Innovative Systems Design and Engineering www.iiste.org
ISSN 2222-1727 (Paper) ISSN 2222-2871 (Online)
Vol 2, No 5, 2011

INS/GPS Based State Estimation of Micro Air Vehicles Using Inertial Sensors

Sadia Riaz (Corresponding author)
Department of Mechanical Engineering, NUST College of E&ME,
National University of Sciences and Technology.
PO Box 46000, Rawalpindi, Pakistan
Tel: 0092-334-5444650 E-mail: saadia-riaz@hotmail.com

Atif Bin Asghar
Department of Mechanical Engineering, NUST College of E&ME,
National University of Sciences and Technology.
PO Box 46000, Rawalpindi, Pakistan
Tel: 0092-334-5212686 E-mail: atifpk78@hotmail.com

Abstract

The most attractive and attention seeking topic of aerospace world is Micro Air Vehicle (MAV) which broadly speaking it can be categorized as significantly smaller aircraft than conventional aircrafts. Micro Air Vehicles can be divided as autonomous, semi-autonomous and remote controlled flying machines which can be fixed wing MAV, Flapping wing MAV and rotary wing MAV. One of the crucial problems regarding Micro Air Vehicle is its stability which is basically concerned with the guidance, navigation and control. State Estimation is an important aspect of navigation and this paper deals with the state estimation problem of micro Air vehicle. Inertial sensors are being used including MEMS Gyro, MEMS Accelerometer, Magnetometer and GPS in Inertial Measurement Unit (IMU) and three Discrete Time Extended Kalman Filter Schemes have been used for the state estimation purpose. Trajectory and required data is recorded in Flight Simulator and MATLAB has been used for the simulations. A comprehensive parametric study is carried out and results are analyzed and briefly discussed.

Keywords: Micro Electro Mechanical System (MEMS), Micro Air Vehicle (MAV), Measurement Covariance Matrix, Process Covariance Matrix

Nomenclature

P_N	Inertial North Position of MAV
P_E	Inertial East Position of MAV
W_N	Wind from North
W_E	Wind from East
V_{air}	Total Airspeed
p	Angular Rate about x-axis
q	Angular Rate about y-axis
r	Angular Rate about z-axis
ϕ	Roll Angle
θ	Pitch Angle
ψ	Yaw Angle

$\bullet$	As superscript shows the rate of change
m_{ox}	Northern Magnetic Field Component
m_{oy}	Eastern Magnetic Field Component
m_{oz}	Vertical Magnetic Field Component
Q	Process Covariance Noise Matrix
R	Process Covariance Noise Matrix

1. Introduction

Bird flight is a fascination of human being for very long and today researchers and scientists have achieved this fascination as the real world application. The term Micro Air Vehicles [1, 2] (MAVs) is used for a new type of remotely controlled, semi-autonomous or autonomous aircraft that is significantly smaller than conventional aircrafts. The DARPA [3] (Defense Advanced Research Project Agency) has provided the specifications for Ornithopter[4] (Flapping Micro Air Vehicle) and according to that specification the flying machines with the size of fifteen centimeters and under the weight of hundred grams are classified as Micro Air Vehicle. The flying machines which copies the bird flight is named as Ornithopter and the one which copies the insect Flight is known as Entomopter. The primary concerns regarding these airborne entities are size, weight, sensors, communication and the computational power.

The most sensitive issue regarding Micro Air Vehicles (MAVs) is accurate navigation[5]of this mini vehicle, because accurate navigation is first step for precise control of it. State Estimation[6] of the vehicle through INS/GPS based system is very helping in this regard and highly studied in the past decades. For Micro Air Vehicles (MAVs), the proposed Inertial Measurement System[7, 8, 9, 10] (INS) consists of MEMS Gyro, MEMS magnetometer, MEMS accelerometer integrated with GPS[11, 12]. In this paper, three Extended Kalman Filter (EKF) schemes have been simulated and interpreted. Flight data has been recorded with the help of Flight Simulator and then the Algorithm is implemented in MATLAB [13]. Single Stage Discrete Time Extended Kalman Filter, Two Stage Discrete Time Extended Kalman Filter [14, 15] and Three Stage Discrete time Extended Kalman Filter has been applied to the INS/GPS based system. In this paper an extensive study has been carried out and the result of different inertial sensors is studied against variable velocity of Micro Air Vehicle (MAV).

2. Mathematical Modeling of INS/GPS based State Estimation

Mathematical Modeling of INS/GPS based state estimation is very important for the navigation purpose. Mathematical Modeling of these three filters has been extensively discussed [16] and the implementation of the Extended Kalman filter on the three schemes is explained in detail. INS/GPS based system is considered as a nonlinear system and system is first linearized for the implementation of Discrete Time Extended Kalman Filter Schemes. The major mathematical relationships used are following.

The update of the states is related to the inputs as shown following [17, 18]:

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \\ \dot{P}_N \\ \dot{P}_E \\ \dot{W}_N \\ \dot{W}_E \end{bmatrix} = \begin{bmatrix} p + q\sin\phi\tan\theta + r\cos\phi\tan\theta \\ q\cos\phi + r\sin\phi \\ q\dfrac{\sin\phi}{\cos\theta} + r\dfrac{\cos\phi}{\cos\theta} \\ V_{air}\cos\psi + W_N \\ V_{air}\sin\psi + W_E \\ 0 \\ 0 \end{bmatrix}$$

Sensor Measurements [17, 18] are related to inputs as shown following:

$$h(\hat{x},u) = \begin{bmatrix} \dfrac{V_{air} q \sin\theta}{g} + \sin\theta \\ \dfrac{V_{air}(r\cos\theta - r\sin\theta)}{g} - \cos\theta\cos\phi \\ \dfrac{-V_{air} q\cos\theta}{g} - \cos\theta\sin\phi \\ P_N \\ P_E \\ \sqrt{V_{air}^2 + 2V_{air}(W_N\cos\psi + W_E\sin\psi) + (W_N^2 + W_E^2)} \\ \tan^{-1}\left(\dfrac{V_{air}\sin\psi + W_N}{V_{air}\cos\psi + W_E}\right) \end{bmatrix}$$

3. Cascaded Extended Kalman Filter State Estimation Schemes

In the Single Seven Stage Discrete Time Extended Kalman Filter [18], the state equations which relate body frame rotations to changes in roll, pitch and heading are nonlinear. Letting the states be roll angle and pitch angle, ϕ and θ, and letting angular rates p, q and r and Airspeed Vair be inputs.

Figure 01: Single Seven State Extended Kalman Filter Scheme [19],

Now consider Two Stage Cascaded Extended Kalman Filter Scheme [16]. As the heading update equation uses the same inputs as the Pitch and Roll equations, it is not unnatural to lump them together in the same estimation block. The exclusiveness of the heading state lies in the output equations. There is not a sensor output equation which will relate heading to accelerometer readings, which is why it was convenient to split heading estimation into it's own stage as mentioned earlier. One of the merits of heading and attitude at the same time is that magnetometer information may be beneficial in the estimation of pitch and roll, since no maneuver will upset the earth's magnetic field, as they may the accelerometer readings. And, depending on the attitude and heading of the MAV, projecting pitch and roll onto the magnetic field vector may refine the pitch and roll estimates.

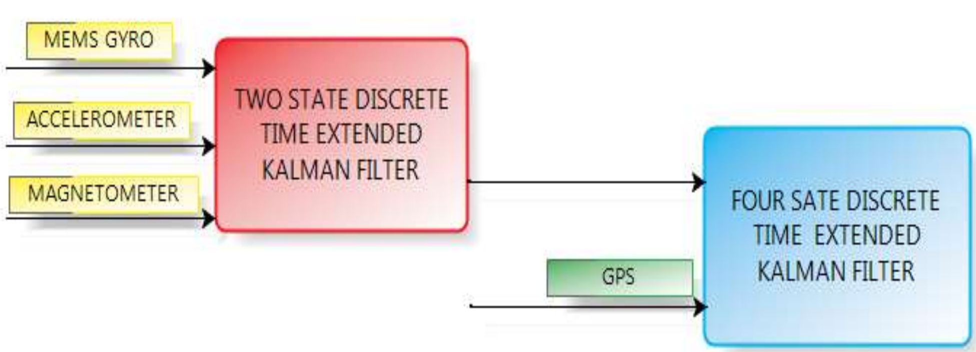


Figure 02: Two stage Cascaded Discrete time Extended Kalman Filter [16].

In three stage Cascaded Extended Kalman Filters [16] work independently, each imparting the information that it estimates to the stage below. This three stage filter assumes the least coupling.

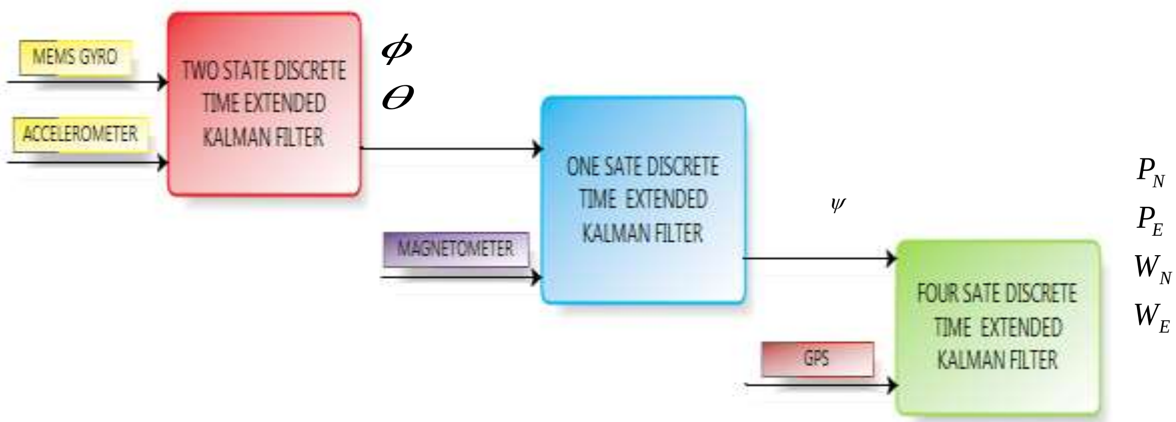
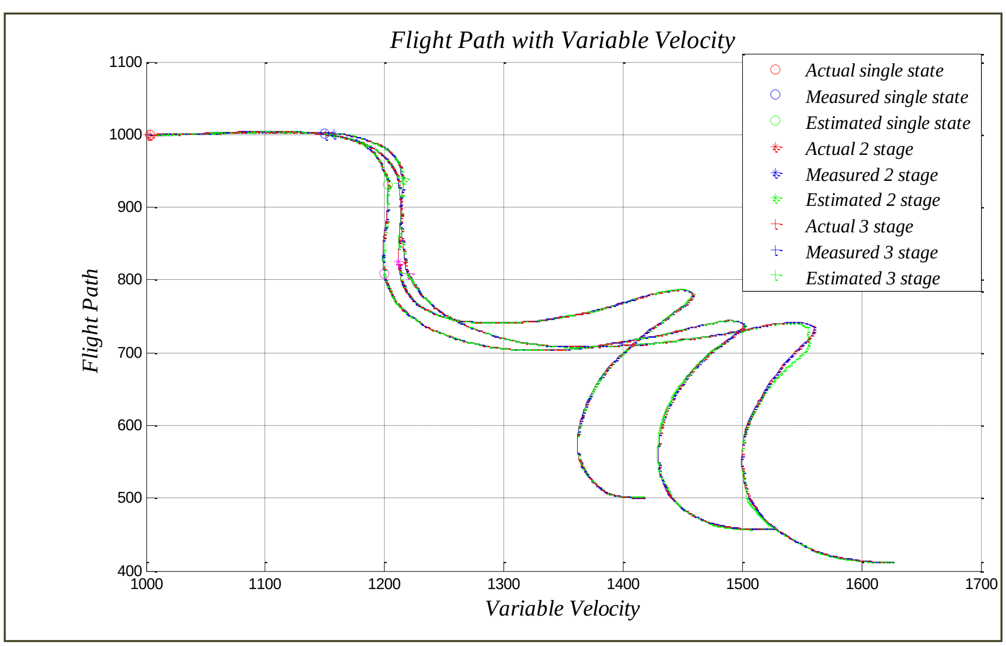


Figure 03: Three stage Cascaded Discrete time Extended Kalman filter [16].

4. Result and analysis

The output of the on-board sensors is mathematically modeled and filtered with the help of Single Seven State Discrete Time Extended Kalman Filtering. The inputs to the filter were angular rates in three directions and velocity of air. The state variables were roll, pitch, yaw, position and wind direction. The measurement variables were acceleration in all 3 directions and components of GPS. Coding was performed to analyze the filter's response to variable inputs and also to compare the three types of filters. Angular rates in three directions (p, q and r) were varied individually in the trajectory and graphs plotted of state variables and measured variables for different types of filters.



The curves shown are that of the flight path of the FMAV through the number of iterations. The values of height as calculated using velocity and the phi angle, the eastern and the northern position were used to calculate a resultant so as to define the flight path of the aircraft. The FMAV flies straight without any changes in its orientation for a while before it takes a deep dive, corresponding to the decrease in pitch angle as seen by the plot of the pitch angle, and then levels up again as the pitch angle levels. The curves in the flight path depict the variations in roll and yaw angle that take place during the flight time, owing to variations in velocity. For each filter, the actual and measured flight path almost overlap while the estimated curve shows some inaccuracies, which is primarily due to the errors involved in several calculations that go into the estimation process. The slight difference in flight paths of the three filters could be associated with the different sensitivity levels of each filter that hinder the estimation of steep gradients.

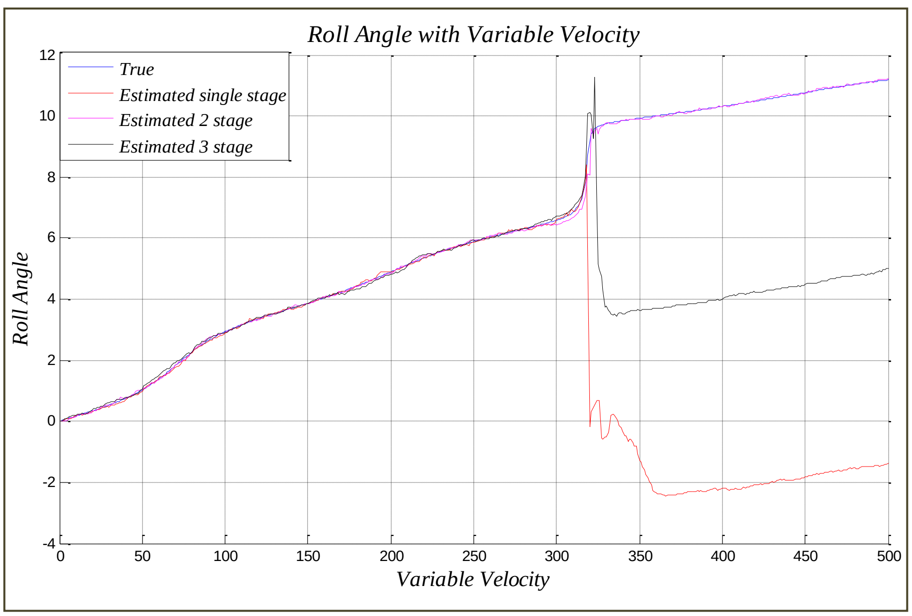


Figure 18: Roll Angle Versus Variable Velocity

The plots shown are those of the state variable phi as it changes with variable velocity. The curves are plotted against the number of iterations, since the variation in velocity was not unidirectional, and was time/iteration dependent. The roll angle keeps on increasing as velocity first decreases and then increases. The variation in roll angle is huge as velocity varies. The variation in roll angle is not owing to variation in velocity; rather it is due to the constant positive angular rate about the x axis (p). The roll rate is high enough for minor changes in velocity to be completely ignored. There is however a surge in roll angle between iterations 300 and 350, owing to a surge in velocity. Comparison between the three types of filters shows that it is the first stage Kalman Filter that is the most accurate. The second and third stage tends to fall apart at certain stages, owing to the increased calculation errors involved with a large number of steps.

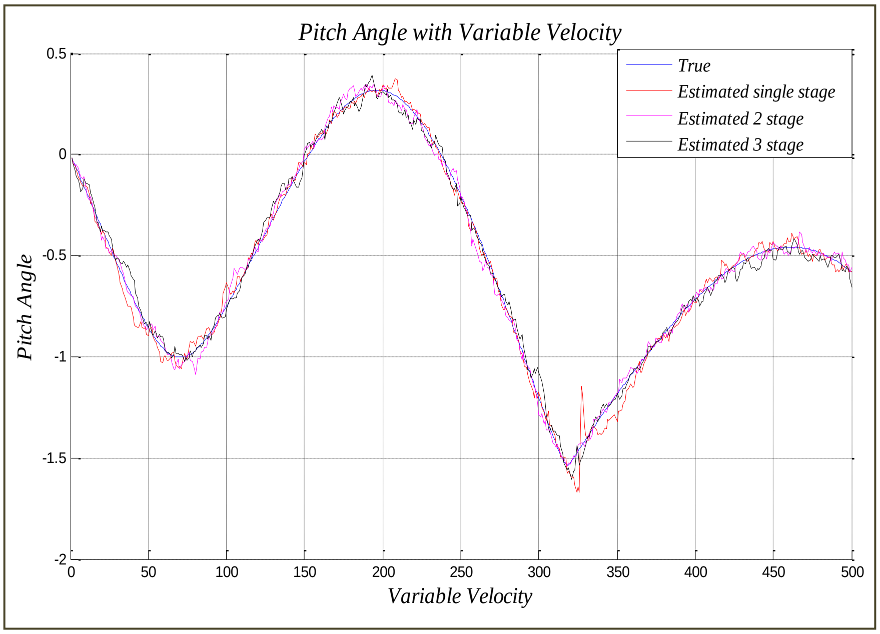


Figure 19: Pitch Angle Versus Variable Velocity

The plots shown are those of the state variable (pitch) as it changes with variable velocity. Pitch angle shows a sinusoidal type curve with trend dependent on how much one factor dominates another. Since the pitch rate is negative as velocity first decreases and then increases, the curves show a varied unsymmetrical sinusoidal pattern. As far as the comparison is concerned, all filters are equally good at tracking the trajectory, though owing to the negative value of pitch angle and nonlinear variation in velocity, the filters show some minor limited oscillations.

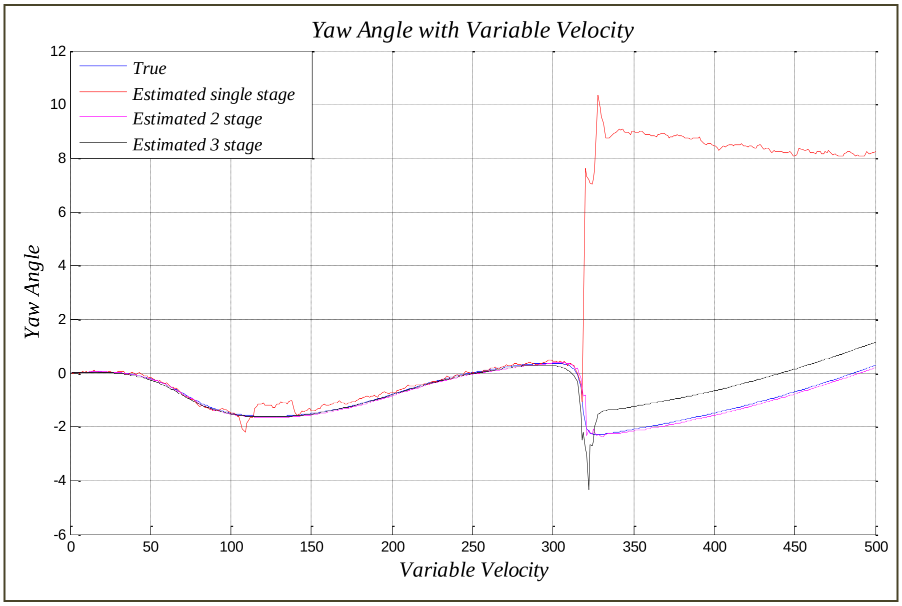


Figure 20: Yaw Angle Versus Variable Velocity

The plots shown are those of yaw angle as it changes with variable velocity. The yaw angular rate, as specified, is not very large and therefore the effect of velocity is more pronounced as compared to any other factor as there were in the case of roll angle and pitch angle. The variation is consistent with the variation of velocity except in iterations where the variation in velocity is not much. All Filters fail to follow the trend very accurately till the end, owing probably to the small value of the yaw angular rate. It is however, the single stage Kalman Filter that follows the trend the most.

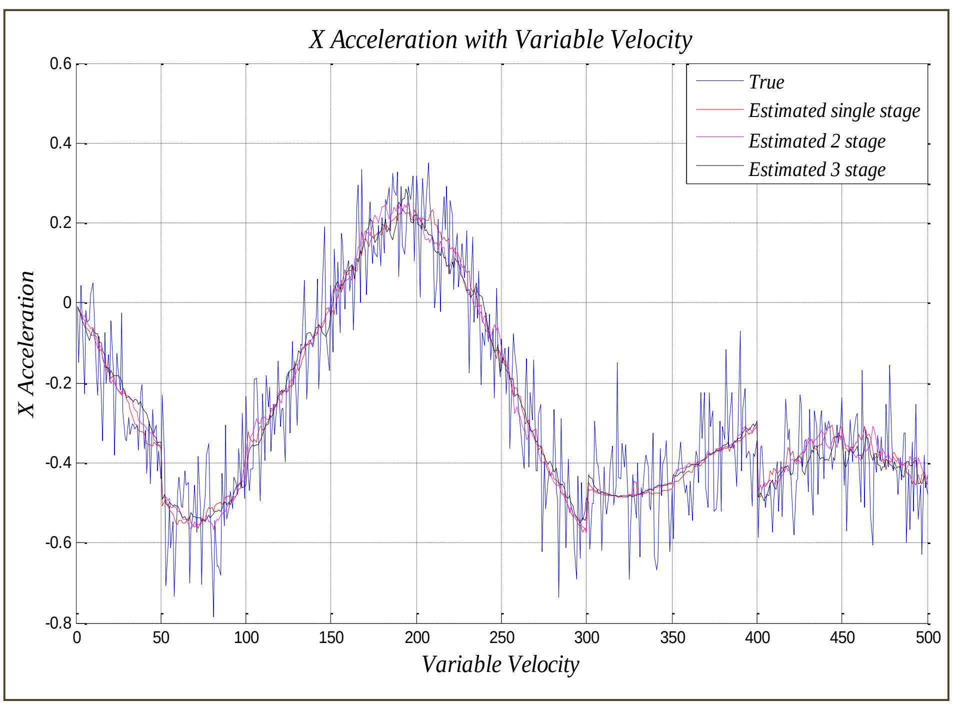


Figure 21: x accelerometer Output Versus Variable Velocity

The plots shown are those of the measurement variable acceleration in the x direction with variable velocity. The trajectory, as plotted shows many oscillations due to the pronounced effect of process and measurement noise. The variation of acceleration is as per the factors that contribute to the value, i.e. linear acceleration and acceleration due to centripetal forces. All filters show good response, as the noise levels are reduced with all filters. The 3rd stage filter is the most inaccurate amongst the three when following the trend, though it is very accurate itself.

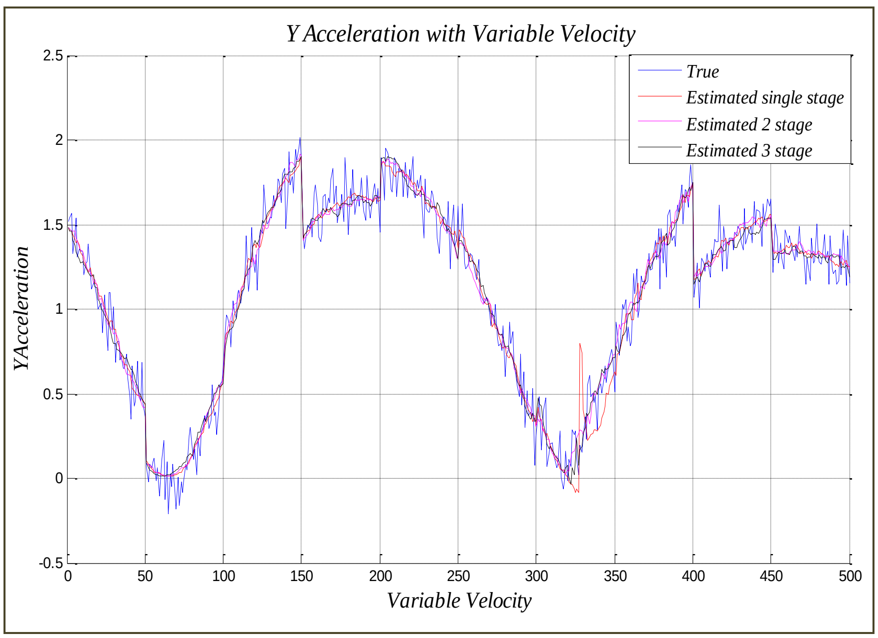


Figure 22: y accelerometer Output Versus Variable Velocity

The plots shown are those of the measurement variable acceleration in the y direction with variable velocity. The trends of acceleration follow the same trend as expected with variation in velocity and the value of pitch angular rate as specified. Noise in the trajectory or actual value is quite a lot owing to the fact that it combines process noise with measurement noise. It is the filters, though, that reduce the noise to a great extent. All the filters are equally good in that respect.

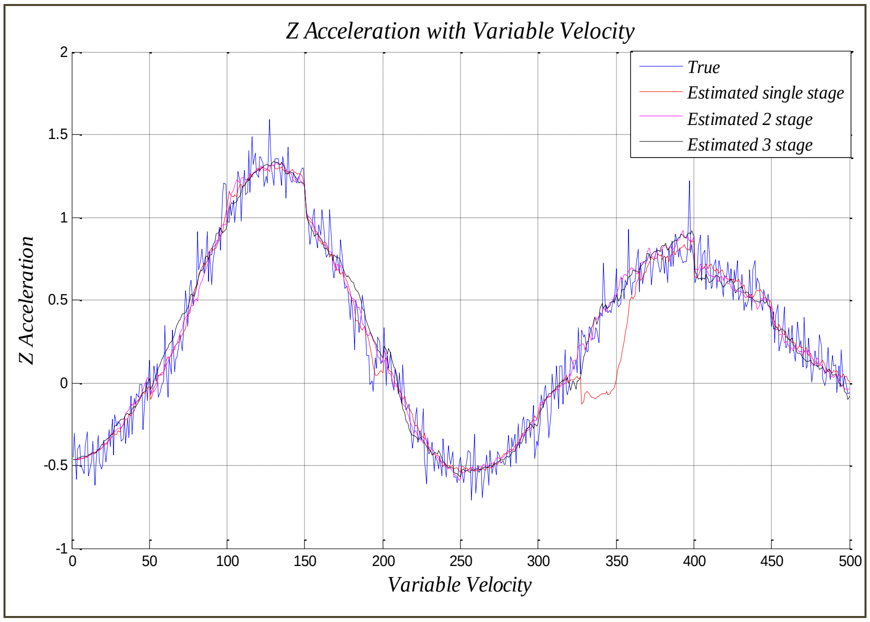


Figure 23: z accelerometer Output Versus Variable Velocity

The above graph shows the variation of accelerometer output in z- direction with respect to the variable velocity and the comparison of the single seven state discrete time extended kalman filter, two stage cascaded extended kalman filter and three stage extended kalman filter is carried out.

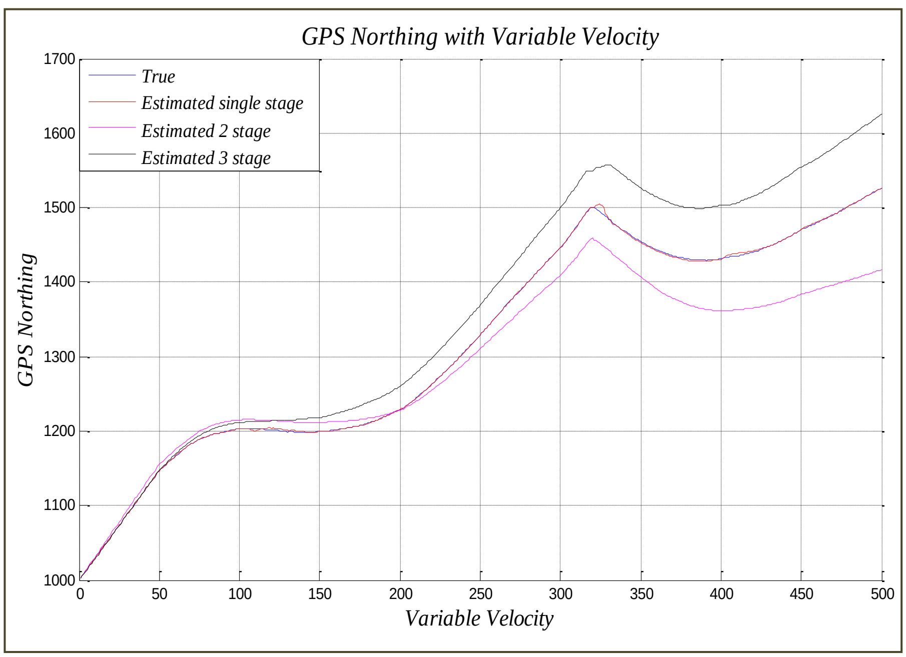


Figure 24: GPS Northing Versus Variable Velocity

The plots shown are those of GPS in the north direction which is also a measurement variable. The value of GPS keeps increasing with variation in velocity because of the continuous increase in roll angle witnessed before. The FMAV continues its flight north bound owing to a positive roll angular rate despite the negative variation in velocity at times. The first stage Kalman Filter plots the trajectory most accurately whereas the 2 stage and 3 stage Kalman Filters lag behind in this regard.

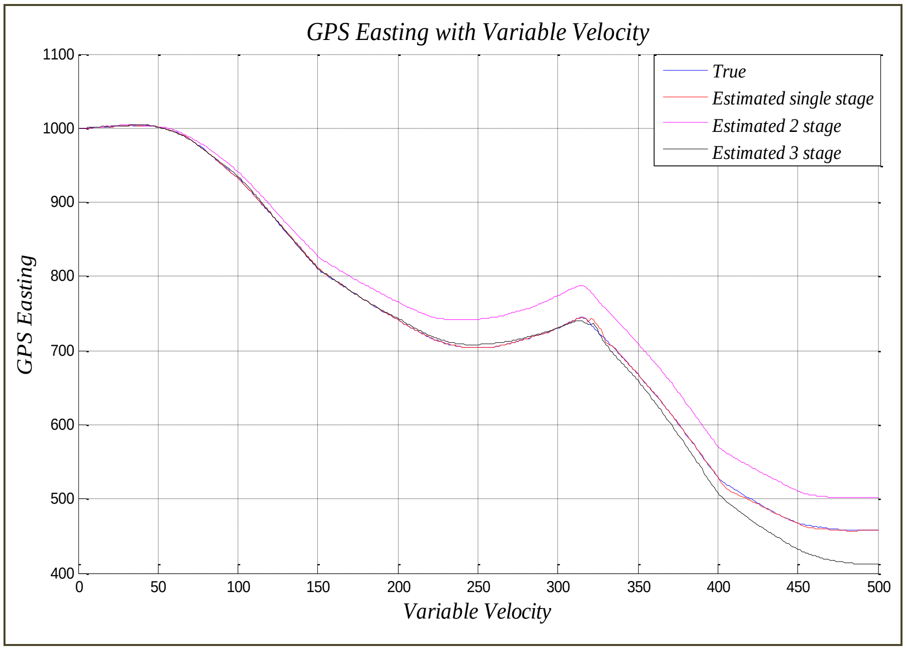


Figure 25: GPS Easting Versus Variable Velocity

The plots shown are those of GPS in the eastern direction. The value of GPS in the eastern direction keeps decreasing with subsequent iterations, which is owing to the negative pitch angular rate and very small yaw angle that has almost no effect on the trends shown. The FMAV continues its flight westwards owing to the variations in the pitch angle, velocity and roll angle. Single stage Kalman Filter is the most accurate whereas the other two types of filters lag behind in one respect or the other.

5. Conclusion

In all the simulations, the Single Seven State is most accurate, stable and showing least drift as compare to the remaining two filters. Even though the single seven state discrete time extended Kalman filter is computationally heavier than the other two cascaded filter schemes but the result produced by this filter are much more accurate and stable.

6. Acknowledgements

The authors are indebted to the College of Electrical and Mechanical Engineering (CEME), National University of Sciences and Technology (NUST), Higher Education Commission (HEC) and Pakistan Science Foundation (PSF) for having made this research possible.

References

http://robotics.eecs.berkeley.edu/~ronf/MFI.

http://robotics.eecs.berkeley.edu/~ronf/MFI.

http://www.ornithopter.net/history_e.html.

James M. McMichael (Program Manager Defense Advanced Research Projects Agency) and Col. Michael S. Francis, USAF (Ret.) (Defense Airborne Reconnaissance Office), “Micro air vehicles - Toward a new dimension in flight” dated 8/7/97

http://www.ornithopter.org/flapflight/birdsfly/birdsfly.html.

Sergio de La Parra Angel, “Low Cost Navigation System for UAV’s” Aerospace Science and Technology, Vol.9, Issue 6, 2005, pp. 504-516, doi: 10.1016/j.ast.2005.06.005

Andrew MarkEldredge, “Improved State Estimation for Miniature Air Vehicle”, M.S. Thesis, Brigham Young University, 2006.

Schmidt, G.T., \Strapdown Inertial Systems - Theory and Applications,"AGARD Lecture Series, No. 95, 1978.

Grewal, M.S., Weill, L.R., and Andrews, A.P., Global Positioning Systems, Inertial Navigation, and Integration, John Wiley and Sons, New York, 2001.

“Integration of MEMS inertial sensor-based GNC of a UAV” by Z. J. Huang and J. C. Fang (huangzhongjun@buaa.edu.cn, fangjiancheng@buaa.edu.cn)from School of Instrumentation & Optoelectronics Engineering Beihang University, Beijing 100083, China. International Journal of Information Technology. Vol. 11 No. 10 2005 (pg 123-132)

Randle, S.J., Horton, M.A., \ Low Cost Navigation Using Micro – Machined Technology," IEEE Intelligent Transportation Systems Conference, 1997.

Sun Hwan Lee and YounMi Park, “System Identification of Dragonfly UAV via Bayesian Estimation”, http://www.stanford.edu/class/cs229/proj2006/LeePa

Grejner-Brzezinska, D.A., and Wang, J., \Gravity Modelling for High-Accuracy GPS/INS Integration," Navigation, Vol. 45, No. 3, 1998, pp. 209-220.

User Manual of Flight Dynamics and Control Toolbox for MATLAB, www.dutchroll.com.

Wolf, R., Eissfeller, B., Hein, G.W., \ A Kalman Filter for the Integration of a Low Cost INS and an attitude GPS," Institute of Geodesy and Navigation, Munich, Germany.

Gaylor, D., Lightsey, E.G., \ GPS/INS Kalman Filter designing for Spacecraft operating in the proximity of the International Space Station," University of Texas - Austin, Austin.

'Mathematical Modeling of INS/GPS Based Navigation System Using Discrete Time Extended Kalman Filter Schemes for Flapping Micro Air Vehicle' by SadiaRiazin International Journal of Micro Air Vehicle, March 2011

"Optimal state estimation Kalman, H_∞ and nonlinear approaches" by Dan Simon, Cleveland State University. A John Wiley &Sons, INC., Publication.

"State estimation for micro air vehicles" by Randal W. Beard, Department of Electrical and Computer Engineering, Brigham Young University, Provo, Utah. Studies in Computational Intelligence (SCI) 70, 173–199 (2007). Springer-Verlag Berlin Heidelberg 2007

'Single Seven State Discrete Time Extended Kalman Filter for Micro AirVehicle' by Dr. Afzaal M. Malik1 and Sadia Riaz2, World Congress of Engineering (WCE), International Conference of Mechanical Engineering (ICME-2010).