Innovative Systems Design and Engineering www.iiste.org
ISSN 2222-1727 (Paper) ISSN 2222-2871 (Online)
Vol 2, No 3

INS/GPS Based State Estimation of Micro Air Vehicles Parametric Study Using Extended Kalman Filter (EKF) Schemes

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Abstract

Micro Air Vehicles (MAVs) are classified as the small scale aircrafts which can be remote controlled, semi-autonomous and autonomous. They are highly sensitive to the wind gust and therefore the control of Micro Air Vehicle is a very challenging area. To control an aircraft, the first step is the precise navigation of the MAV and state estimation is the pre requisite. In this paper the states (roll, pitch, yaw, position and wind direction) are estimated with the help of Discrete Time Extended Kalman Filter operating on Inertial Measurement Unit (IMU) which consists of MEMS Gyro, MEMS Accelerometer, MEMS Magnetometer and GPS. These sensors are based on MEMS (Micro Electro Mechanical System) technique which is very helpful for size and weight reduction. Three techniques of Discrete Time Extended Kalman Filter are used named as Single state Discrete Time Extended Kalman, Cascaded Two Stage Discrete Time Extended Kalman Filter and Cascaded Three Stage Discrete Time Extended Kalman Filter. The simulations obtained from these filters are compared and analyzed. Trajectory and sensors data is recorded from Flight Simulator software, and then compared with the simulations obtained from Extended Kalman Filter with the help of MATLAB Software.

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

Real world application is the inherent driver for the majority of research in robotics [1]. It is often the current limitations in technology or design constraints that lead the way to new advances and often work around to the development of these robots. In developing these airborne entities, primary concerns are the size, weight, sensors, communication and the computational power [2]. The term Micro Air Vehicles (MAVs) [3, 4, 5] is used for a new type of remote controlled, semi-autonomous or autonomous aircraft that is significantly smaller than conventional air crafts [6,7]. By defense Advanced Research Project Agency (DARPA), Micro Air Vehicles are small (usually defined to be less than 15 cm in length and 100gms of weight) autonomous aircrafts which have a great potential in fact-finding missions in confined spaces or inside buildings, including both civilian search and rescue missions and military surveillance and reconnaissance missions. The vehicle must fly 30 to 60 m/sec, fast enough to overcome head winds and have an endurance of 20 to 60 minutes to provide adequate range and mission time. Technological feasibility follows from advances in several micro technologies, including the rapid evolution of Micro Electro Mechanical System (MEMS) technology [8, 9]. These systems combine microelectronics components with comparable sized mechanical elements of varying complexity to achieve useful and often unique functionality (e.g. integrated systems of sensors, actuators and processors). To apply Micro Electro Mechanical Systems (MEMS) on inertial sensors [10, 11] for the GNC of MAVs is an extremely challenging area. Inertial Navigation System (INS) includes MEMS gyro, Accelerometer, Magnetometer and barometer. MEMS inertial sensors are of utmost importance in GNC system. This system, like all other real systems, will be considered non-linear and it will be first linearized for the application of the Extended Kalman Filter (EKF) [12, 13, 14, 15].

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. The major mathematical relationships used are following.

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

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

Sensor Measurements [17] 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.

Innovative Systems Design and Engineering
ISSN 2222-1727 (Paper) ISSN 2222-2871 (Online)
Vol 2, No 3

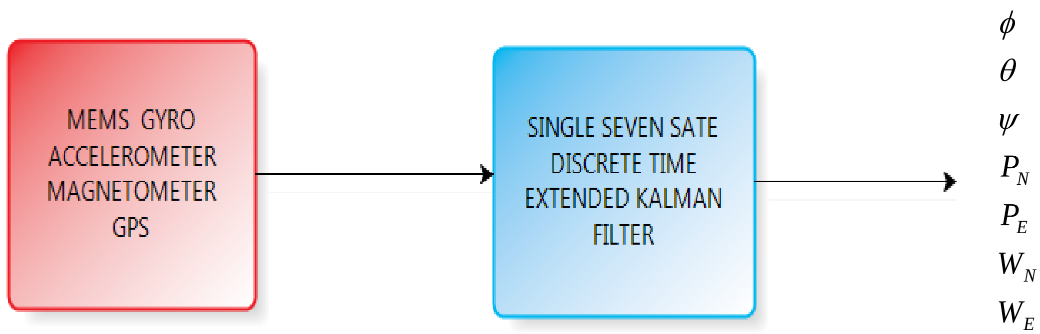

Figure 01: Single Seven State Extended Kalman Filter Scheme [19],

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.

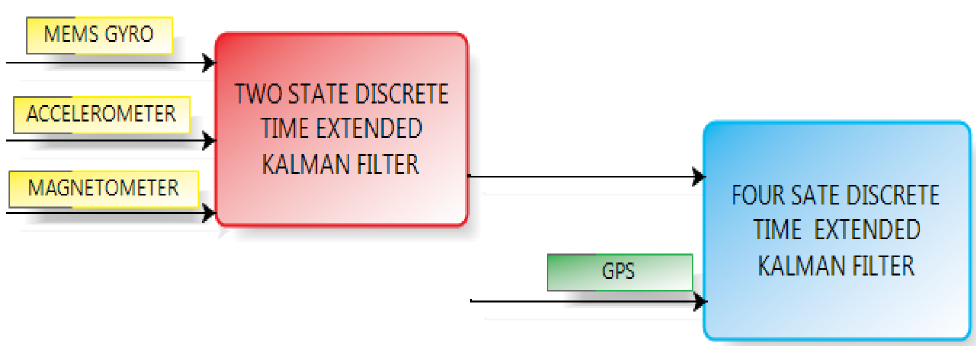

Figure 02: Two stage Cascaded Discrete time Extended Kalman Filter [16].

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.

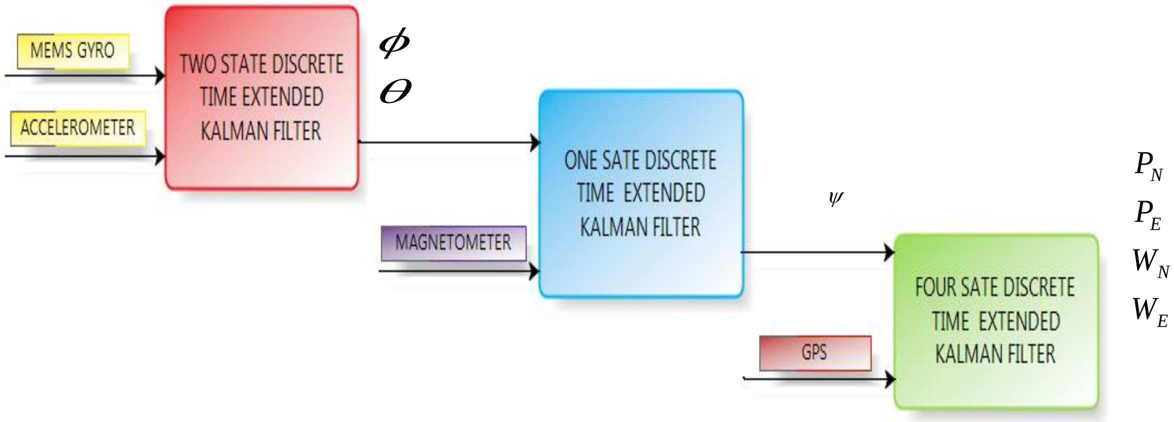

Figure 03: Three stage Cascaded Discrete time Extended Kalman filter [16].

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.

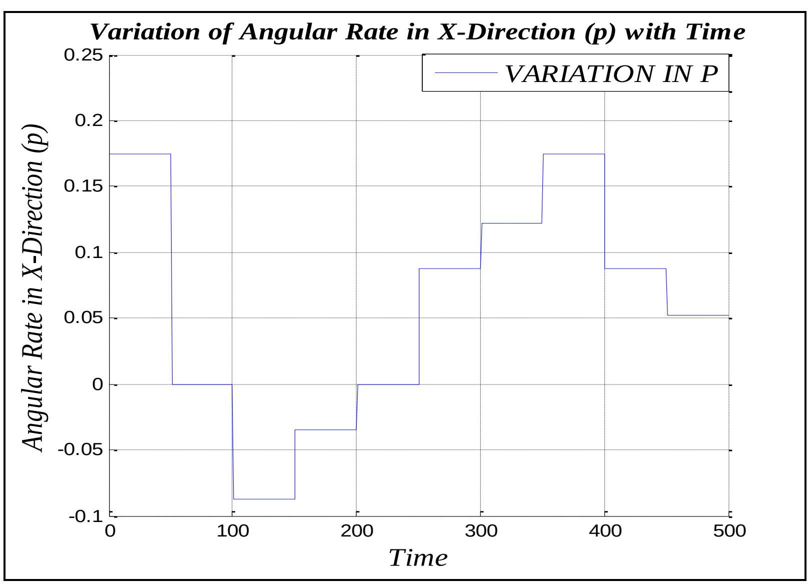

Figure 04: Variation of angular rate in x-direction with respect to time

The Above Graph shows the variation of angular rate in x-direction (p) with time. The angular rate in x-direction (p) first decreases with time and then it keeps on increasing with time. In the end of flight maneuver the angular rate in x direction (p) with time decreases.

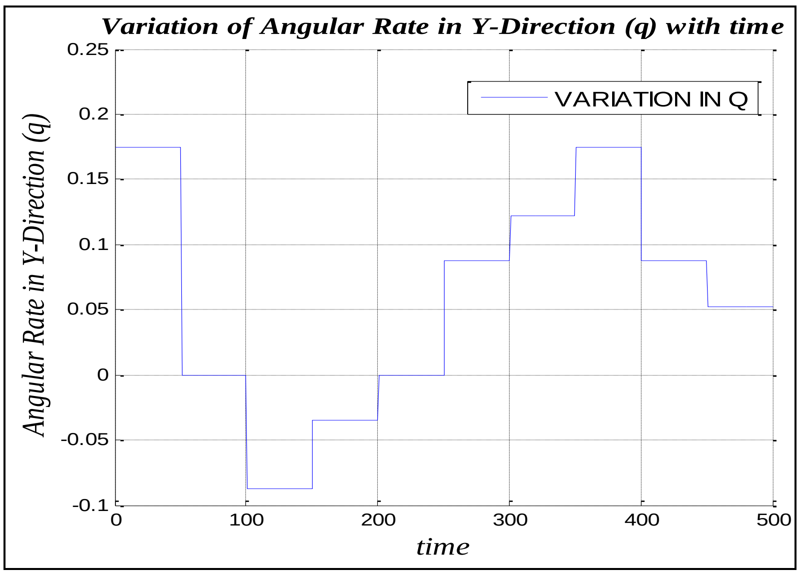

Figure 05: Variation of angular rate in y-direction with respect to time

The Above Graph shows the variation of angular rate in y-direction (q) with time. The angular rate in y-direction (q) first decreases with time and then it keeps on increasing with time. In the end of flight maneuver the angular rate in y direction (q) with time decreases.

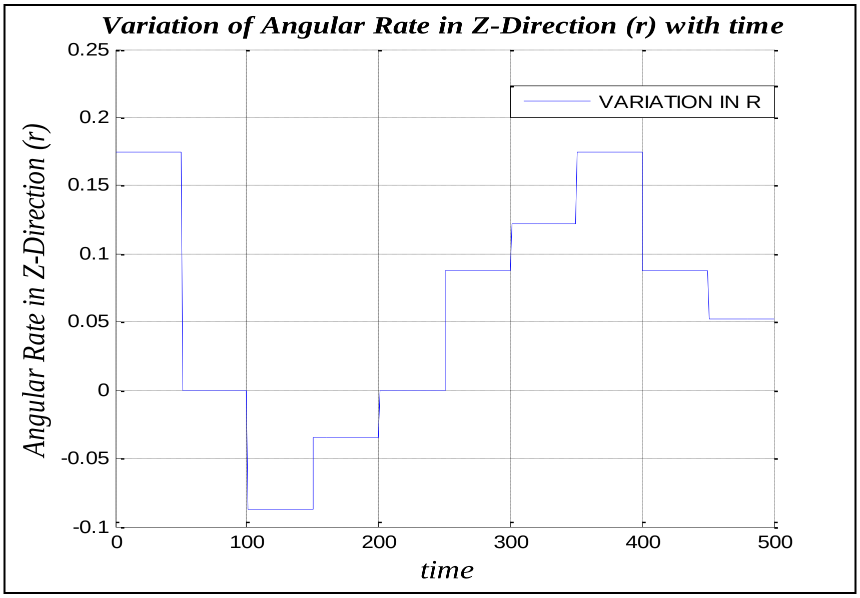

Figure 06: Variation of angular rate in z-direction with respect to time

The Above Graph shows the variation of angular rate in z-direction (r) with time. The angular rate in z-direction (r) first decreases with time and then it keeps on increasing with time. In the end of flight maneuver the angular rate in z-direction (r) with time decreases.

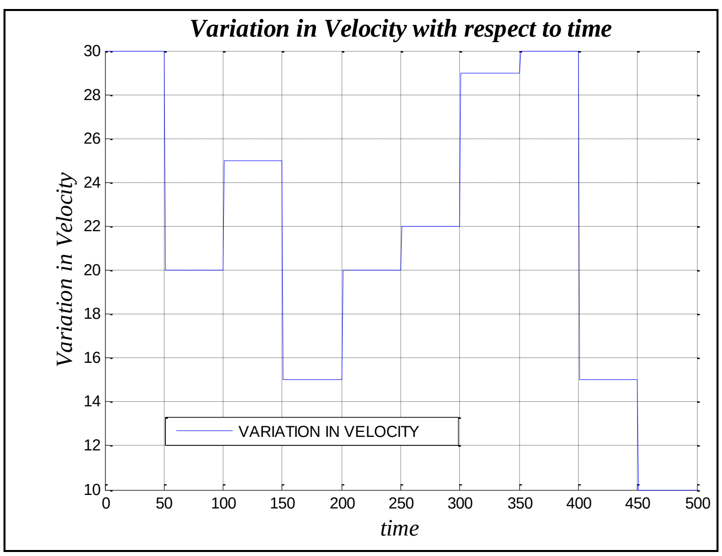

Figure 07: Variation of velocity with respect to time

The Above Graph shows the variation of velocity (Vair) with time. The velocity (Vair) first decreases with time and then it keep on increasing with time. In the end of flight maneuver the velocity (Vair) with time decreases.

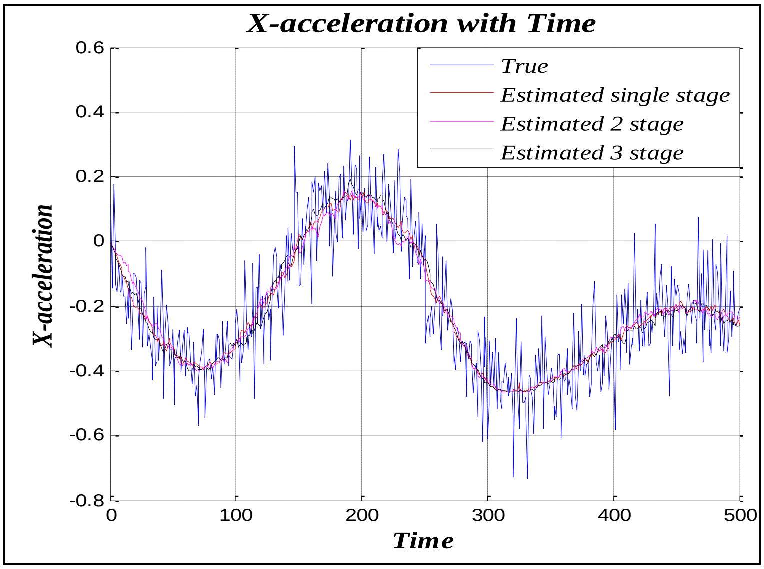

Figure 08: x-Accelerometer Output Versus Time

The above graph shows the variation of accelerometer output with respect to the time. The blue trajectory shows the actual recorded trajectory. The variation in this trajectory shows the combination of process noise and measurement noise. This is because the accelerometer output does not only depend upon the inputs (p, q, r and Vair) but it also depends on the different state variables.

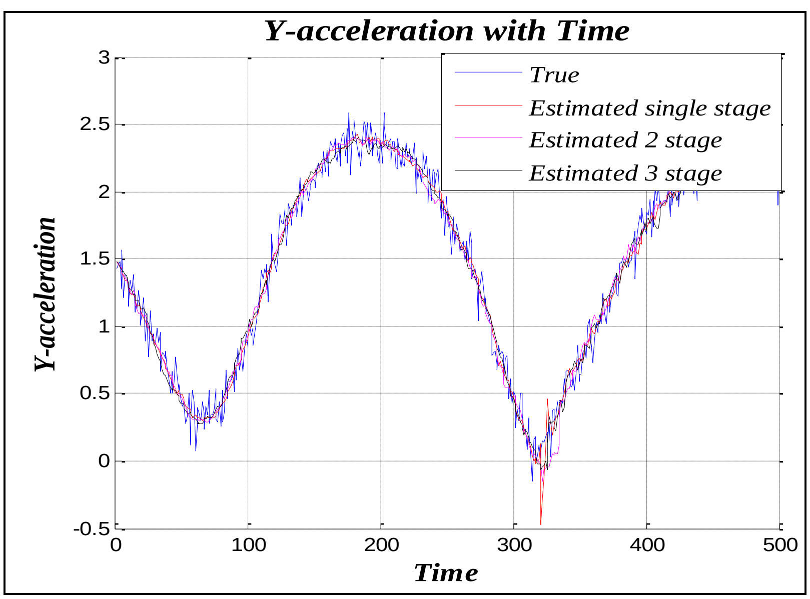

Figure 09: y-Accelerometer Output Versus time

The above graph shows the variation of accelerometer output in y-direction with respect to time. It decreases first with time and then it increases for some time. Then again it goes down with time and after that it increases again. The accelerometer output depends on the body dynamics and the gravitational acceleration as well.

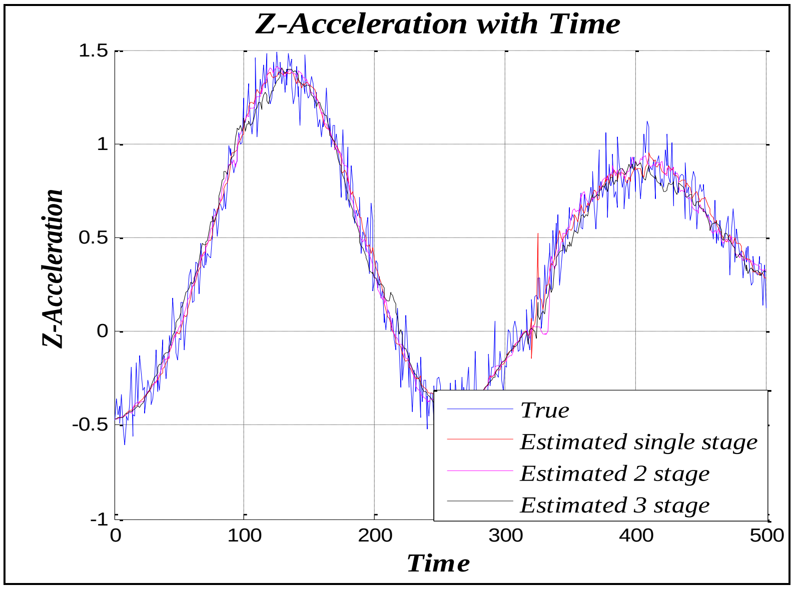

Figure 10: z-Accelerometer Output Versus time

The above graph shows the variation of accelerometer output in z- direction with respect to the time 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.

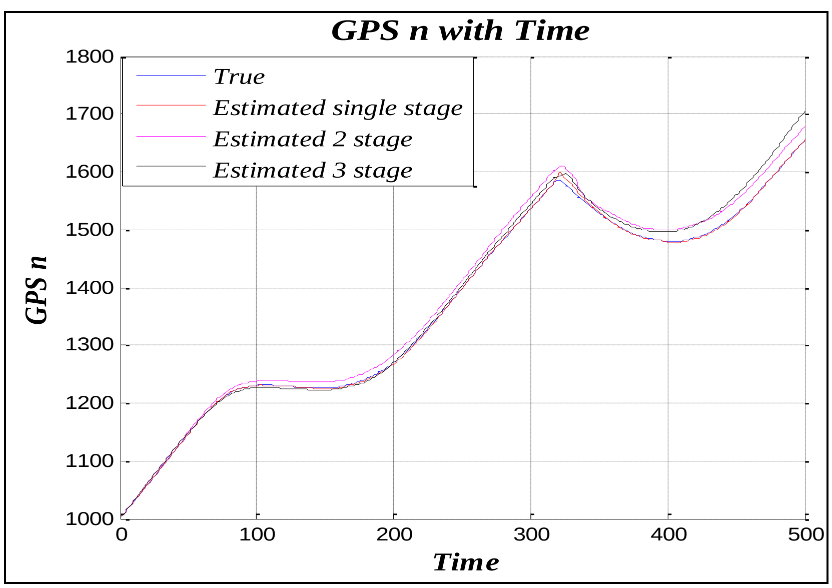

Figure 11: GPS northing Versus Time

The above graph shows the variation of GPS reading in north direction with respect to time. GPSn shows that the MAV is going towards north direction but at some points it moves in south direction but overall it follows a northward movement.

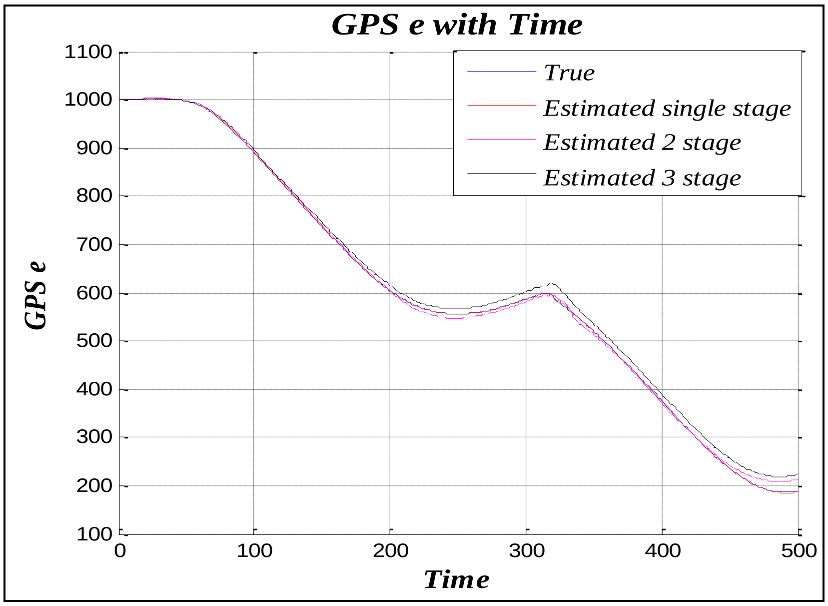

Figure 12: GPS Easting Versus Time

The above graph shows the variation of GPS reading in east direction with respect to time. GPSe shows that the MAV is going towards west direction but at some points it moves in east direction but overall it follows a westward movement.

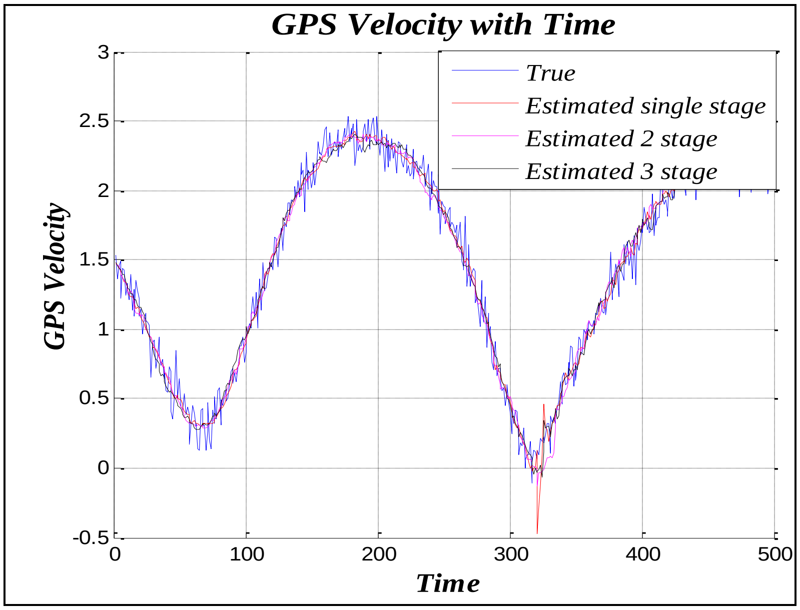

Figure 13: GPS Velocity Versus Time

The above graph shows the variation of GPS velocity with respect to the time. GPS velocity actually represents the velocity of MAV. There is an unsymmetrical sinusoidal curve followed by the MAV's velocity with respect to time which shows that the velocity of MAV increases and decreases repeatedly.

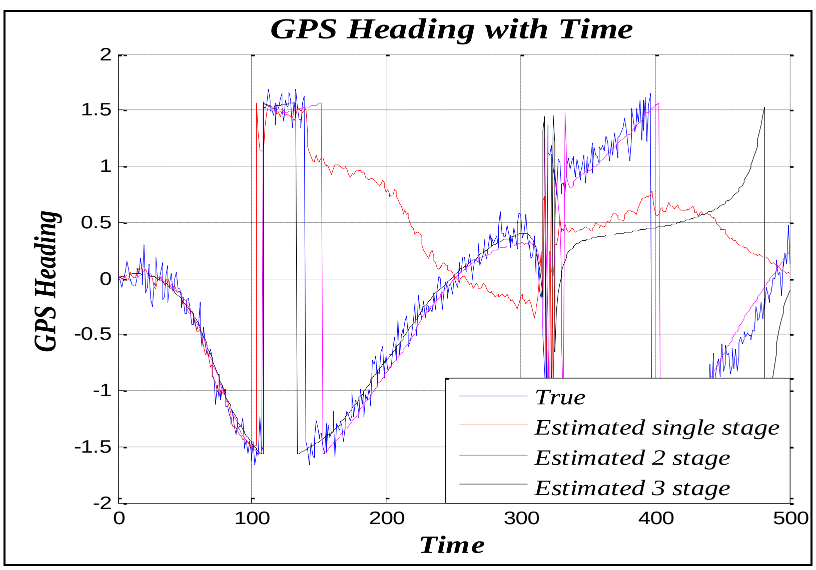

Figure 14: GPS heading Versus Time

The above graph shows the variation of GPS heading with respect to time. GPS heading actually represents the heading of the MAV. GPS heading is dependent on the yaw angle, Vair, wind in north and east direction

(Wn and We). So basically it is dependent on four parameters and the variation cannot be justified with the variation of a single parameter. But the actual variation of aircraft heading is shown with time and it increases and decreases again and again.

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.

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