\omega^{\mathbf{b}} = \begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}$.

$$\mathbf{\Omega}^{\mathbf{b}}_{\mathbf{ib}} = \begin{bmatrix} 0 & -\omega^b_z & \omega^b_y \\ \omega^b_z & 0 & -\omega^b_x \\ -\omega^b_y & \omega^b_x & 0 \end{bmatrix} \tag{2}$$

2.2 Discrete time navigation equations

The navigation equation Eq. (1) is solved by the Euler method for position,velocity and direction cosine matrix according as developed in (Groves, 2008).

$$\begin{bmatrix} \dot{\mathbf{r}}^{\mathbf{n}}_{\mathbf{k}} \\ \dot{\mathbf{v}}^{\mathbf{n}} \\ \mathbf{R}^{\mathbf{n}}_{\mathbf{b}}(\mathbf{k}) \end{bmatrix} = \begin{bmatrix} \mathbf{r}^{\mathbf{n}}_{\mathbf{k-1}} + \mathbf{T_s}\mathbf{v}^{\mathbf{n}}_{\mathbf{k}} \\ \mathbf{v}^{\mathbf{n}}_{\mathbf{k-1}} + \mathbf{T_s}(\mathbf{R}^{\mathbf{n}}_{\mathbf{b}}(\mathbf{k})\mathbf{a}^{\mathbf{b}} + \mathbf{g}^{\mathbf{n}}) \\ \mathbf{R}^{\mathbf{n}}_{\mathbf{b}}(\mathbf{k-1})\mathbf{\Omega}^{\mathbf{b}}_{\mathbf{ib}}\mathbf{T_s} \end{bmatrix} \tag{3}$$

Where T_s denote the sampling time.

The navigation system is designed to work over short distances, less than 5 km; for that reason, corriolis acceleration due to the rotation of the earth is zero.

3. EXTENDED KALMAN FILTERING

The Extended Kalman filter is a recursive estimation that can be employed when the state model or the observation model are nonlinear. The EKF develops a Gaussian approximation to the joint distribution of state $\mathbf{x}$ and measurements $\mathbf{y}$ using a Taylor series based transformation, see (Grewal and Andrews, 2001; Dan, 2006). The state $\mathbf{x} \,\epsilon\, R^n$ considered by the EKF is governed by the non-linear discrete stochastic difference equation.

$$\mathbf{x_k} = f(\mathbf{x_{k-1}}, \mathbf{w_{k-1}}) \tag{4}$$

with a measurement $\mathbf{z} \,\epsilon\, R^m$ that is

$$\mathbf{z_k} = h(\mathbf{x_k}, \mathbf{v_k}) \tag{5}$$

where the random variable $\mathbf{w_k}$ and $\mathbf{v_k}$ represent the process and measurement noise respectively. They are assumed to be independent of each other, white, and with normal probability distributions $p(w) \sim N(0, Q)$ and $p(v) \sim N(0, R)$ (Zhang *et al.*, 2005).

The extended Kalman filter is separated to two steps.

Prediction:

$$\hat{x}^-_k = f(\hat{x}_{k-1}) \tag{6}$$

$$p_k^- = F_{k-1} p_{k-1}^- F_{k-1}^T + Q_k \tag{7}$$

Update:

$$K_k = p_k^- H_k^T [H_k p_k^- H_k^T + R_k]^{-1} \tag{8}$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k[z_k - h_k(x)] \tag{9}$$

$$p_k^+ = [I - K_k H_k] p_k^- \tag{10}$$

where the matrices F_{k-1} and H_k are the Jacobian matrices of f and h around the current estimate of the state.

$$F_{k-1} = \frac{\partial f(x_{k-1})}{\partial x} \mid_{x=\hat{x}_{k-1}^-} \tag{11}$$

$$H_k = \frac{\partial h(x_k)}{\partial x} \mid_{x=\hat{x}_k^-} \tag{12}$$

4. UNSCENTED KALMAN FILTER

The Unscented Kalman Filter UKF, see (Merwe and Wan, 2004), is based on the Unscented transformation UT, that consist in propagate a set of sigma point χ_i Eq. (13), Eq. (16) through the nonlinear system $\mathbf{x_k} = f(\mathbf{x_{k-1}}, \mathbf{w_{k-1}})$ Eq. (14) and observation model $\mathbf{z_k} = h(\mathbf{x_k}, \mathbf{v_k})$ Eq. (17). Then,capture the desired moments (mean and covariance) of the joint distribution of state $\mathbf{x}$ and measurements $\mathbf{y}$ Eq. (15), Eq. (18).

The prediction and update steps of the UKF can computed as follows:
Prediction:

$$\begin{aligned} &\chi_0 = \bar{x} \\ &\chi_i = \bar{x} + \sqrt{(n+\lambda)P_{xx}}; i = 1, \ldots, n \\ &\chi_i = \bar{x} - \sqrt{(n+\lambda)P_{xx}}; i = n+1, \ldots, 2n \\ &W_0 = \tfrac{\lambda}{n+\lambda} \\ &W_i = \tfrac{1}{2(n+\lambda)}, i = 1, \ldots, 2n \end{aligned} \tag{13}$$

$$y_i = f(\chi_i) \tag{14}$$

$$\begin{aligned} &\hat{x}^- = \textstyle\sum_{i=0}^{2n} W_i y_i \\ &P_{xx}^- = \textstyle\sum_{i=0}^{2n} W_i (y_i - \hat{x}^-)(y_i - \hat{x}^-)^T + Q_k \end{aligned} \tag{15}$$

Update:

$$\begin{aligned} &\chi_0 = \hat{x}^- \\ &\chi_i = \hat{x}^- + \sqrt{(n+\lambda)P_{xx}^-}; \quad i = 1, \ldots, n \\ &\chi_i = \hat{x}^- - \sqrt{(n+\lambda)P_{xx}^-}; \quad i = n+1, \ldots, 2n \end{aligned} \tag{16}$$

$$z_i = h(\chi_i) \tag{17}$$

$$\begin{aligned} &\hat{z}^- = \textstyle\sum_{i=0}^{2n} W_i z_i \\ &P_{yy} = \textstyle\sum_{i=0}^{2n} W_i (z_i - \hat{y}^-)(z_i - \hat{z}^-)^T + R_k \\ &P_{xy} = \textstyle\sum_{i=0}^{2n} W_i (y_i - \hat{x}^-)(z_i - \hat{z}^-)^T \end{aligned} \tag{18}$$

$$\begin{aligned} &K = P_{xy} P_{yy}^{-1} \\ &\hat{x}^+ = \hat{x}^- + K(z - \hat{z}^-) \\ &P_{xx}^+ = P_{xx}^- - K P_{yy} K^T \end{aligned} \tag{19}$$

The advantage of UT over the Taylor series based approximation is that UT is better at capturing the higher order moments caused by the non-linear transform (Hartikainen *et al.*, 2011).

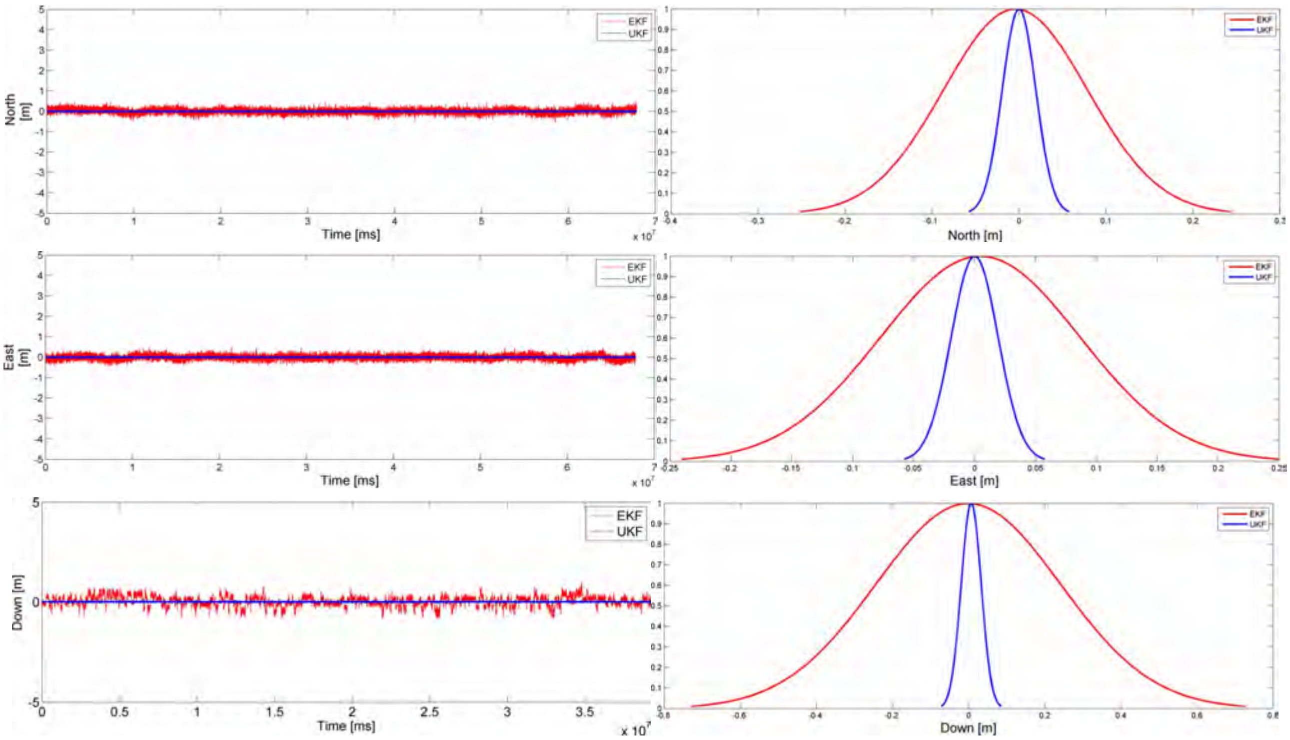

Figure 2. Estimated Position of filters EKF and UKF in NED Frame

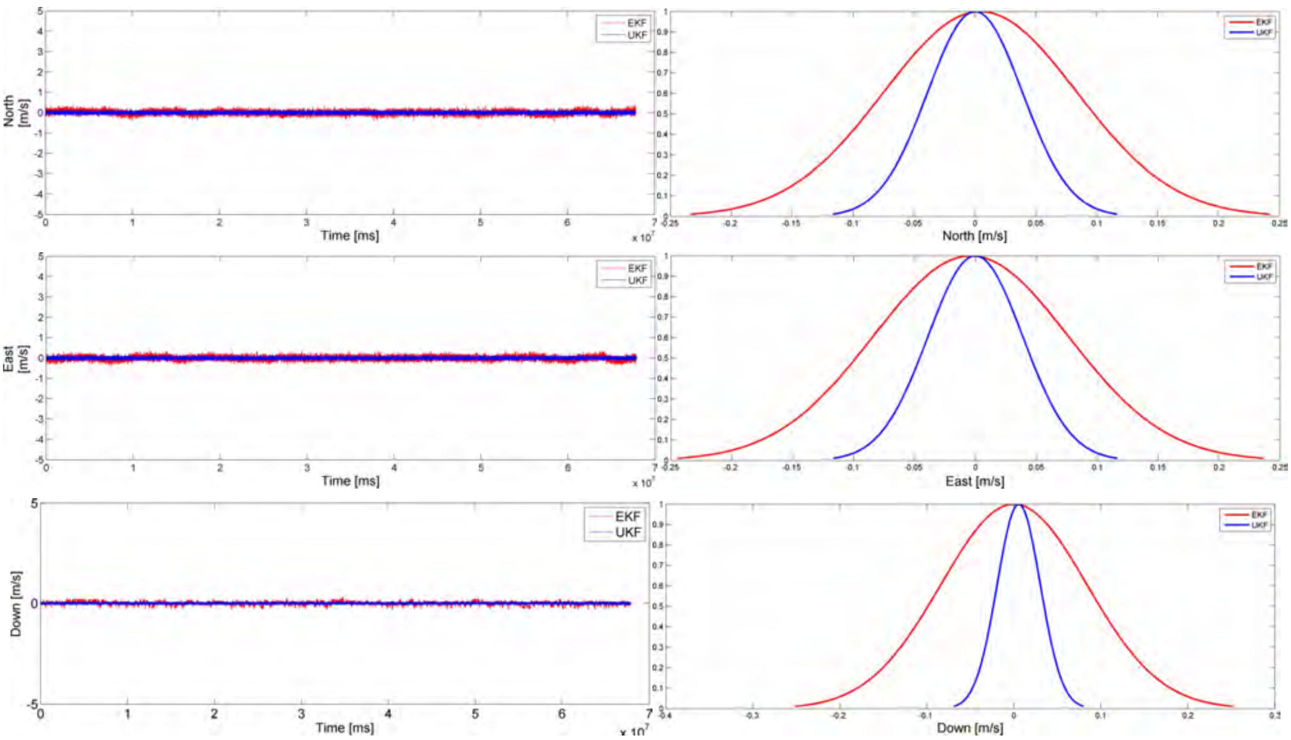

Figure 3. Estimated velocity of filters EKF and UKF in NED Frame

5. TEST AND RESULTS

The following section presents the results for two simulation experiments: stationary test and path test,these tests have the purpose of evaluating sensor system fusion performance INS / GPS proposed in this paper.For this, we take the data of acceleration and angular velocity measured by the Inertial Measurement Unit ADIS16407 in steady state for 19 hours with a frequency of 33 Hz,then, the data are then processed by the algorithms EKF, UKF.

The estimated position, velocity and attitude are plotted in Fig. 2, Fig. 3 and Fig. 4. In Tab. 1 shows the results of media and standard deviation.

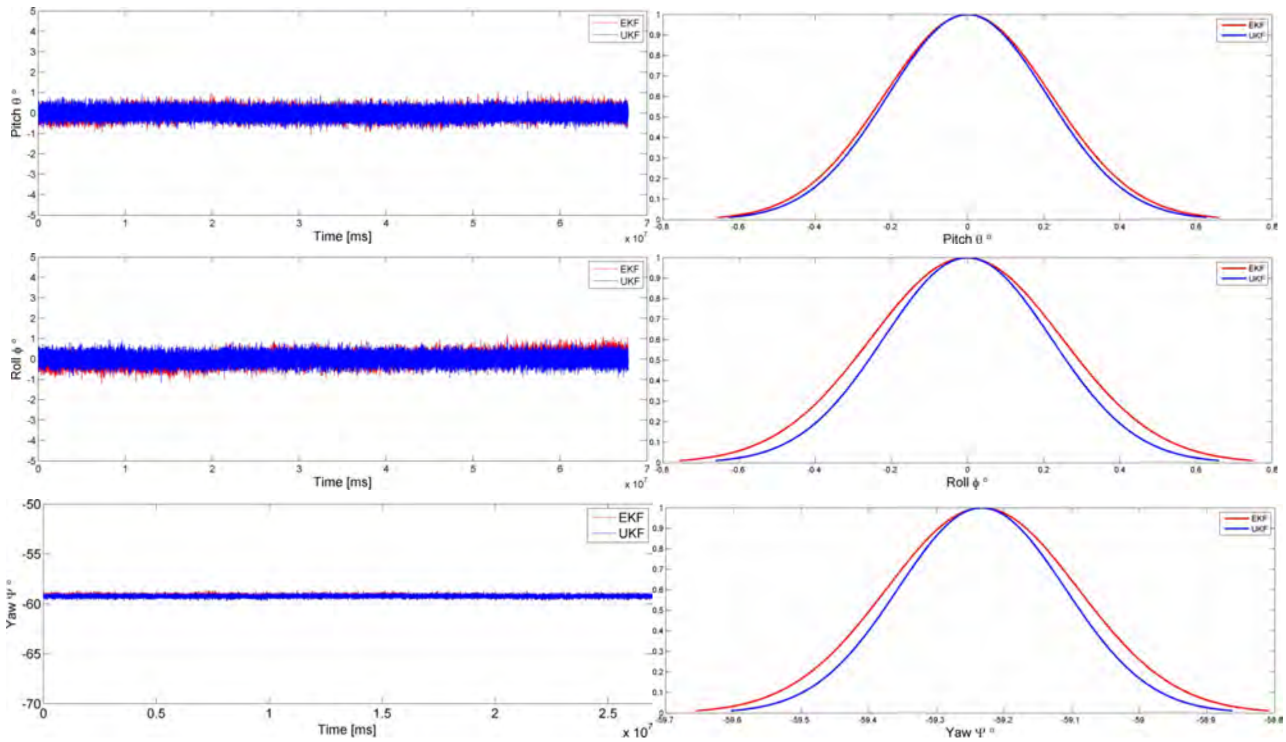

Figure 4. Estimated attitude of filters EKF and UKF in NED Frame

Fig. 2, Fig. 3 and Fig. 4 shows the convergence in each of the states of navigation: position velocity and orientation. The figures show greater accuracy of estimated variables by UKF as shown in the probability distribution function of each graph.

Table 1. Mean and Standard Deviation.

State	$\bar{X}$ *EKF*	$\bar{X}$ *UKF*	σ *EKF*	σ *UKF*
Position North	4.67×10^{-3}	1.61×10^{-5}	8.18×10^{-2}	1.92×10^{-2}
Position East	-4.13×10^{-3}	-4.94×10^{-5}	8.26×10^{-2}	1.92×10^{-2}
Position Down	1.88×10^{-2}	6.90×10^{-3}	2.42×10^{-1}	2.61×10^{-2}
Velocity North	4.38×10^{-3}	3.01×10^{-5}	7.92×10^{-2}	3.88×10^{-2}
Velocity East	-3.88×10^{-3}	-9.29×10^{-5}	8.01×10^{-2}	3.88×10^{-2}
Velocity Down	5.92×10^{-3}	5.51×10^{-3}	8.39×10^{-2}	2.48×10^{-2}
Pitch θ°	7.32×10^{-4}	8.42×10^{-5}	2.19×10^{-1}	2.09×10^{-1}
Roll ϕ°	-2.56×10^{-3}	-1.63×10^{-4}	2.51×10^{-1}	2.20×10^{-1}
Yaw ψ°	-59.2324	-59.2334	1.41×10^{-1}	1.23×10^{-1}

$\bar{X}$ *: Mean.*

σ*: Standard Deviation.*

The second test is intended to determine behavior of system INS/ GPS along in a path.GPS receiver used was a Trimble Copernicus II, this measures the NED coordinate position with a frequency of 1Hz, the acceleration data and angular velocity are measured all the way by the IMU ADIS16407 with a frequency of 33 Mhz.

The Fig. 5, Fig. 6 and Fig. 7 show parth of the trajectory followed by the vehicle.The Fig. 8 shows the estimated full trajectory. The Tab. 1 shows the RMSE for each of the estimated states and data acquired by the GPS.

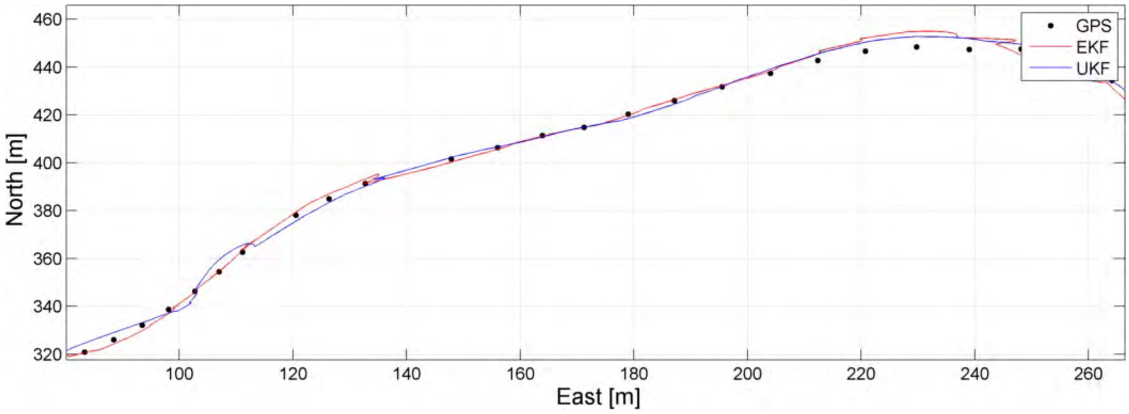

Figure 5. Position NE

The Fig. 5 shows the estimated trajectory for each of the filter (red and blue lines) and GPS measurements (black dots) during this path the number of visible satellites was 5 and GPS measurements are updated every 1 second, however, it shows that the system is estimated from the INS position every 30 ms until the next measurement.

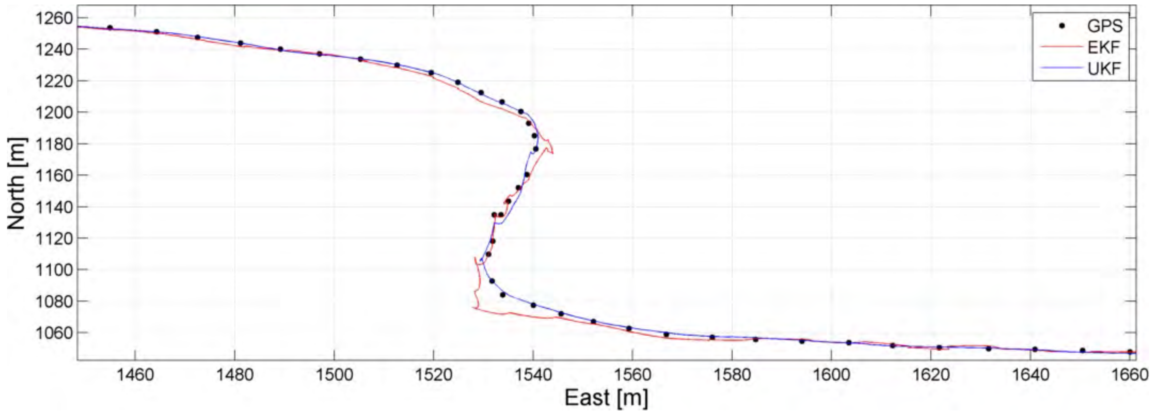

Figure 6. Position NE

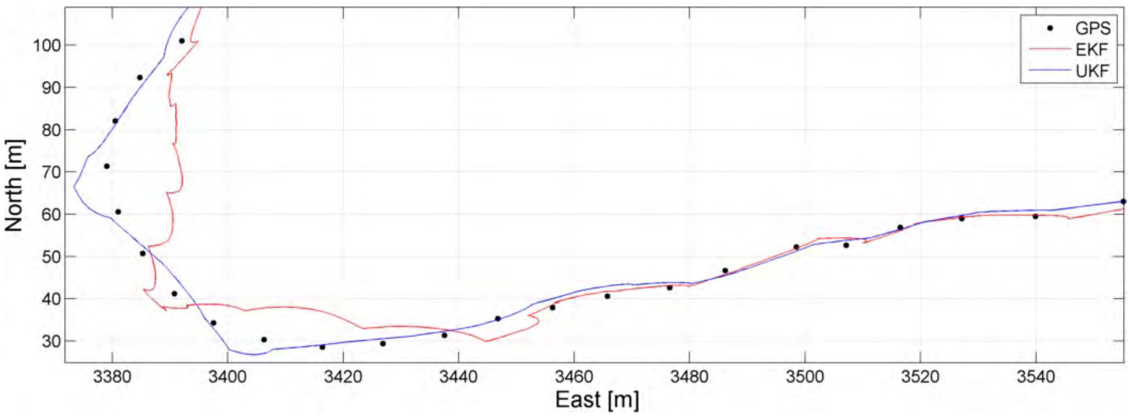

Figure 7. Position NE

The Fig. 6 and Fig. 7 show strong dynamic paths. Both filters do not have any divergence of solution, however, there is less degradation of the estimate given by the filter more robust UKF presented in such paths. This is corroborated by

ISSN 2176-5480

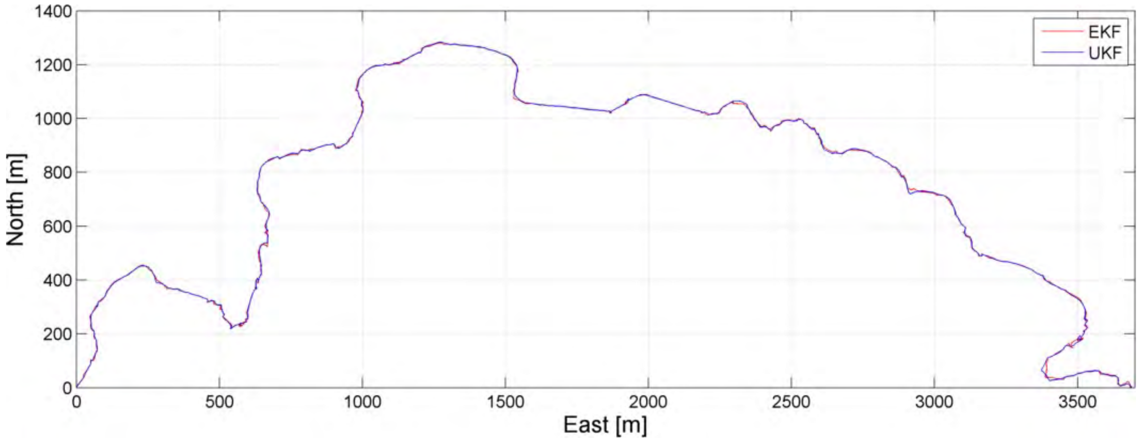

Figure 8. Position NE

finding the root mean square error between the averages for the GPS position and estimated, Eq. (20), for each of the filters in the full path.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{20}$$

Where y_i GPS Data and $\hat{y}_i$ Estimated data.

Table 2. Root-Mean-Square Error RMSE

State	*RMSE EKF*	*RMSE UKF*
PositionNorth	10.0	8.9
Position East	5.5	5.1
Position Down	7.0	5.5

ISSN 2176-5480

6. CONCLUSIONS

The algorithms EKF, UKF used, allowed the fusion of data from an Inertial Navigation System (INS) with MEMS technology and data of global positioning system (GPS). The results obtained show that: The navigation system that has as core the UKF filter presents lower standard deviation and RMSE for each of the estimated state variables.Therefore, the results of simulation tests establish that the UKF filter has a higher degree of accuracy with a smaller standard deviation in the estimated states by EKF filter also has a better dynamic performance to strong nonlinearities given by the proposed model, therefore, this system is a good choice for use as a navigation system in low-cost aerial platforms and small size such as unmanned aerial vehicles UAVs for civil use.

7. ACKNOWLEDGEMENTS

The authors would like to thank Colciencias and Universidad Militar Nueva Ganada for financing this proyect.

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