Unmanned Aerial Vehicle Tracking System with Out-Of-Sequence Measurement in a Discrete Time-Delayed Extended Kalman Filter

by

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Thesis Defense

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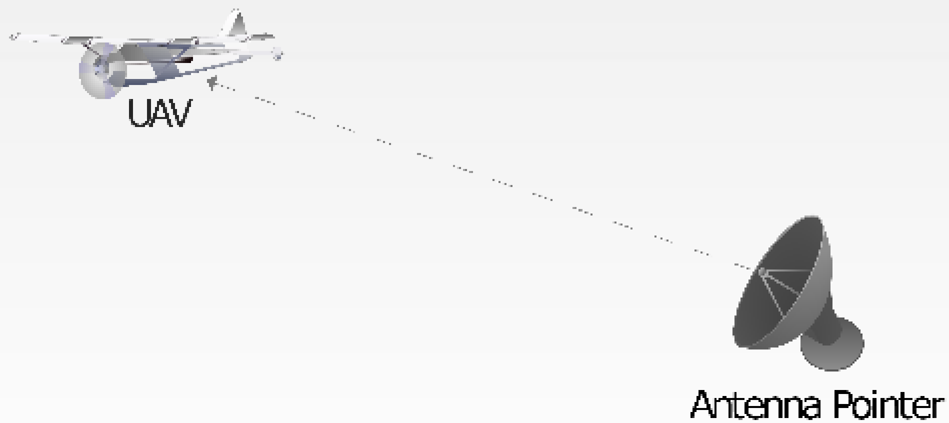
Preview

The purpose of this study is to develop an algorithm that can accurately track an Unmanned Aerial System, pointing an antenna and a camera towards it. For this we will use a GPS sensor coupled with a camera and a combination of two different Kalman filters.



Outline

- Motivation
- Literature Review
- Contributions
- Aircraft Model, Sensors and Kalman Filters
- Simulation
- Results
- Conclusion
- Future Work

Motivation

- Improve the robustness of a UAS mission by making the communication link more reliable. This is achieved by having an accurate tracking system that points an antenna towards the aircraft.
- Offer a different method to comply with the Line-Of-Sight (LOS) requirement of the Federal Aviation Administration by mounting a camera in the tracking system.

Literature Review

- The OOSM problem was first addressed by Hilton, Martin and Blair whom developed a negative-time update technique
- Nettleton presented the first optimal algorithm to solve the OOSM problem, which consisted in running a Kalman filter behind real time
- Larsen developed a Kalman filter which used the measurements extrapolated forward in time
- Julier expanded the work of Larsen to solve the OOSM problem when random time delays are present.
- Beard explains a method of state estimation for GPS and camera measurements

Contributions

- Design an autonomous system to point an antenna and a camera towards a flying UAS to maintain communication and visual LOS to satisfy FAA requirements
- Combine the work of Larsen and Beard in a single filter to improve the estimations and fuse out-of-sequence measurements with random delays

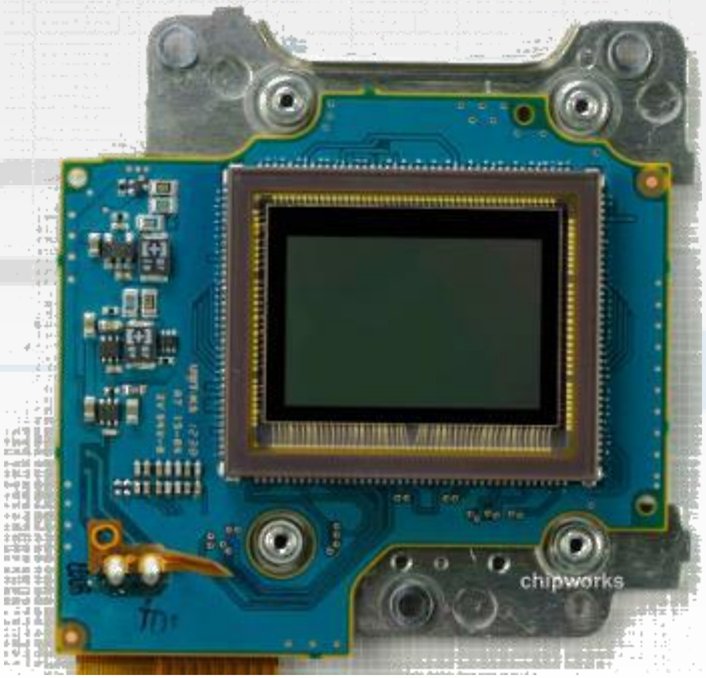
Aircraft Model

GPS Sensor

- Navigation system supported by satellites which provides location information for objects on or near earth’s surface
- Developed by the US Department of Defense and functional since 1993
- The system is supported by a constellation of 24 satellites orbits around the earth at an altitude of 20,180 km from the surface of the earth
- At least four satellites needs to observe an object to determine its location

Camera Sensor

- Device that converts an optical image into an electronic signal
- Camera sensors evolved from using video camera tubes to semiconductor charged-coupled devices or active pixel sensors in CMOS or NMOS



GPS Coupled with Camera

- GPS has slow update frequency, 1-2 Hz
- GPS accuracy is independent of distance to the tracking system, therefore at medium and long distances it has a relatively accurate measurement
- Camera is a fast sensor, 15-30 updates per second
- Camera can estimate the position of an object at short range, but is not usable at longer ranges

Kalman Filter

- Optimal recursive data processing algorithm
- Incorporates all the information that is provided to the filter
- Process all available measurements to estimate the current values of the variables of interest
- Ponders the system dynamics, the statistical description of the noises of the system, measurement errors and uncertainties in the dynamics model
- Considers all past and present data without the need of storing the previous measurements

Kalman Filter

The Kalman filter consists of two sets of equations

- Time Update Equations
  - Which propagates the states forward in time
- Measurement Update Equations
  - Which corrects the estimation with the measurements received

Kalman Filter

Assuming a linear system dynamics defined by

$\dot{x} = Ax + Bu + \xi$

$y[n] = Cx[n] + \eta[n]$

And the discrete Kalman filter has the form

$\dot{\hat{x}} = A\hat{x} + Bu$

$\hat{x}^{+} = \hat{x}^{-} + L(y[t_n] - C\hat{x}^{-})$, where the second term is a correction due to the sensor reading.

Lets define the estimation error as

$\tilde{x} = x - \hat{x}$

Kalman Filter

And the covariance matrix of the estimation error at time t as

$P(t) \triangleq E\{\tilde{x}(t)\tilde{x}(t)^T\}$

Noting that small eigenvalues of $P(t)$ imply small variances, and therefore low average estimation errors.

Therefore, the Kalman filter is derived by finding L that minimizes the sum of the eigenvalues of $P(t)$.

Kalman Filter

Time Update Equations

Differentiating $\tilde{x}$ we get

$$\dot{\tilde{x}} = \dot{x} - \dot{\hat{x}}$$

$$\dot{\tilde{x}} = Ax + Bu + \xi - A\hat{x} - Bu$$

$$\dot{\tilde{x}} = A\tilde{x} + \xi$$

Solving the differential equation with initial conditions $\tilde{x}_0$ we have

$$\tilde{x}(t) = e^{At}\tilde{x}_0 + \int_0^t e^{A(t-\tau)}\xi(\tau)d\tau$$

Kalman Filter
Time Update Equations

Now we can compute the evolution of the error covariance P as

$$\dot{P} = \frac{d}{dt} E\{\tilde{x}\tilde{x}^T\}$$

$$\dot{P} = E\{\dot{\tilde{x}}\tilde{x}^T + \tilde{x}\dot{\tilde{x}}^T\}$$

$$\dot{P} = \mathrm{E}\{\mathrm{A}\tilde{x}\tilde{x}^T + \xi\tilde{x}^T + \tilde{x}\tilde{x}^T A^T + \tilde{x}\xi^T\}$$

$$\dot{P} = AP + PA^T + E\{\xi\tilde{x}^T\} + E\{\tilde{x}\xi^T\}$$

Kalman Filter

Time Update Equations

Computing $E\{\tilde{x}\xi^T\}$ as

$$E\{\tilde{x}\xi^T\} = E\{e^{At}\tilde{x}_0\xi^T(t) + \int_0^t e^{A(t-\tau)}\xi(\tau)\xi^T(\tau)d\tau\}$$

$$E\{\tilde{x}\xi^T\} = \int_0^t e^{A(t-\tau)}Q\delta(t-\tau)d\tau$$

$$E\{\tilde{x}\xi^T\} = \frac{1}{2}Q$$

Since Q is symmetric, we have that P evolves between measurements as

$$\dot{P} = AP + PA^T + Q$$

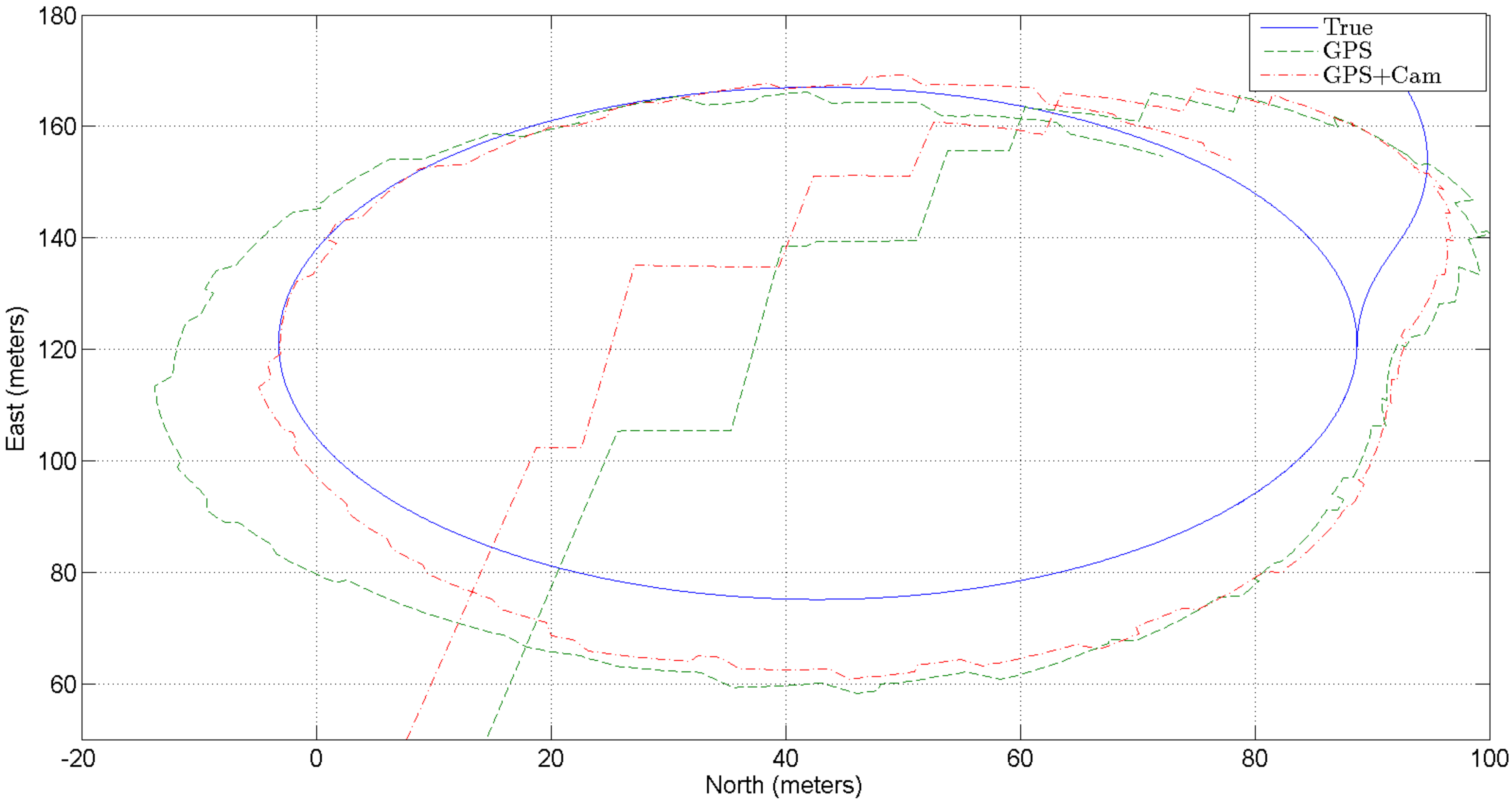
Extended Kalman Filter

Delayed Extended Kalman Filter

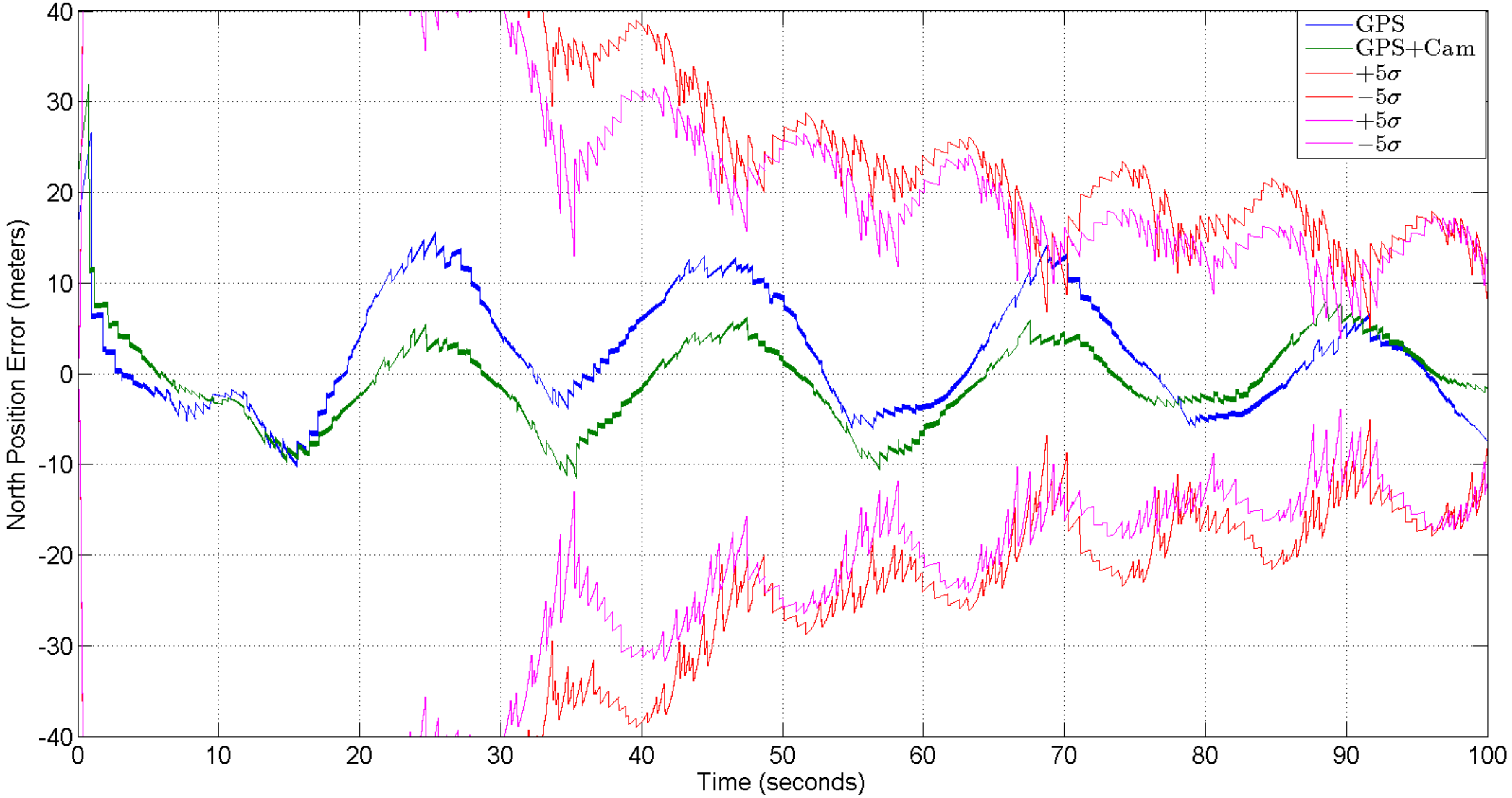
Simulation

Simulation

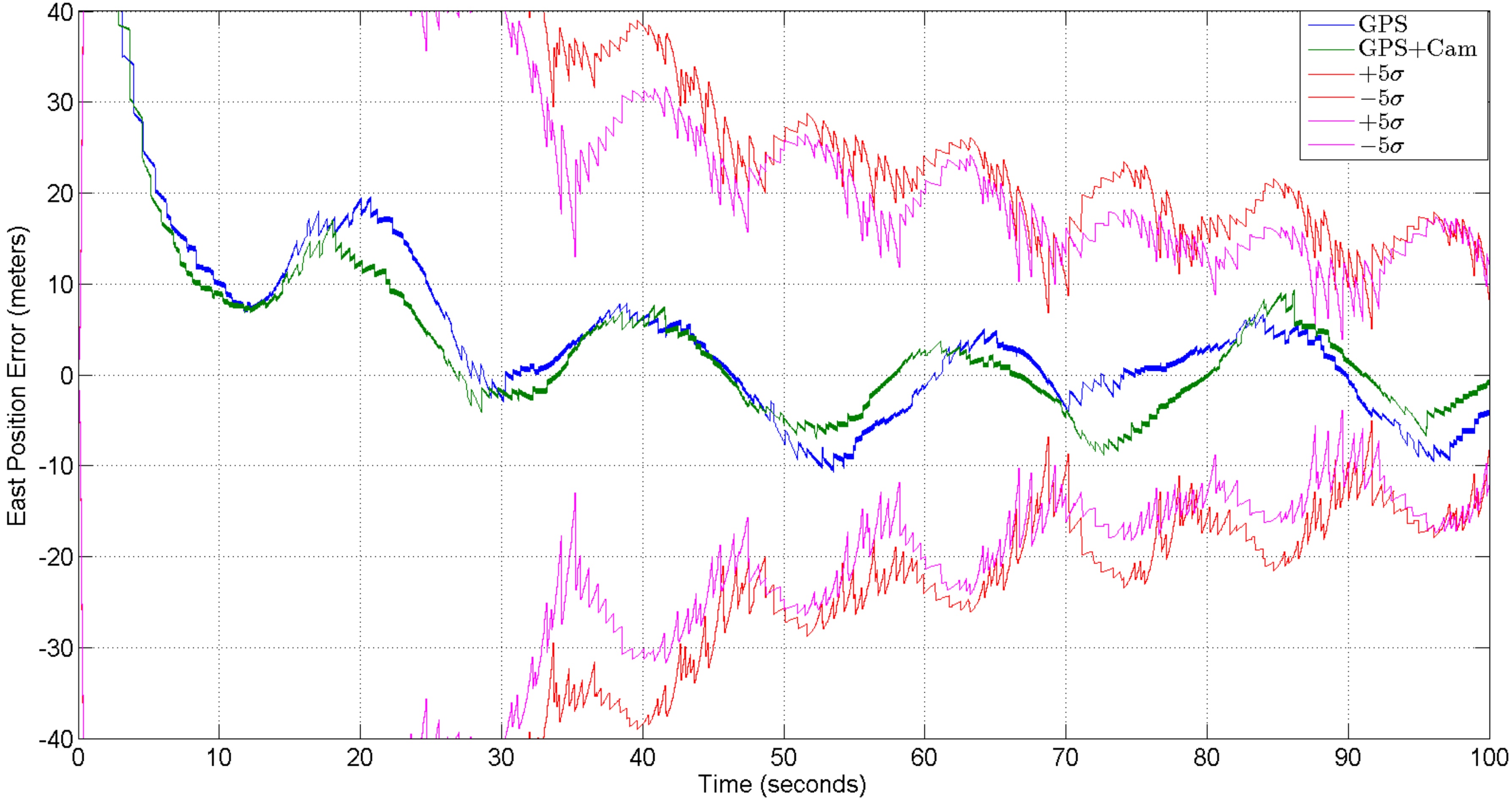
UAV Trajectory



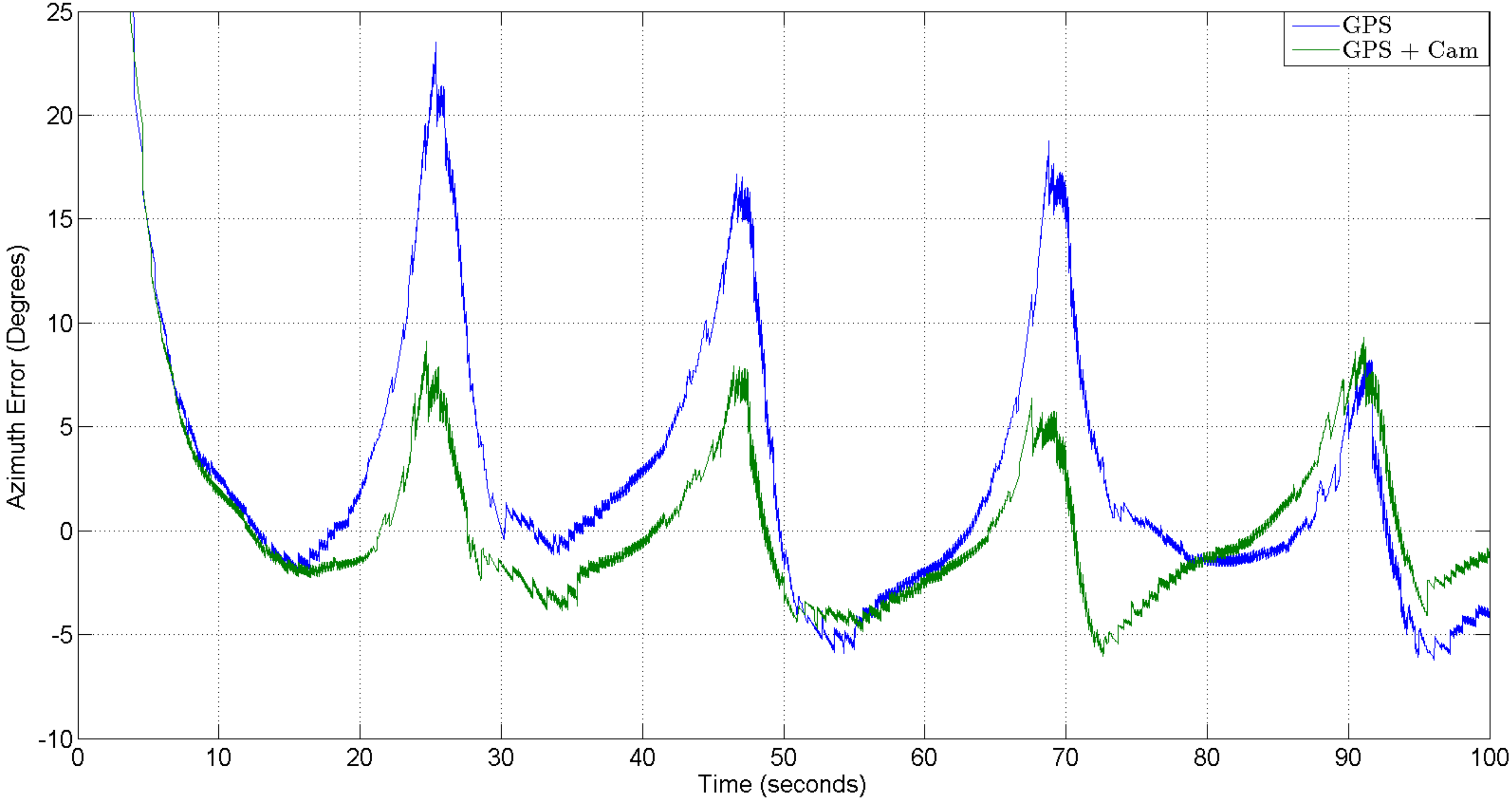
Error in North Position



Error in East Position

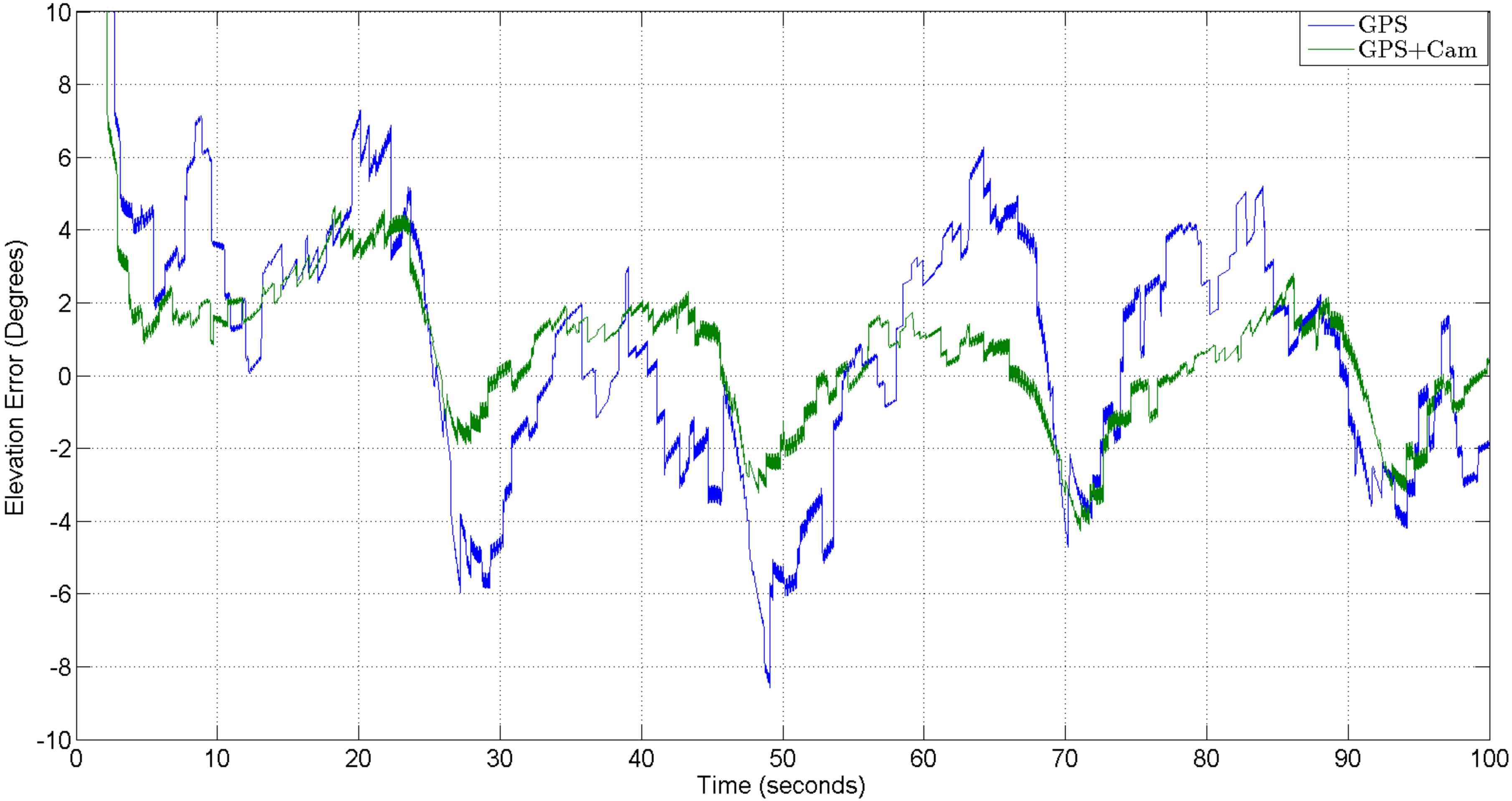


Error in Azimuth Angle



Results GPS vs GPS+Camera

Error in Elevation Angle



Results – EKF vs DEKF

Results – Delay of 0, 0.25, 0.50, and 0.75 sec

Conclusion

Future Work

Summary