Real Time Sensor Fusion for Micro Aerial Vehicles using Low cost Systems

Sanketh.Ailneni, Sudesh.K.Kashyap, N.Shantha Kumar
National Aerospace Laboratories (CSIR-NAL)
Bangalore, 560017, Karnataka, India
Email: sanketh.ailneni@gmail.com, sudesh@nal.res.in, nskumar@nal.res.in

Abstract - Novel sensor fusion architecture is proposed to provide complete navigational solution for micro aerial vehicles (MAV) using low cost sensors and micro controller. The approach uses a nonlinear complementary filter (NCF) to estimate direction cosine matrix (DCM), the estimated attitude and heading from DCM are used in turn to predict MAV position in North and East direction and a two state extended Kalman filter (EKF) based estimator to estimate altitude and vertical speed. The emphasis is on the EKF estimator which is driven by only one measurement without losing observability. The fusion algorithm uses tri-axial accelerometers, rate gyroscopes & magnetometers, pressure altitude and global positioning system (GPS) measurements. The proposed architecture is computationally less intensive and is implemented for real time application on a low cost microcontroller based autopilot board to provide the complete navigational solution at 50 Hz.

Keywords— Sensor Fusion, Non-linear Complementyr Filter, Direction Cosine Matrix, Extended Kalman Filter, MEMS.

I. Introduction

Navigation has long been a subject dealing with multisensor integration. Over the past few decades, precise navigation guidance and control of a micro aerial vehicle (MAV) has been a challenge with given low cost Micro-Electro-Mechanical Systems (MEMS) and limited computational capabilities onboard. For this reason, it has been a usual practice in the micro aerial vehicle community to operate the inner-loop control at higher frequency when compared to outer-loop guidance, based on the availability of navigational state estimates available onboard. The design of nonlinear filters to provide navigational state estimates is a very challenging problem that has received a considerable amount of attention in the literature over the past few decades [1], [1]. EKF, Unscented Kalman Filter (UKF) and State-Dependent Riccati Equation (SDRE) fusion algorithms are well accepted estimation techniques for non linear systems [3], [4], [5]. One of the limitations of these algorithms is the large computational requirements, which demand for high end microcontrollers and causing the overall pricing of the autopilot board go high. Thus providing a low cost accurate solution is a challenging design consideration. Of numerous attempts made Mahony.et.al for the first time has provided one such solution for attitude and heading estimation by posing kinematics directly on the special orthogonal *SO* (3) group driven by reconstructed attitude and angular velocity measurements [6] [7]. Such nonlinear observers have strong robustness performance dealing with gyroscopic bias estimation in real time [8].

Typical sensor suit for unmanned systems comprise of inertial measurement unit (IMU) and GPS which operate at different frequencies. Fusion of these sensors to provide navigational state estimates is usually addressed as INS/GPS fusion. [9], [10] and [11] present various INS/GPS fusion architectures for unmanned aerial vehicles. All this fusion architectures are driven by Kalman filter based estimation techniques which becomes hard to realize in real time on low cost micro controllers without floating point unit operations.

This paper presents novel sensor fusion architecture to provide navigational state estimates of a MAV at 50 Hz. NCF based deterministic nonlinear observer is used to estimate attitude, heading and slowly time varying gyroscopic bias. A simple dead reckoning has been carried out to update horizontal GPS position (latitude and longitude) information between GPS reports. The vertical channel information from GPS is not usually reliable thus stating a need to estimate altitude and vertical speed accurately. A 2 state EKF based estimation is carried out by fusing IMU data with the barometer to estimate altitude and vertical speed, while estimated vertical speed is in turn used to drive the NCF. The proposed fusion architecture has been validated against the flight test data obtained from an open source autopilot board. Furthermore, the architecture has been implemented real time on in-house developed autopilot board comprising of low cost systems. To the best of our knowledge, this is the first paper addressing a novel sensor fusion for micro aerial vehicles considering the computational limitations on low cost microcontrollers.

The rest of the paper is structured as follows: Section II presents sensor fusion methodologies, their state equations and finally proposes fusion architecture to provide navigational state estimates at 50 Hz. Section III presents evaluation of fusion architecture in Software in the Loop Simulation (SILS) setup for 6 DOF model of a MAV. Section IV presents fusion architecture validation using flight test data obtained from an open source autopilot board. Section V shows the performance of proposed fusion architecture onboard an in house developed autopilot board.

II. Sensor Fusion

Typical MEMS sensor suit on a MAV comprise of IMU (tri-axial accelerometers, gyroscopes and Magnetometer), MTK 3329 GPS and barometer, which are operated at different frequencies. Estimator and sensor fusion algorithms to estimate orientation, position, course over ground, vertical

978-1-4799-7862-5/15/$31.00 © 2015 IEEE

speed and altitude is primary requirement for any MAV. This section presents detailed state estimator kinematic equations and sensor fusion methodologies employed.

A. Non-linear Complementary Filter (NCF)

Direction cosine matrix (DCM) is a rotation matrix that describes the orientation of one coordinate system with respect to another. The basic idea is that the rotation matrix that defines the orientation of an aircraft can be maintained by integrating the nonlinear differential equation that describes the kinematics of the rotation. The attitude kinematics is represented in DCM form and nonlinear complementary filter is explicitly implemented on *SO* (3) formed by DCM [6]. A detailed *Lyapunov* stability analysis and the robustness characteristics of such a nonlinear observer can be found in [7] & [10].

$$
\begin{aligned}
&\dot{\Re}_B^I = \Re_B^I\left(\left(\Omega - b_{skew}\right) + k_p\left(y_m\right)_{skew}\right);\\
&\dot{b} = -k_I y_m\\
&y_m = \left(Y_{err} + RP_{err}\right)\\
&Y_{err} = \psi_m^B \times \Re_I^B \psi_m^I\\
&RP_{err} = \left(\int \Re_B^I a_m^B\right) \times \left(\int \begin{bmatrix} 0\\ 0\\ g \end{bmatrix} + d\vec{V}_I\right)\\
&where\ \Omega = \begin{bmatrix} 0 & -r_m & q_m\\ r_m & 0 & -p_m\\ -q_m & p_m & 0 \end{bmatrix}
\end{aligned}
\quad \textbf{(1)}
$$

Where, $\times$ represents cross product, $\Re_B^I = \left(\Re_I^B\right)^T \in SO(3)$ relative orientation of body frame with respect to the inertial frame, k_p k_I represent filter constants, Y_{err} represents the error in yaw rate, RP_{err} represent error in roll rate and pitch rate, b represent vector of slowly time varying gyroscopic bias estimates, a_m^B represent accelerometer measurement vector ($a_{x_m}, a_{y_m}, a_{z_m}$) in body frame, $\vec{V}_I = [v_n \quad v_e \quad v_d]$ represent inertial velocities in North-East-Down (NED), p_m q_m r_m represent tri-axial gyroscope measurements, b_{skew} & $\left(y_m\right)_{skew}$ represent skew symmetric matrix formed by the vectors b & y_m respectively. The integral in (1) is implemented between the IMU reports. The inertial velocities in north and east are obtained as:

$$
\begin{aligned}
v_n &= \left|V_g\right|\cos\left(\chi_m\right)\\
v_e &= \left|V_g\right|\sin\left(\chi_m\right)
\end{aligned}
\quad \textbf{(2)}
$$

And v_d is obtained from an EKF based estimator, which will be presented in next section, while v_n & v_e between the GPS reports are obtained from simple Euler integration discussed in next section, while V_g and χ_m in (2) represent ground speed and course over ground measurements from GPS.

Note: *The constant bias components of accelerometers and gyroscopes can be calibrated off-line and removed from the output of the sensors. Hence, the effects of constant bias on the output of the sensors are neglected.*

B. Dead reckoning between GPS update

GPS update rate is polled usually at 1 Hz to 5 Hz based on the sensor specification, which are 10 to 50 times lesser sampling rate compared to IMU. Thus to have the outer loop guidance (vector field approach) at 50 Hz it is necessary to predict the horizontal (navigation) position and course over ground between GPS reports. This can be achieved by integrating the inertial navigation mechanization equations [12] [14] in inertial frame at every IMU update.

$$
\begin{aligned}
&\begin{bmatrix} \dot{\lambda}\\ \dot{\mu} \end{bmatrix} = \begin{bmatrix} \dfrac{v_n}{R_M + h}\\ \dfrac{v_e}{\left(R_N + h\right)c_\lambda} \end{bmatrix}\\
&\begin{bmatrix} \dot{v}_n\\ \dot{v}_e \end{bmatrix} = \Re_B^I \begin{bmatrix} a_{x_m}(\mathrm{t})\\ a_{y_m}(\mathrm{t})\\ a_{z_m}(\mathrm{t}) \end{bmatrix} + \begin{bmatrix} \dfrac{v_n v_d}{R_M + h} - \dfrac{v_e^2 t_\lambda}{R_N + h}\\ \dfrac{v_e\left(v_d + v_n t_\lambda\right)}{R_N + h} \end{bmatrix}
\end{aligned}
\quad \textbf{(3)}
$$

Where λ, μ, h denote position (latitude, longitude and altitude), v_n, v_e, v_d denote velocities, R_M , R_N respectively denote the Earth's meridional and normal radius of curvature, $R_0 \approx 6378137m$, $e = 0.081819190843$ denote the Earth's radius and eccentricity respectively, the expressions for R_M and R_N are given as:

$$
R_M = R_0 \frac{\left(1 - e^2\right)}{\left(1 - e^2 s_\lambda^2\right)^{\frac{3}{2}}};\, R_N = \frac{R_0}{\left(1 - e^2 s_\lambda^2\right)^{\frac{1}{2}}} \quad \textbf{(4)}
$$

A simple first order Euler integration is performed on (3) between the GPS update for every IMU update, i.e. integrating accelerations to obtain velocities in north and east and in turn integrating these velocities to obtain horizontal position (λ, μ). A typical first order Euler integration [13] for x being a state vector and sample time '*dt*' is given by:

$$
x_{update} = x_{prev} + \dot{x}dt \quad \textbf{(5)}
$$

Where, x_{prev} represents previous update and $\dot{x}$ represent state kinematics. Further the updated course over ground (χ) is obtained as:

$$\chi = \tan^{-1}\left(\frac{v_{e_{updated}}}{v_{n_{updated}}}\right) \quad \textbf{(6)}$$

C. Extended Kalman Filter (EKF)

An observable, nonlinear dynamical system where the process dynamics is continuous and the measurement is discrete, as

$$\dot{x}(t) = f(x(t)) + \Gamma_c w(t)$$
$$z_k = h(x_k) + v_k \quad \textbf{(7)}$$

Where, $x \in \mathbb{R}^n$ denotes the n-dimensional state vector of the system. $f(.): D_x \rightarrow \mathbb{R}^n$ is a finite nonlinear mapping of system states to system inputs, $z_k \in D_z \subset \mathbb{R}^p$ denotes the p-dimensional system measurement, $h(.): D_x \subset \mathbb{R}^n \rightarrow \mathbb{R}^p$ is a nonlinear mapping of system states to output. $\Gamma_c \in \mathbb{R}^{n \times w}$ Denotes the continuous process noise scaling matrix, $w \in D_w \subset \mathbb{R}^w$ denotes the w-dimensional random process noise, $v \in D_v \subset \mathbb{R}^v$ denote the v-dimensional random measurement noise. The process and measurement noise are assumed to be zero mean, band-limited, AWGN (additive white Gaussian noise) processes given by

$$E\left[w(t)w(t-\tau)^T\right] = Q\delta(t-\tau) = \begin{cases} Q \rightarrow t = \tau \\ 0 \rightarrow t \neq \tau \end{cases}$$
$$E\left[v_k v_j^{\ T}\right] = R_k \delta_{kj} = \begin{cases} R_k \rightarrow k = j \\ 0 \rightarrow k \neq j \end{cases} \quad \textbf{(8)}$$

Where Q is the continuous process noise covariance, R_k is the discrete measurement noise covariance, $\delta(.)$ is the Dirac delta function and δ_{kj} is the Kronecker delta function. The random variables w and v_k are uncorrelated and are denoted as $w \sim \mathbb{N}(0 \ \ Q)$ & $v \sim \mathbb{N}(0 \ \ R_k)$ respectively. The EKF prediction and correction formulation for such a system is given as [15], [16] [17]:

$$\hat{x}(t) = \hat{x}_{k-1}, P(t) = P_{k-1}$$
$$\dot{\hat{x}}(t) = f(\hat{x}(t))$$
$$\dot{P}(t) = F(t)P(t) + P(t)F^T(t) + \Gamma_c Q \Gamma_c^{\ T}$$
$$K_k = P_k^{\ -} H_k^{\ T}\left(H_k P_k^{\ -} H_k^{\ T} + R_k\right)^{-1}$$
$$P_k^{\ -} = P(t) + \dot{P}(t)\Delta t$$
$$\hat{x}_k = \hat{x}_k^{\ -} + K_k\left(z_k - z_k^-\right),$$
$$\hat{x}_k^- = \hat{x}(t) + \dot{\hat{x}}(t).\Delta t, z_k^- = h\left(\hat{x}_k^-\right) \quad \textbf{(9)}$$
$$P_k = (I - K_k H_k)P_k^-$$

Where the initialized state estimate and the initialized state error covariance matrix are $\hat{x}(0) = \hat{x}_0 = E\left[x(0.\Delta t)\right] = E\left[x_0\right]$ and $P(0) = P_0 = E\left[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\right]$.

<u>*2 state EKF*</u>: The altitude and vertical speed data available from GPS is not reliable, thus stating a need to estimate altitude and vertical speed which play a crucial role in guidance and control of MAV. This is achieved by fusing the IMU, GPS and barometer information, which are operated at different frequencies using EKF based suboptimal estimator [1]. The process model for EKF is obtained from inertial navigation state kinematics and is given as [12]:

$$\underbrace{\begin{bmatrix} \dot{h} \\ \dot{v}_d \end{bmatrix}}_{x} = \underbrace{\begin{bmatrix} -v_d \\ \Re_B^I(3,:)a_m^B + \dfrac{-v_d^2}{R_M + h} - \dfrac{v_e^2}{R_N + h} + g \end{bmatrix}}_{f} \quad \textbf{(10)}$$

Where, 'g' denote the acceleration due to gravity. The measurement model for EKF is altitude measurement obtained from barometer at 5 Hz. The Jacobian entries $F(\mathrm{t}) = \dfrac{\partial f}{\partial x(t)}\Big|_{x(\mathrm{t}) = \hat{x}(\mathrm{t})}$, $H_k = \dfrac{\partial h}{\partial x_k}\Big|_{x_k = \hat{x}_k^-}$ and Γ for the EKF are given as:

$$F = \begin{bmatrix} 0 & -1 \\ \dfrac{v_d^2}{(R_M + h)^2} + \dfrac{v_e^2}{(R_N + h)^2} & \dfrac{-2v_d}{(R_M + h)} \end{bmatrix}$$
$$\Gamma = \begin{bmatrix} zeros(1,3) \\ \Re_B^I(3,:) \end{bmatrix} \quad \textbf{(11)}$$
$$H = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

The process noise covariance Q and measurement noise covariance R is given as:

$$Q = \sigma_{a_m}^2 I_{3\times 3} \ ; \mathrm{R} = \sigma_{baro}^2 \quad \textbf{(12)}$$

Where I represent identity matrix and σ_{a_m}, σ_{baro} represent standard deviation of accelerometer and barometer measurements.

<u>*Observability*</u>: To study the observability of the 2 state EKF estimator, we use H_k and *F(t) to construct observability index(I_b).*

$$I_b = rank\begin{bmatrix} H \\ HF \end{bmatrix} = rank\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} = 2 \quad \textbf{(13)}$$

Thus it can be seen that the system is observable irrespective of the entries in Jacobian matrix $F(t)$.

D. Novel Architecture

The proposed sensor fusion architecture for a micro aerial vehicle using low cost systems is shown in Fig. 1. IMU and GPS measurements are used to estimate attitude, heading and rotation matrix ($\Re_B^I$), while a 50 Hz update of horizontal position (λ, μ) and course over ground (χ) is obtained by a simple first order Euler integration of inertial navigation equations. Thus obtained 50 Hz update is in turn used to fuse barometer measurement to obtain vertical speed (v_d) and altitude (h). Further, the updated horizontal velocities (v_n, v_e) and estimated vertical speed is in turn used in NCF based attitude and heading estimator.

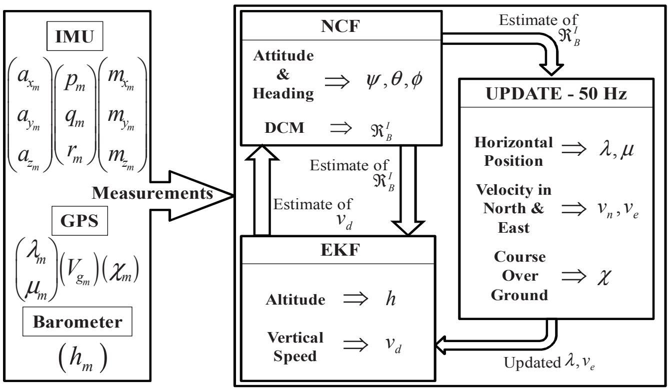

Fig. 1: Schematic of proposed sensor fusion architecture

The architecture shown in Fig. 1 is computationally less intensive and can be implemented in real time on a low cost microcontroller operating at clock cycle of 24 MHz. The EKF estimator is possible to realize because of implementing a lower order system which is driven by single measurement leading to '*no matrix inversion*' during Kalman gain computation.

III. SOFTWARE IN THE LOOP SIMULATIONS

A 6 DOF model of 1m span MAV [20] is used for the simulation study. The inner & outer control loops are of proportional-integral-derivative type equipped with saturation to control surfaces [18]. The performance characterization of the proposed sensor fusion architecture is carried out in closed loop simulation environment, where the system dynamics and the senor dynamics are simulated in 6 DOF model of MAV. This section presents mathematical model for sensor simulation and few closed loop simulation results.

A. Sensor Mathematical model

Typical MEMS sensors are usually corrupted with noise, constant and time varying bias components, thus it's inherent to model them in simulation and account for them in sensor fusion. The tri-axial gyroscopes (p_m, q_m, r_m), tri-axial accelerometers ($a_{x_m}, a_{y_m}, a_{z_m}$), GPS and barometer measurements are assumed to be modeled as shown below:

$$\begin{aligned}
p_m(t) &= p(t) + b_p(t) + w_p & \lambda_m(t) &= \lambda(t) + v_\lambda \\
q_m(t) &= q(t) + b_q(t) + w_q & \mu_m(t) &= \mu(t) + v_\mu \\
r_m(t) &= r(t) + b_r(t) + w_r & V_{g_m}(t) &= V_g(t) + v_{V_g} \\
a_{x_m}(t) &= a_x(t) + w_{a_x} & \chi_m(t) &= \chi(t) + v_\chi \\
a_{y_m}(t) &= a_y(t) + w_{a_y} & & \\
a_{z_m}(t) &= a_z(t) + w_{a_z} & h_m(t) &= h(t) + v_h
\end{aligned} \quad \textbf{(14)}$$

Where, $\left(p(t), q(t), r(t)\right)$; $\left(a_x(t), a_y(t), a_z(t)\right)$ are the true values of the angular velocities & linear accelerations; $\left(b_p(t), b_q(t), b_r(t)\right)$ are the *slowly time varying* bias components modelled as summation of *rate random walk* and the *correlated* noise (modelled as first order Gauss Markov process); $\left(w_p, w_q, w_r\right)$ & $\left(w_{a_x}, w_{a_y}, w_{a_z}\right)$ denote the error due to *sampling noise* which are typically modelled as zero mean, band-limited, additive white Gaussian noise.

B. Simulation Senario & Results

For simulation, the sensor noise parameters are given as follows: $\sigma_{p,q,r} = 0.1$ °/s, $\sigma_{bp,q,r} = 0.1$ °/s, $\sigma_{ax,ay,az} = 0.1$ m/s^2. The time constant for the *correlated* noise process is chosen as $\tau = 100$ s. The GPS noise parameters are given as $\sigma_{\lambda,\mu} = 6 \times 10^{-5}$ *deg*, which approximately translates to 10 *m* error in the x and y axes. The update rate of the IMU is at 50 Hz and that of the GPS is at 5 Hz. The filter constants for simulation are as follows: $k_p = 0.1$, $k_I = 0.01$, $\sigma_{a_m} = 0.005$ m/s^2, $\sigma_{baro} = 5m$. The simulation trajectory is shown in Fig. 2, which includes level flight trajectory with coordinated turn maneuvers at the waypoints. Closed loop simulations are carried out and the state estimates from proposed sensor fusion architecture are compared against the true system states to compute the estimation error. Fig. 3 shows the error in state estimates from NCF and 2 state EKF. It is observed that the estimation error in Euler angles is within ± 2 *degrees*, while altitude estimation error is ± 1 m and vertical speed estimation error is within ± 1 m/sec. Thus the proposed sensor fusion is robust in estimating MAV states to perform closed loop guidance.

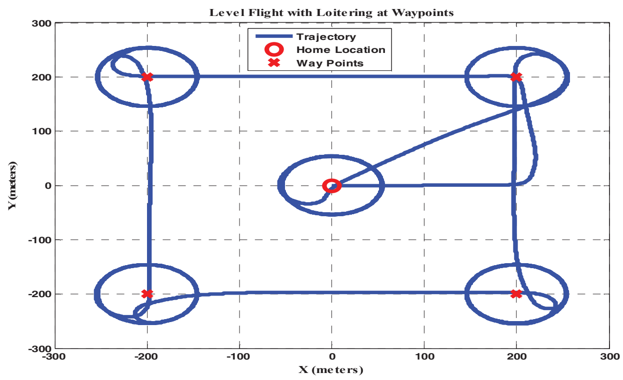

Fig. 2: Simulated trajectory in SILS

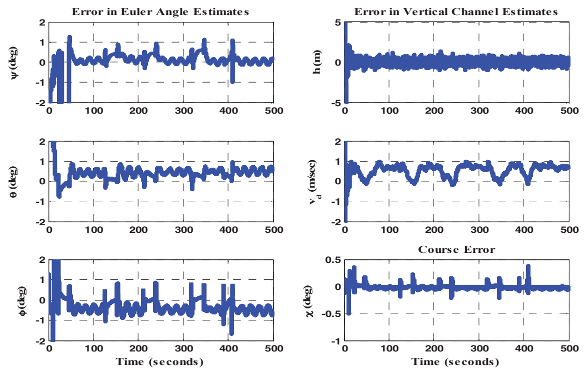

Fig. 3: Error in State Estimates from Sensor Fusion Architecture in SILS

IV. VALIDATION USING FLIGHT TEST DATA

A commercially off the shelf (COTS) autopilot board [19] is used to collect sensor data (IMU, GPS and barometer) on a micro aerial vehicle. The collected flight test data is used to validate the proposed sensor fusion architecture by fusing the available sensor data offline in MATLAB/SIMULINK environment. Fig. 4 shows the performance of NCF estimator through Euler angle estimates. Fig. 5 shows a 50 Hz update in position obtained from the proposed sensor fusion architecture. Fig. 6 shows the performance of the 2 state EKF, it is seen that the altitude and vertical speed estimates are comparable with the reference data obtained from open source autopilot board.

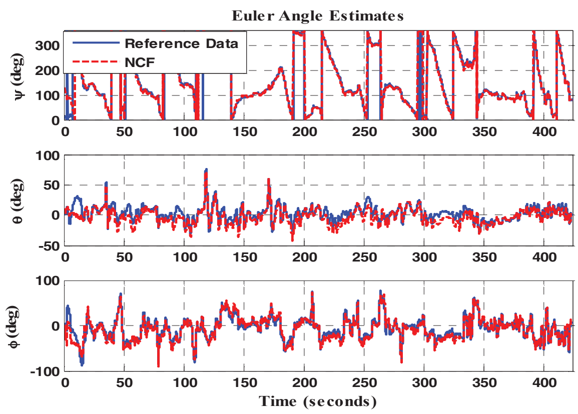

Fig. 4: NCF estimates validation against flight test data

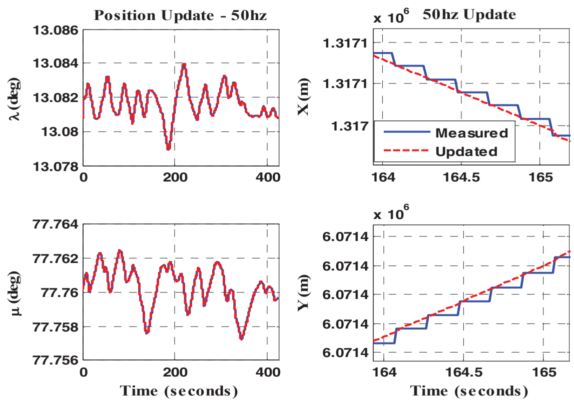

Fig. 5: First order Euler integration between GPS update

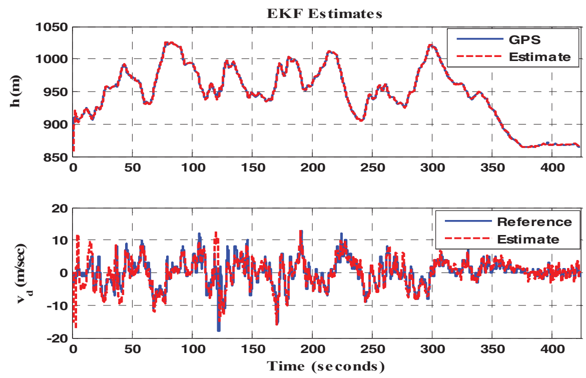

Fig. 6: Performance of 2 state EKF

V. FLIGHT TEST RESULTS

Flight tests are carried out on in-house designed MAV [20] using in-house autopilot board. The autopilot has a low cost microcontroller with cycle speed of 24 MHz with various onboard sensors. The filter constants for NCF are k_p= 0.1, k_I= 0.01. The EKF tuning parameters, process noise covariance matrix Q and measurement covariance matrix R are choose based on the sensor specifications.

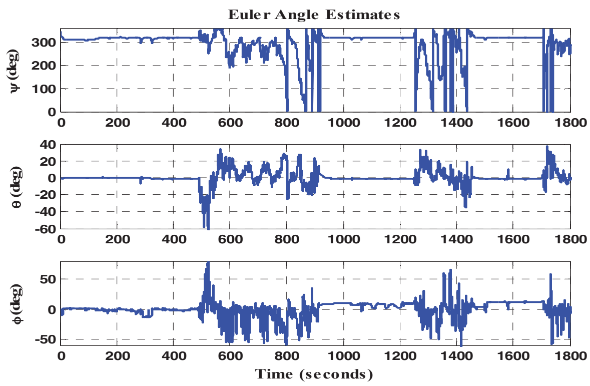

Fig. 7: Euler angle estimates onboard low cost microcontroller

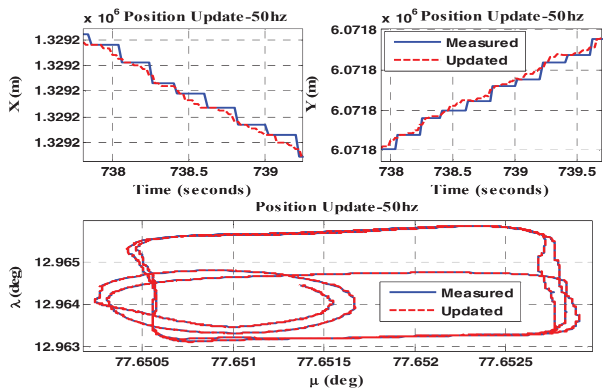

Fig. 8: MAV localization performance using Euler integration

Fig. 7 shows the Euler angle estimates obtained from non linear complementary filter. Fig. 8 & Fig. 9 shows a 50 Hz update in position and course over ground obtained during flight tests from the sensor fusion architecture. Fig. 10 shows the altitude and vertical speed estimates obtained from 2 state EKF onboard a low cost micro controller. During flight tests as there is no reference data available for comparison only the estimates are presented in Fig. 7 & Fig. 10, while the position and course update in Fig. 8 & Fig. 9 is cross compared against the GPS measurements.

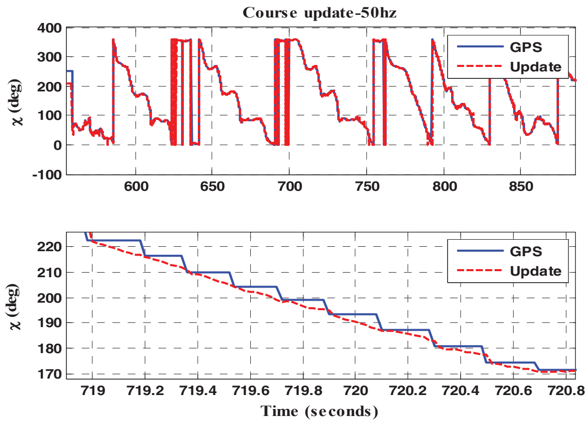

Fig. 9: 50 Hz update of Course over ground

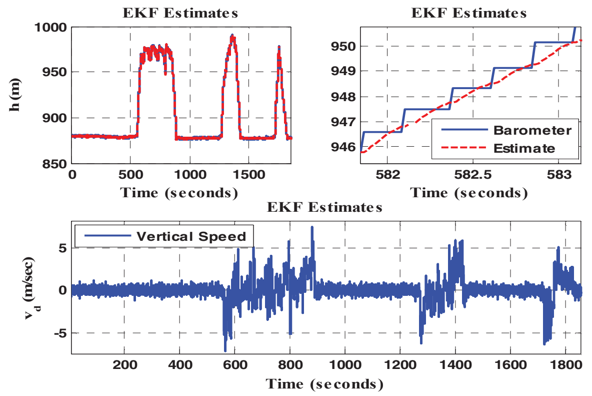

Fig. 10: Performance of 2 state EKF on low cost microcontroller

VI. CONCLUSION

Novel sensor fusion architecture is presented to estimate attitude, heading, altitude and vertical speed of a micro aerial vehicle. The fusion architecture is designed to implement on a low cost micro controller to provide complete real time navigational solution. The proposed fusion algorithms are evaluated in closed loop simulation setup formed by 6 DOF model of a MAV. Furthermore, the fusion architecture is validated in flight on low cost autopilot board onboard MAV.

APPENDIX

In (9) the Kalman gain '*K*' computation has the term $\left(H_k P_k^- H_k^T + R_k\right)^{-1}$, which is usually computationally intensive while implementing on a microcontroller. As the proposed EKF is of a lower order system where, H_k & R_k are as presented in (11) & (12). By simple math it is seen that the inverse term is a single number, which leads to no matrix inversion thus less computational load on the microcontroller.

ACKNOWLEDGMENT

The authors express their sincere gratitude to the MAV Autopilot development team & Flight test team at CSIR-NAL headed by Dr G.K. Singh & Dr C.M. Ananda.

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