Satellite and Inertial Attitude and Positioning System

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Outline

- Project Introduction
- Theoretical Background
  - Inertial navigation
  - GPS navigation
  - Kalman filter
- Equipment List
- Progress
  - Results
  - Future Work
- Conclusion

Project Introduction

- Goal
  - Fuse a GPS and an Inertial Measurement Unit using a Kalman Filter
- Significance
  - The final system will have the same functionality and cost less than traditional Inertial Navigation Systems

Project Introduction

- Global Positioning System (GPS)
  - Absolute position
  - Accurate, but slow and prone to loss of signal

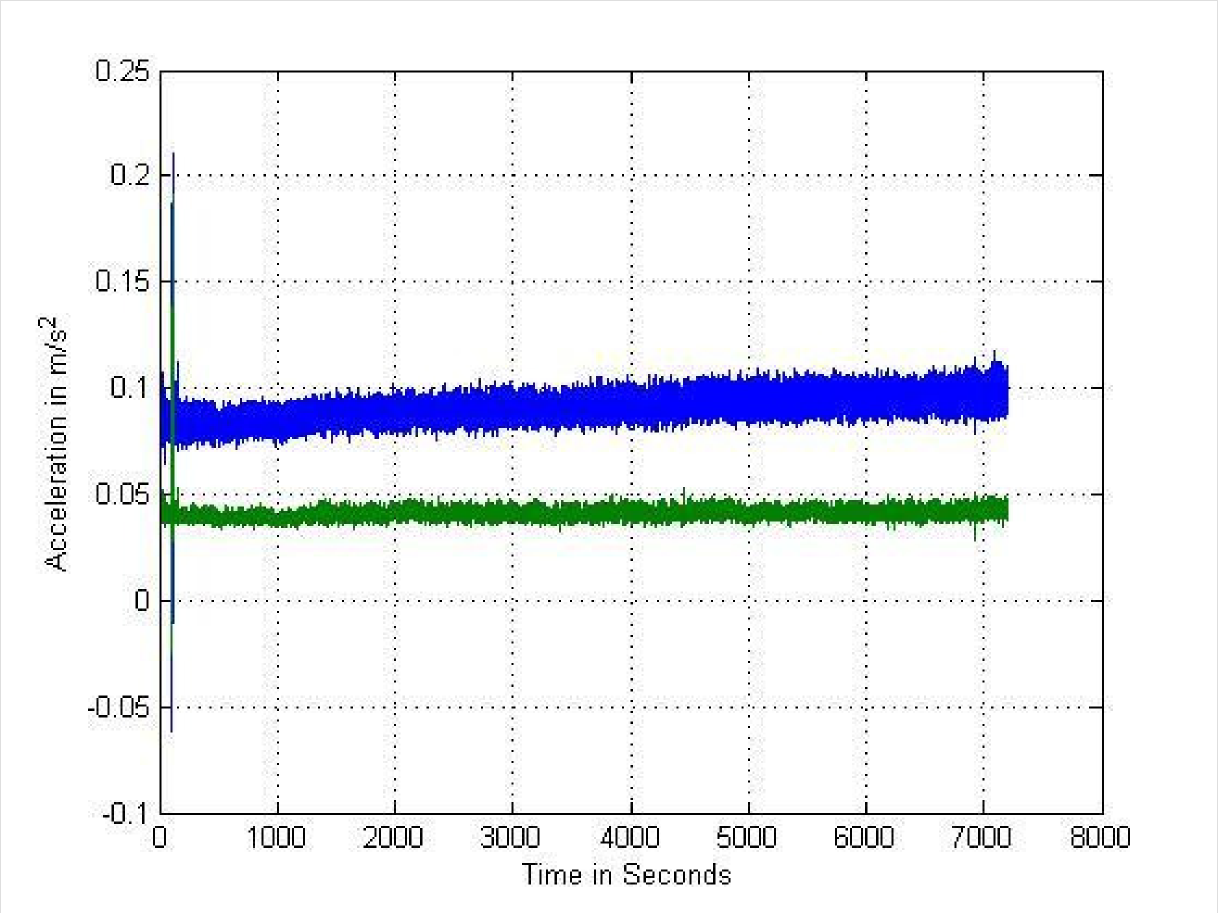
Project Introduction

- Inertial Measurement Unit (IMU)
  - Provides acceleration, angular rates, and magnetic readings
  - Can generate attitude and relative position using strapdown algorithm
  - Fast, but noisy measurements.

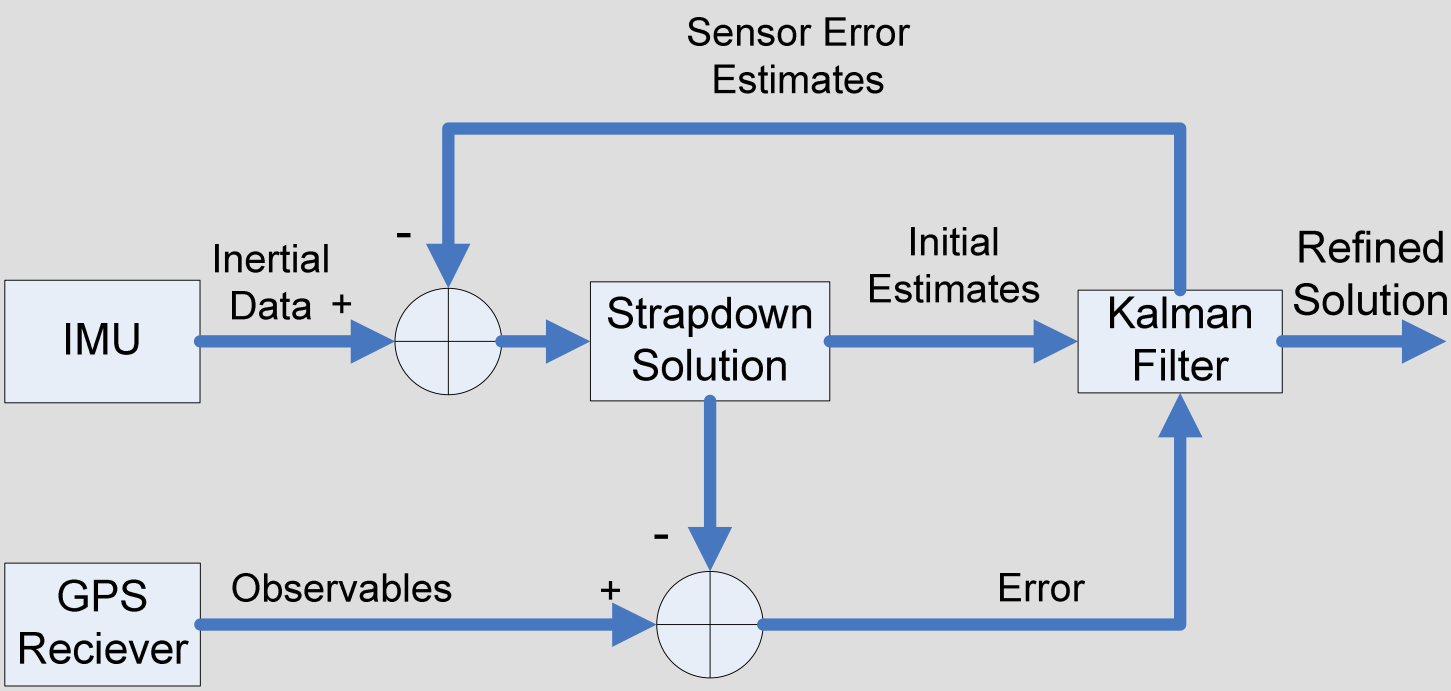
Project Introduction

- MEMS IMU Advantages
  - Low cost
- MEMS IMU Drawbacks
  - Bias value
  - Bias drift
  - White noise

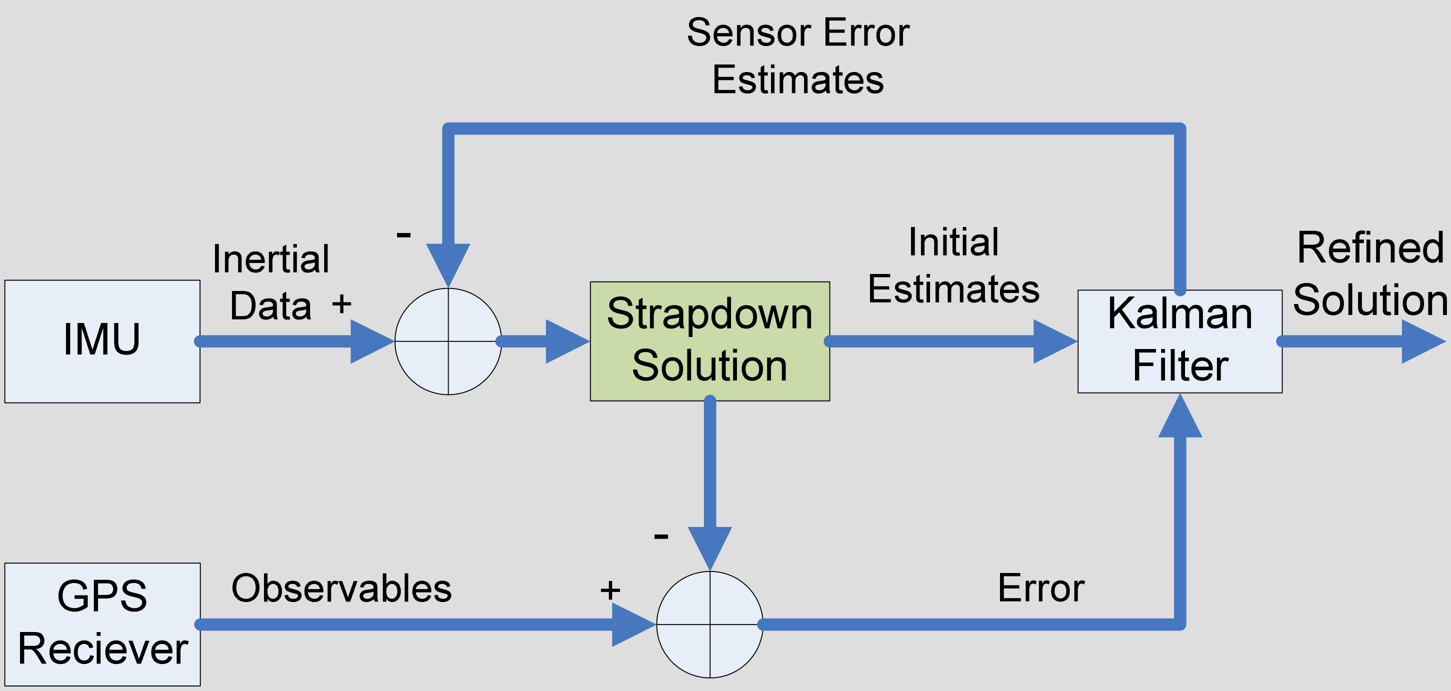
Project Introduction



Project Introduction



Strapdown Solution

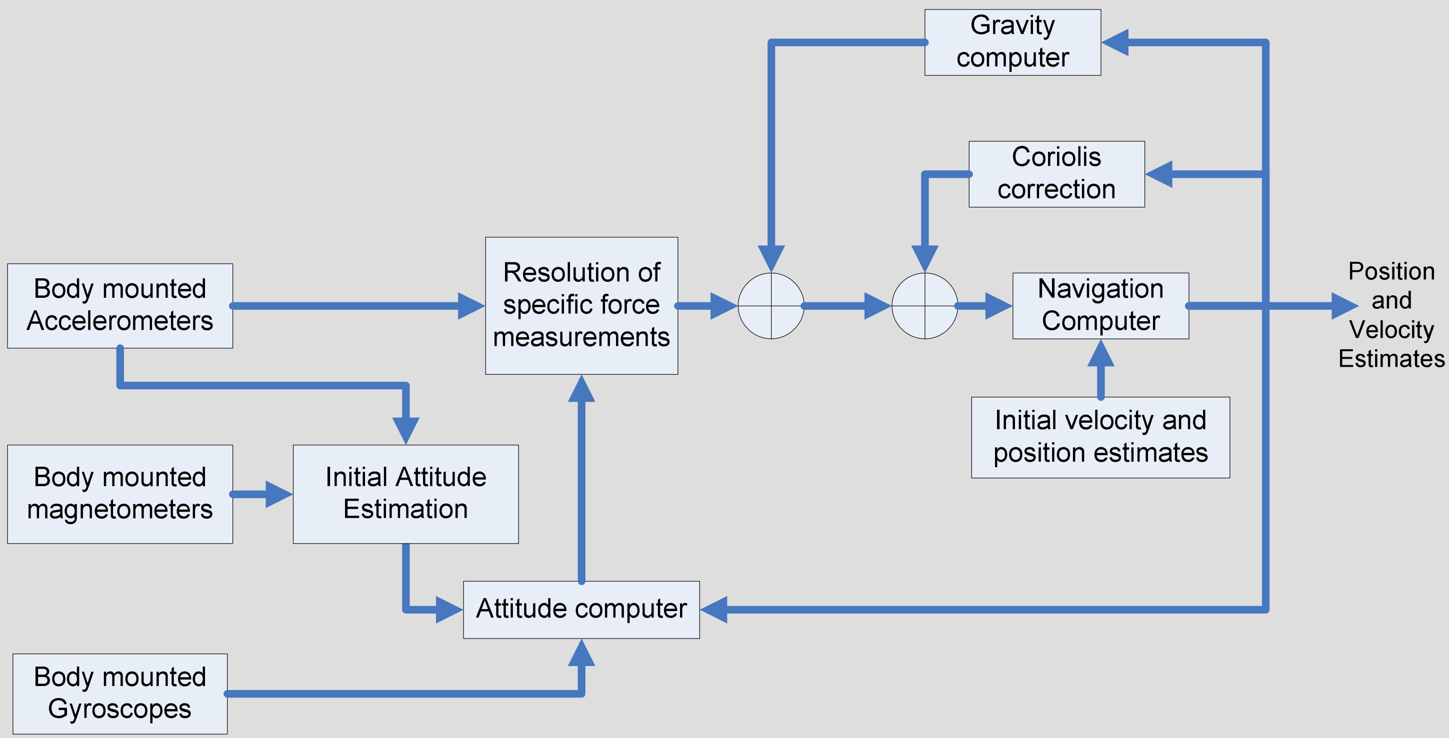


Theoretical Background

- Inertial Navigation System (INS)
  - Dead reckoning with inertial measurement unit (IMU)
  - Strapdown navigation
    - Closed loop controls and integrators

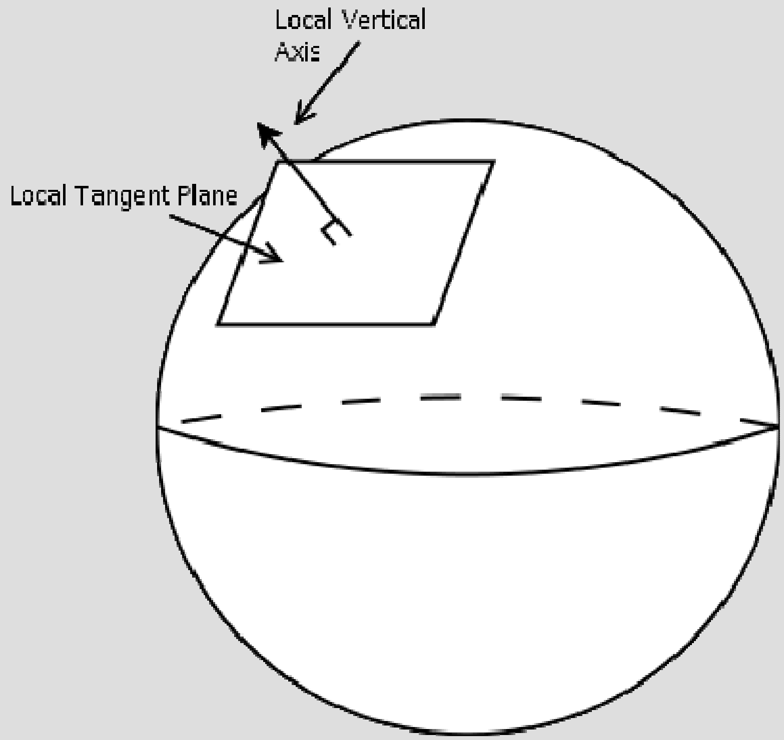
Theoretical Background

- Strapdown Solution



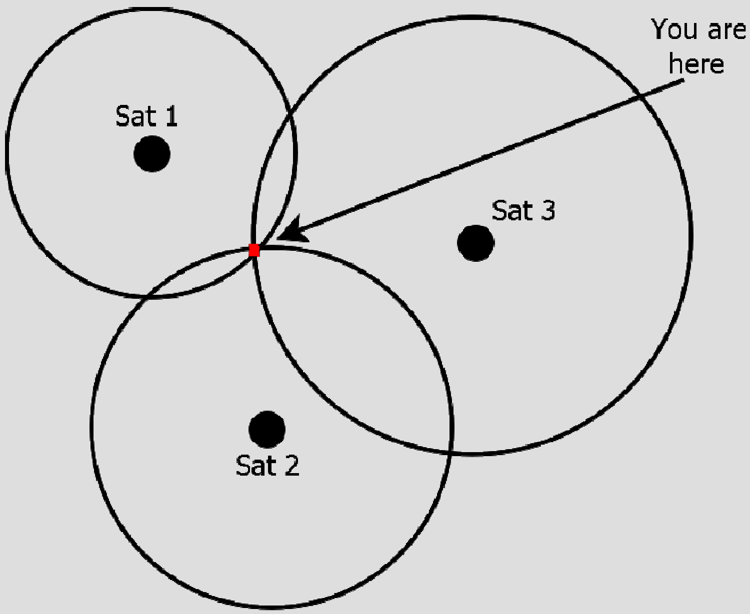
Theoretical Background

- Local tangent plane navigation

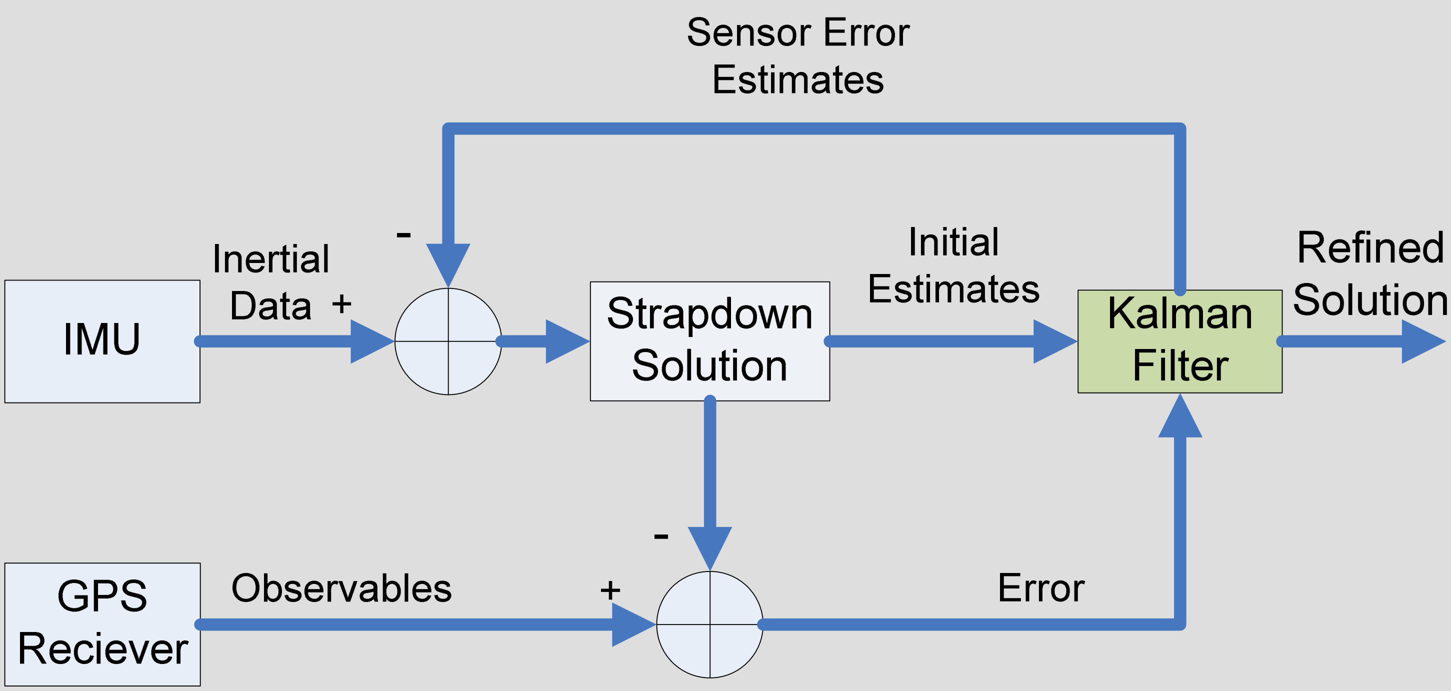


Theoretical Background

- GPS navigation
  - Trilateration with satellite messages
  - Timing ambiguity: need at least 4 satellites



Kalman Filter



Kalman Filter

- Optimal linear state estimator
- Estimates system states through noisy measurements
- Need: system model and signal models

Kalman Filter

- System Model
  - Position (3)
  - Velocity (3)
  - Acceleration Bias (3)
  - Quaternion (Attitude) (4)
  - Angular Rates Bias (3)
- Observables
  - GPS ENU Position(3)
  - GPS ENU Velocity(3)

Kalman Filter

- Signal Model
  - First Order Model (Gauss Markov)
  - Requires signal variance and autocorrelation time constant

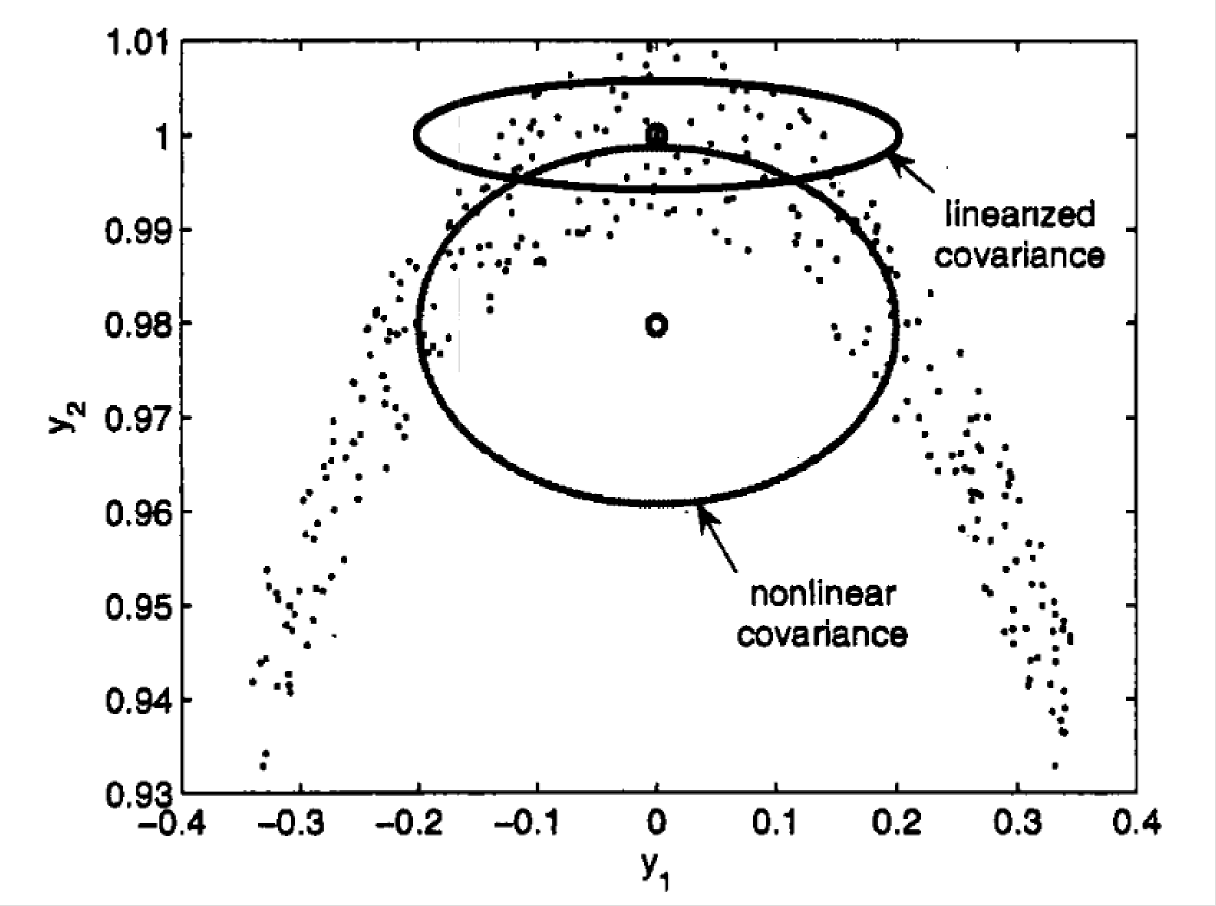
Kalman Filter

- Extended Kalman filter
  - Linearizes about an operating point
  - Can be inaccurate for highly nonlinear systems

Kalman Filter

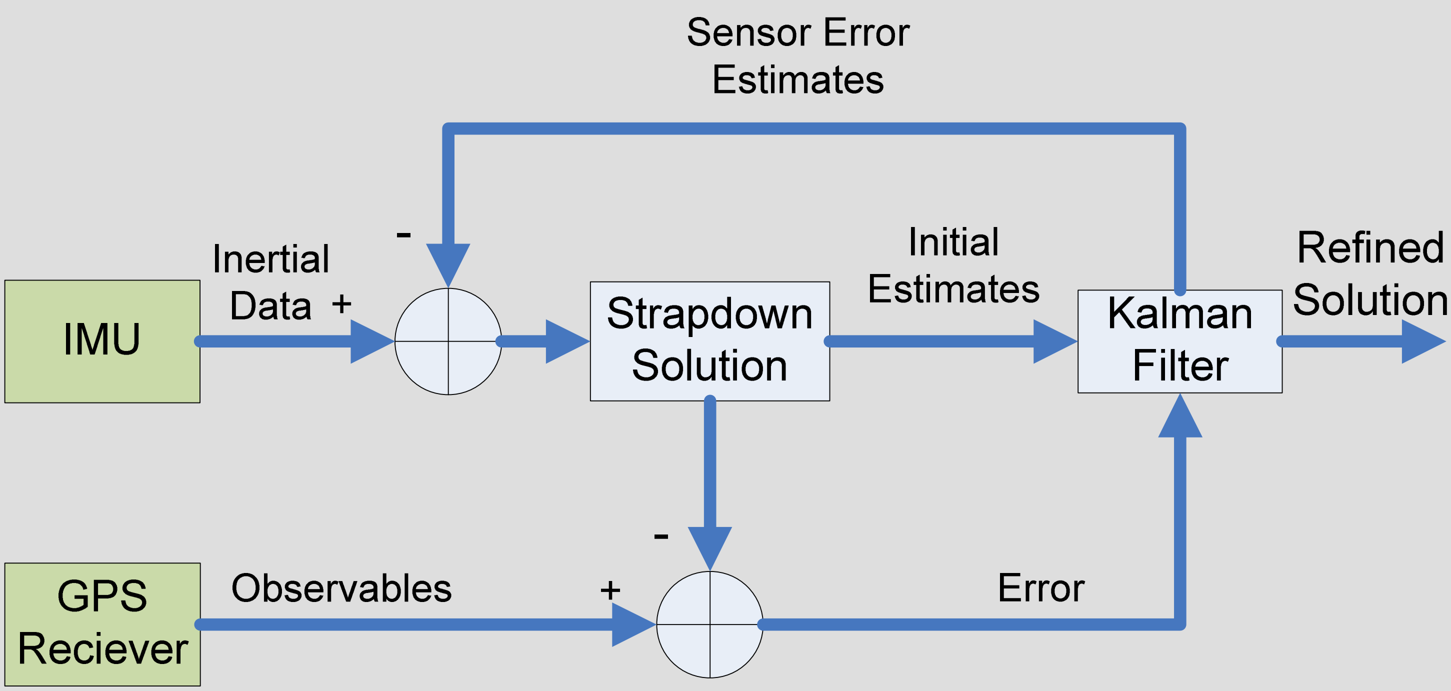
- Unscented Kalman filter
  - Generates a finite number of sigma points which have the same mean and variance as the input
  - Evaluates the nonlinear function only on the sigma points
  - Robust to high nonlinearity

Kalman Filter



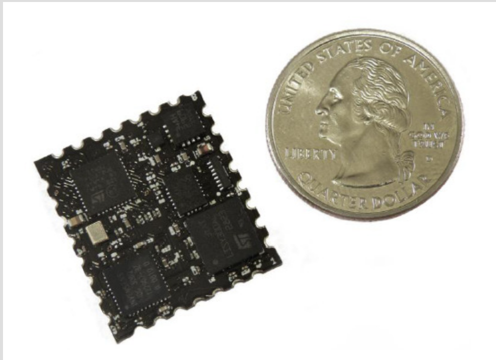
D. Simon, Optimal State Estimation. Hoboken, NJ: John Wiley & Sons, 2006.

Progress


Sensor Error
Estimates
Inertial
Data +
-
IMU
Strapdown
Solution
Initial
Estimates
Kalman
Filter
Refined
Solution
-
GPS
Reciever
Observables
+
Error

Equipment List

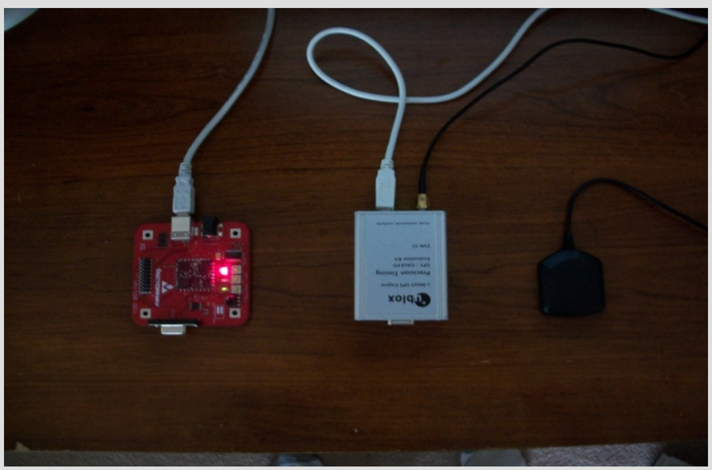
- Vector Nav VN-100
  - Three sets of MEMS sensors
    - Magnetometers
    - Gyroscopes
    - Accelerometers
- uBlox EVK-5T
  - LEA-5T GPS module
  - Accurate up to 2 meters RMS



Experimental Results

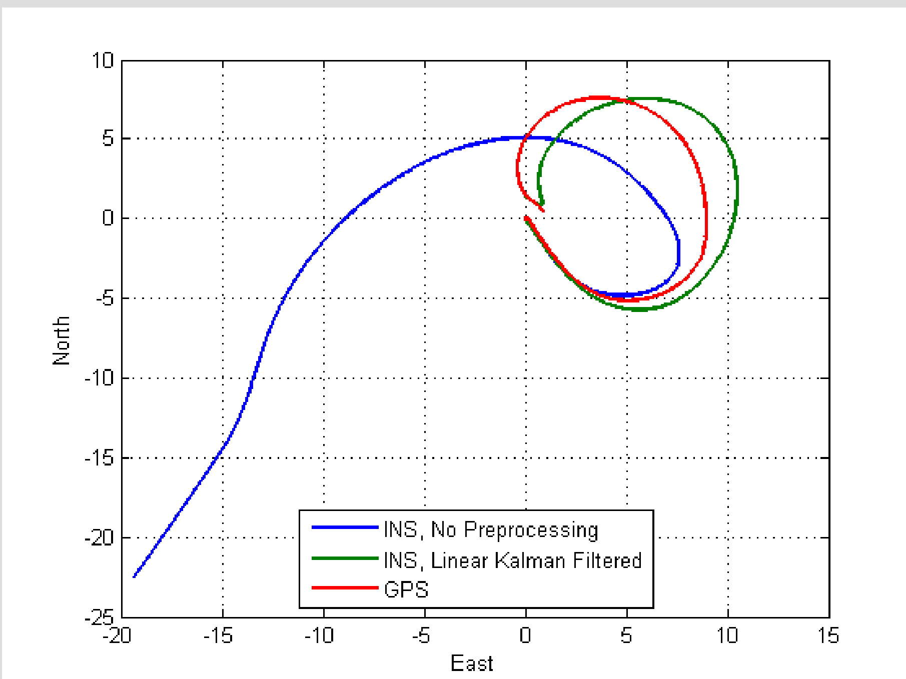
Experimental Results

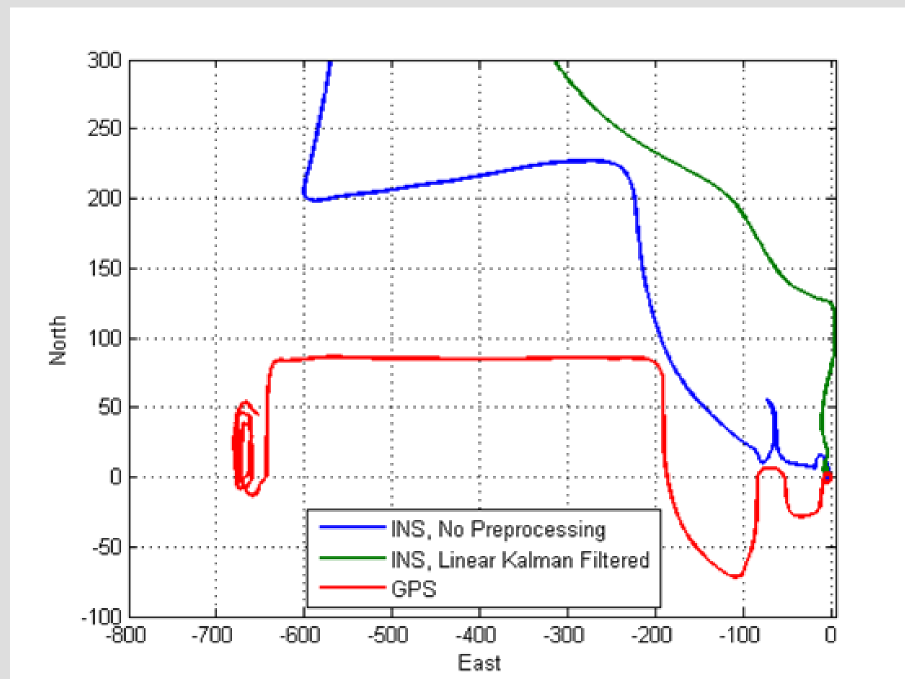
- Experimental Setup



Experimental Results

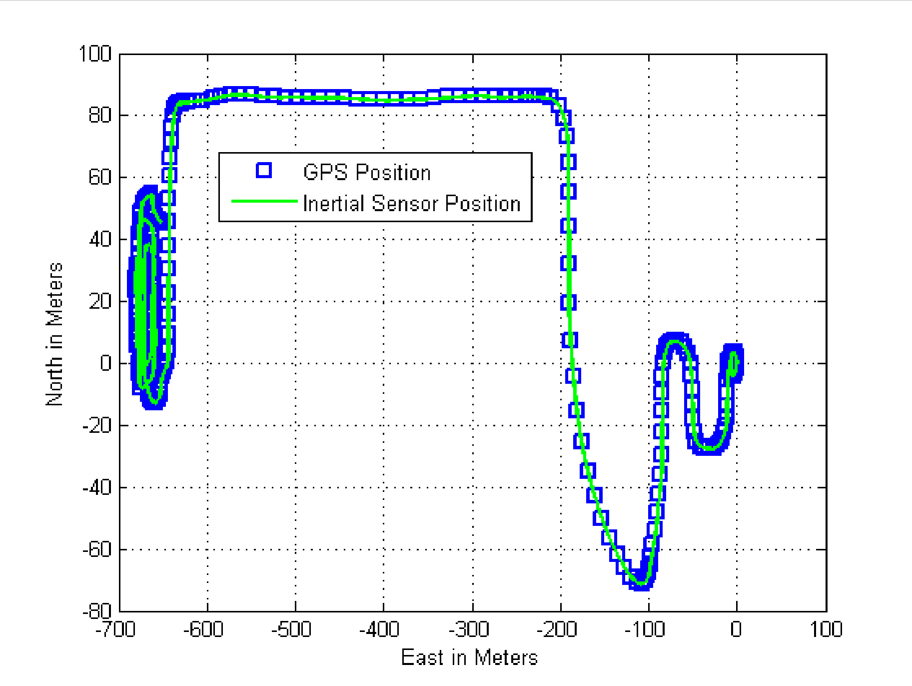
- Strapdown Solution and Linear Kalman Filter

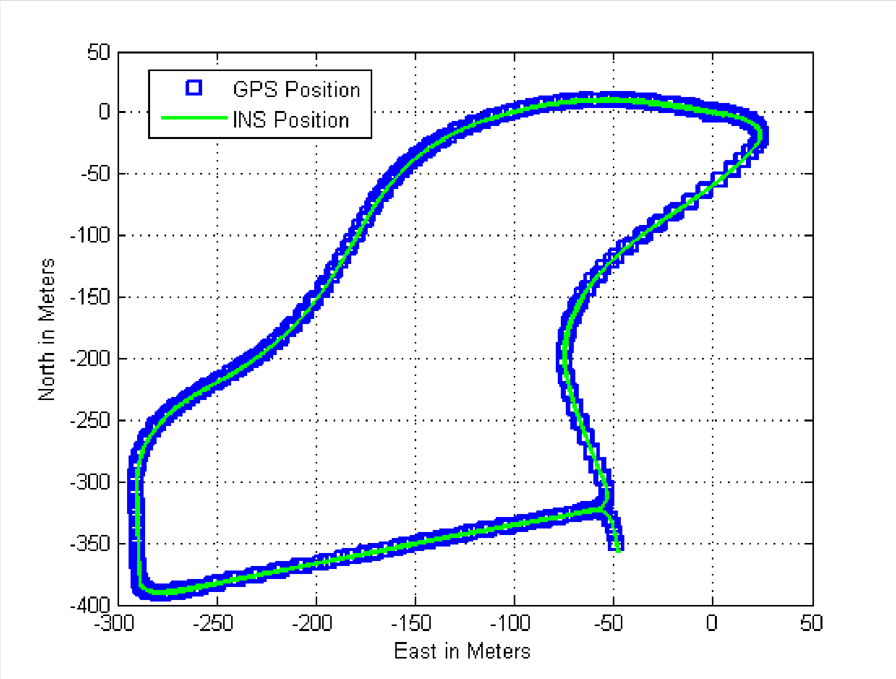




Experimental Results

- Unscented Kalman filter





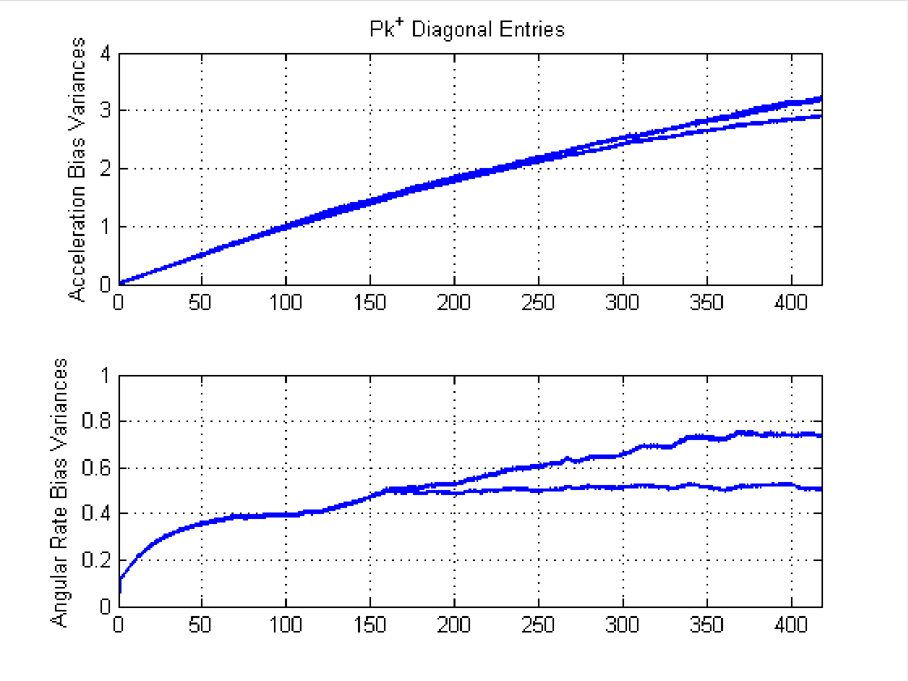
Experimental Results

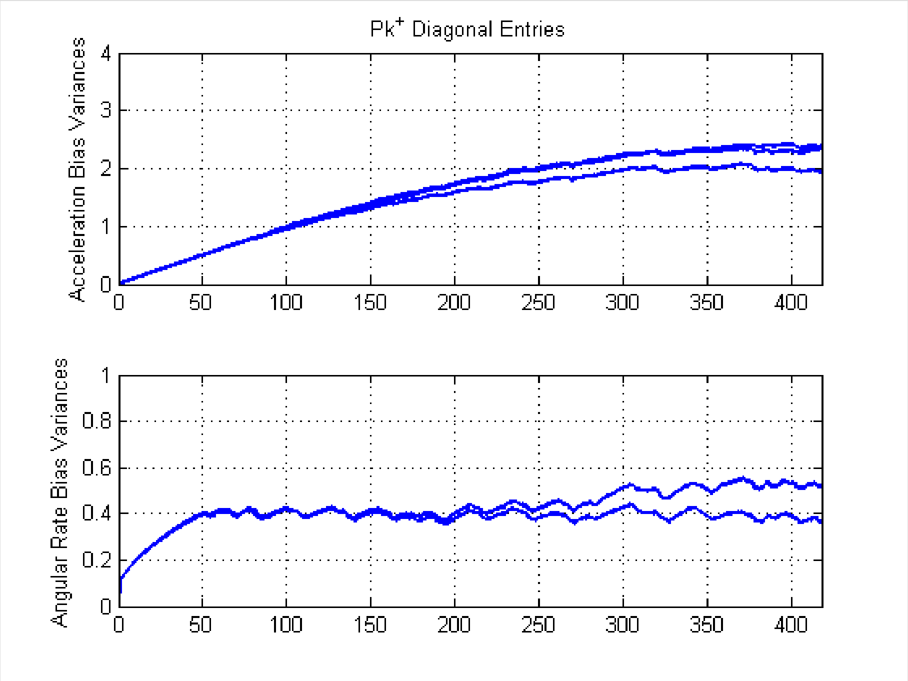
- Error between GPS and UKF INS solution

GPS Interpolation	Position Mean	Position Std Dev	Velocity Mean	Velocity Std Dev	Velocity Observables
Not	0.2083	0.8222	0.1442	0.1411	With
Not	0.2015	0.4930	8.2015	4.2729	Without
Interp.	0.0050	0.0029	0.1133	0.0501	With
Interp.	0.1256	0.0671	8.1268	4.2731	Without

Experimental Results

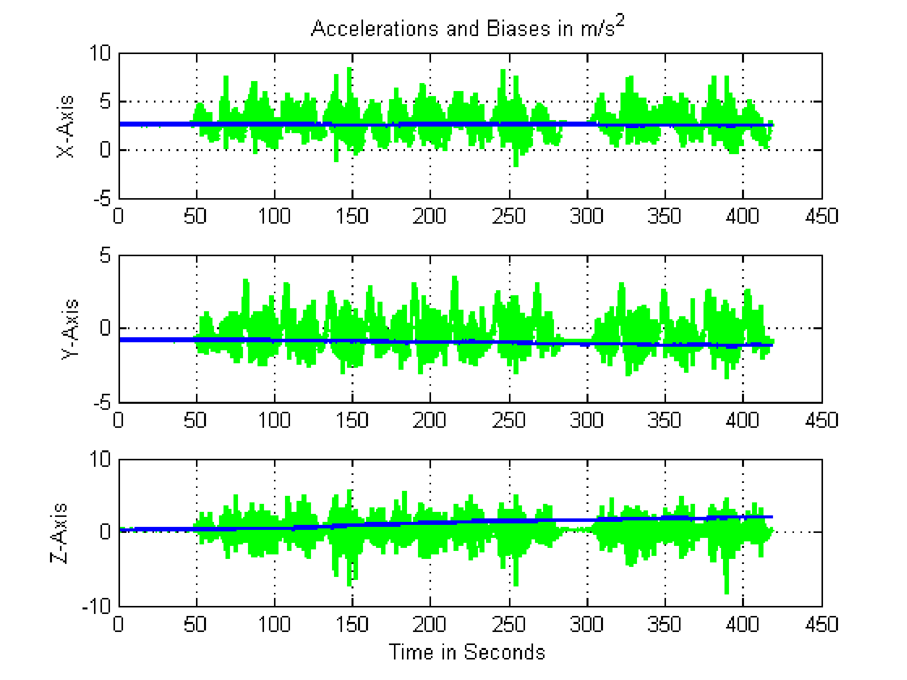
- State Covariance Matrices: Interpolated and Not

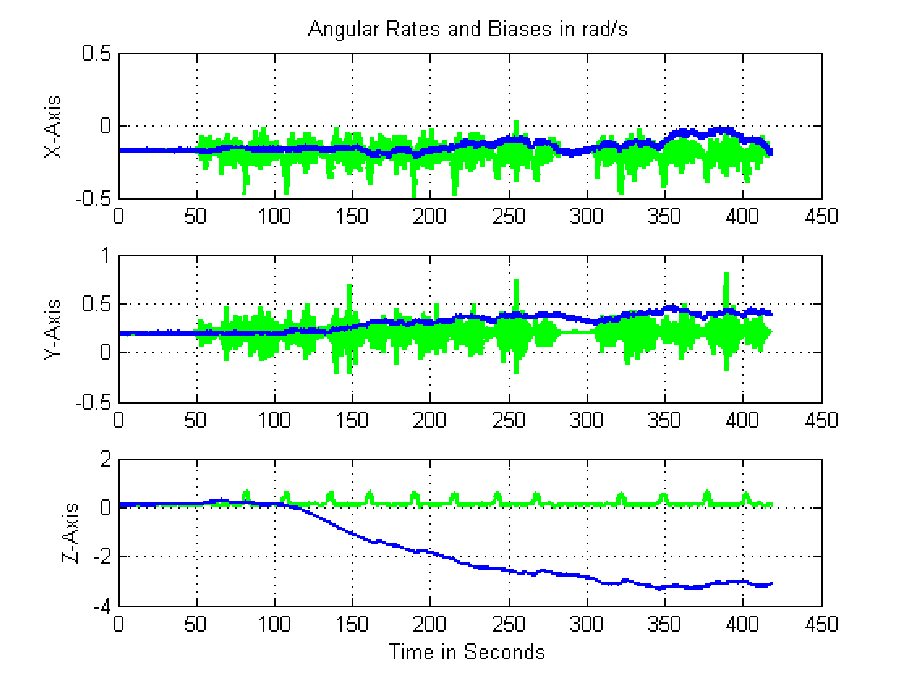




Experimental Results

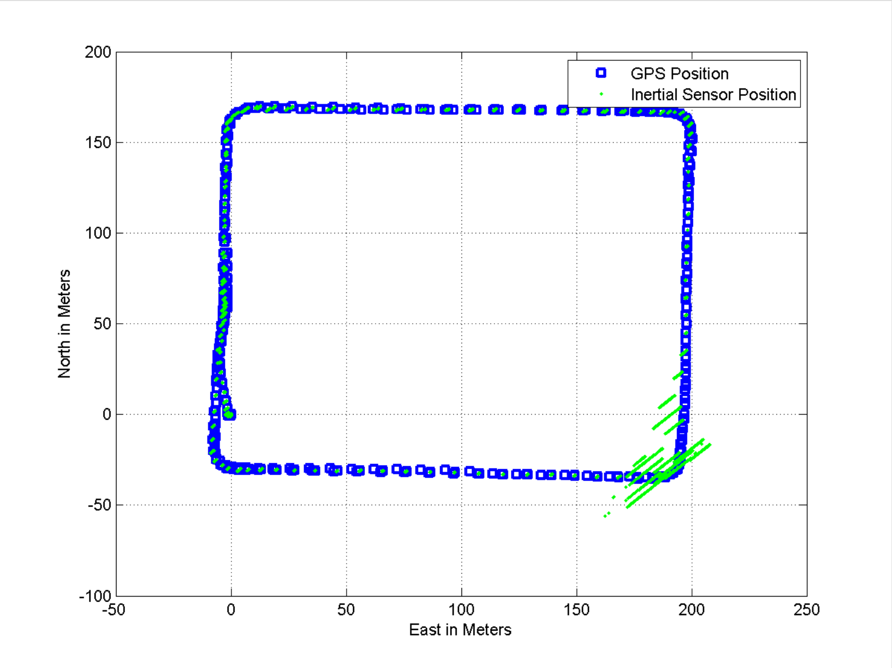
- Bias Estimation Results

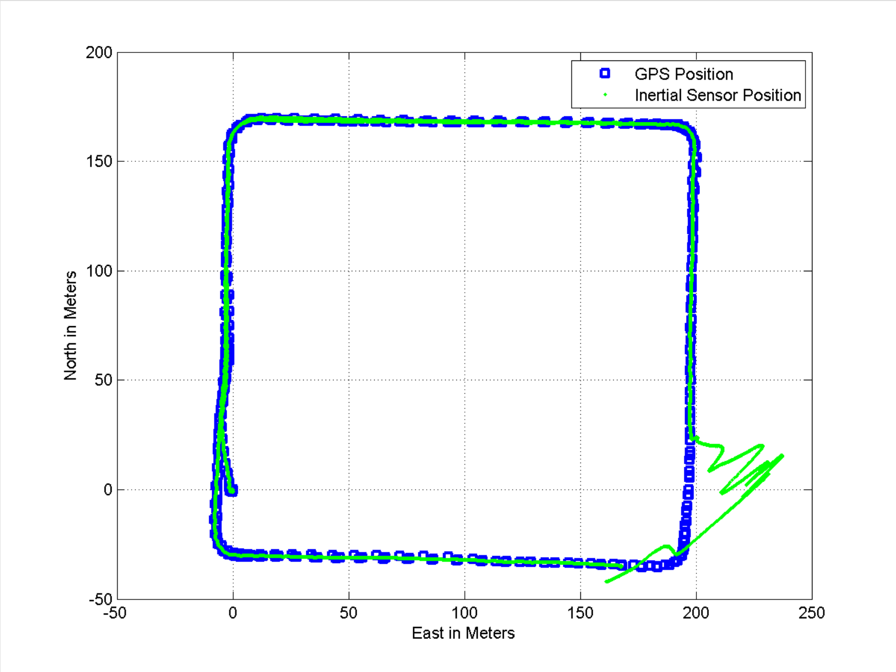




Experimental Results

- GPS Outages





Future Work

- Error Models
  - Find better Gauss-Markov parameters
  - 2^{nd} Order ARMA sensor model
  - Model lever-arm effect
  - Tightly coupled system
- Timing Synchronization
- Attitude Initialization
- Real-Time Hardware Implementation

Conclusions

- Developed system model (strapdown)
- Developed signal model
- Implemented linear and Unscented Kalman filter

References

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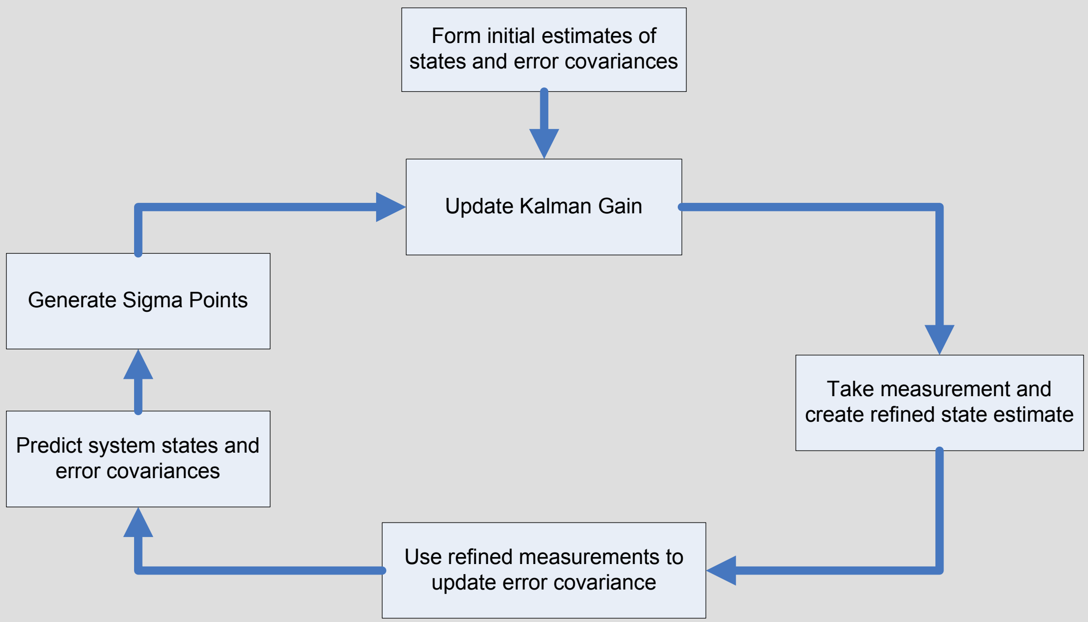
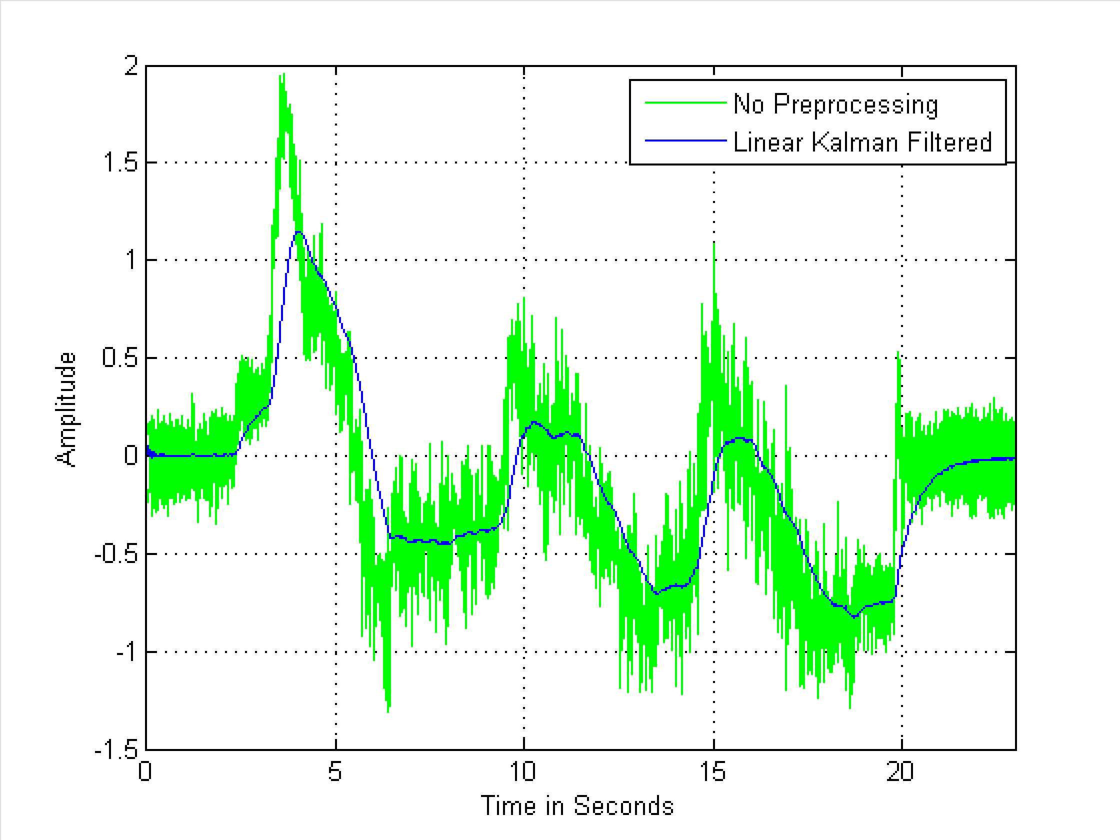
Kalman Filter



Kalman Filter



Sensor Modeling

- Gauss-Markov Process
  - Gaussian Distribution
  - Markov Process

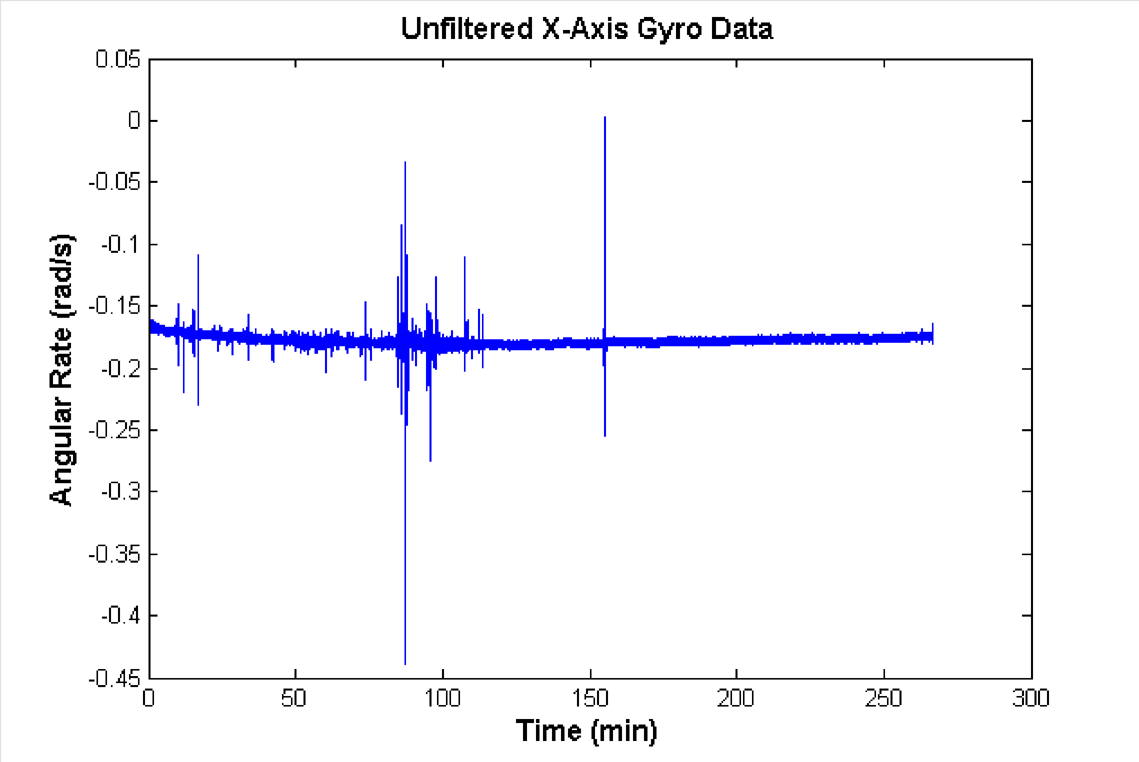
  - Autocorrelation: $R_x(\tau)=\sigma^2 e^{-\alpha|\tau|}$

  - PSD: $S_x(jw)=\frac{2\sigma^2\alpha}{w^2+\alpha^2}$

Sensor Modeling

- Modeling Process
  - Remove mean
  - Focus on a ‘quiet’ portion of data
  - Separate into small segment of data
  - Calculate the variance of each segment
  - Use the mean variance and PSD to find time constant

Sensor Modeling



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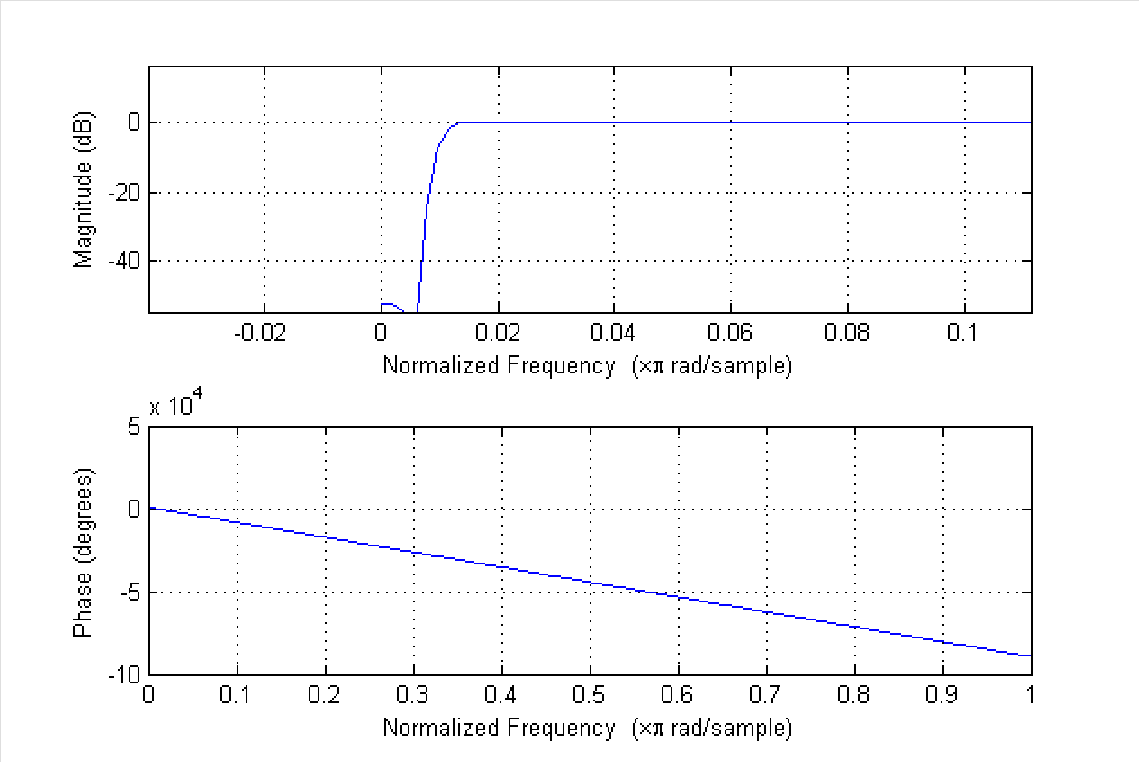

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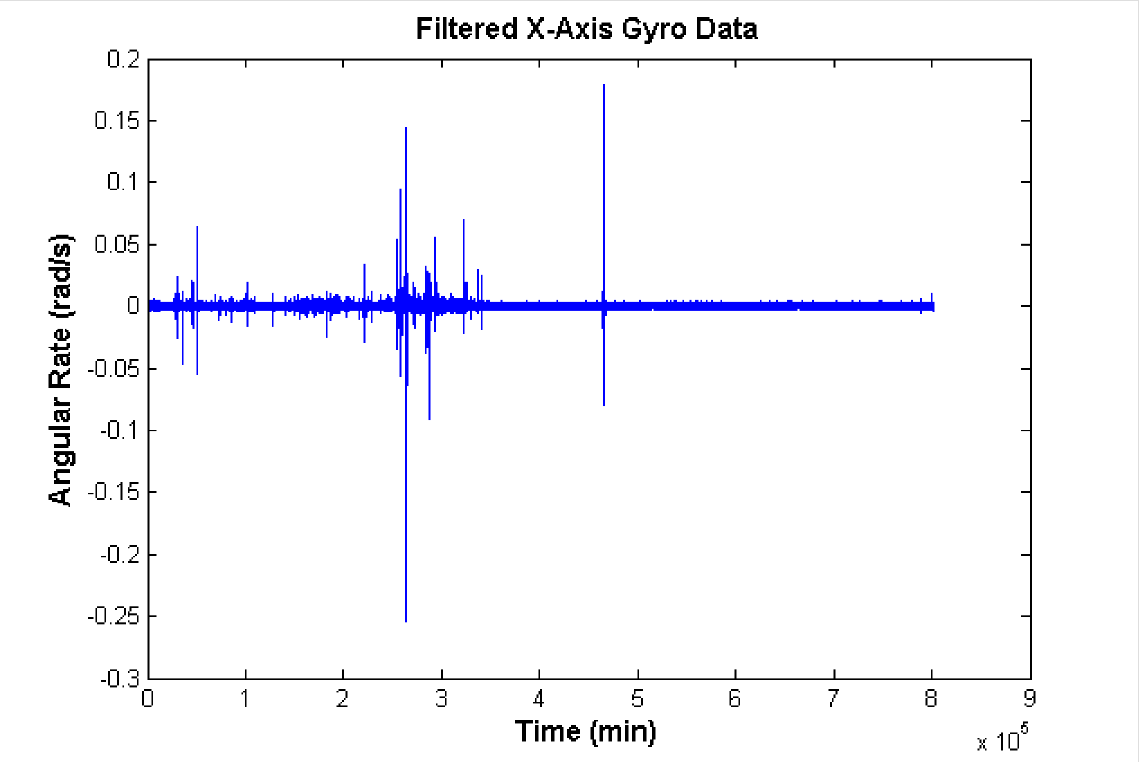

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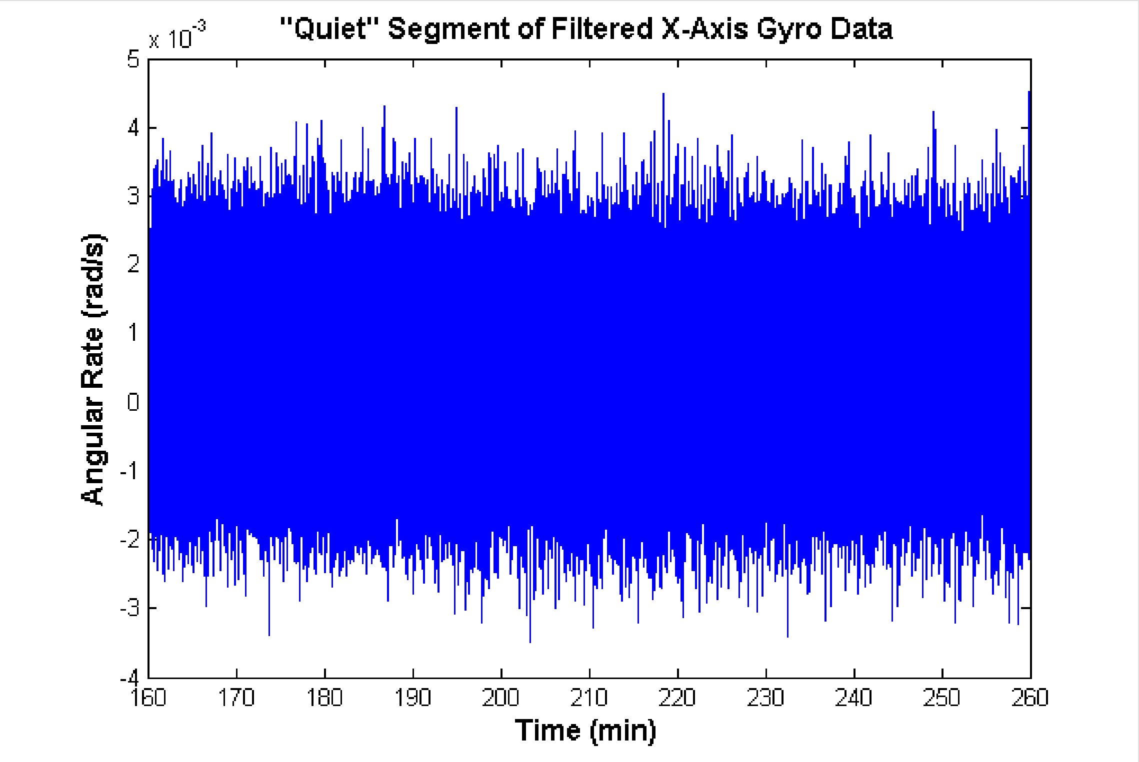

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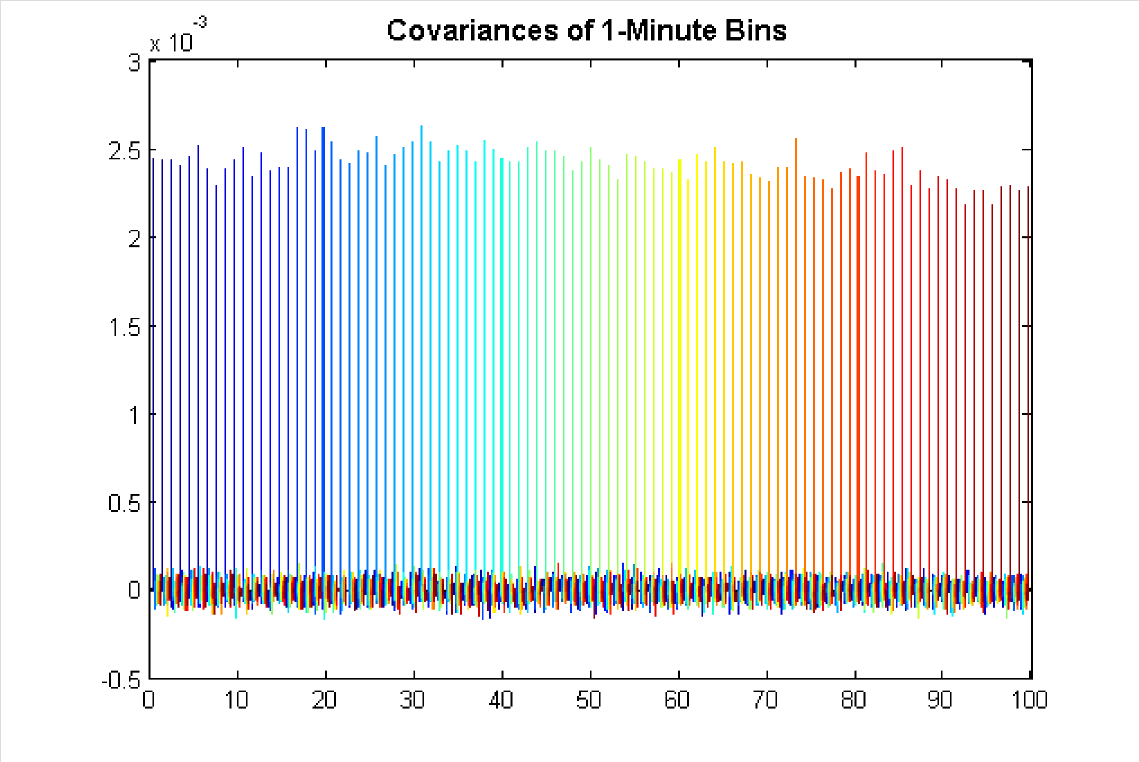

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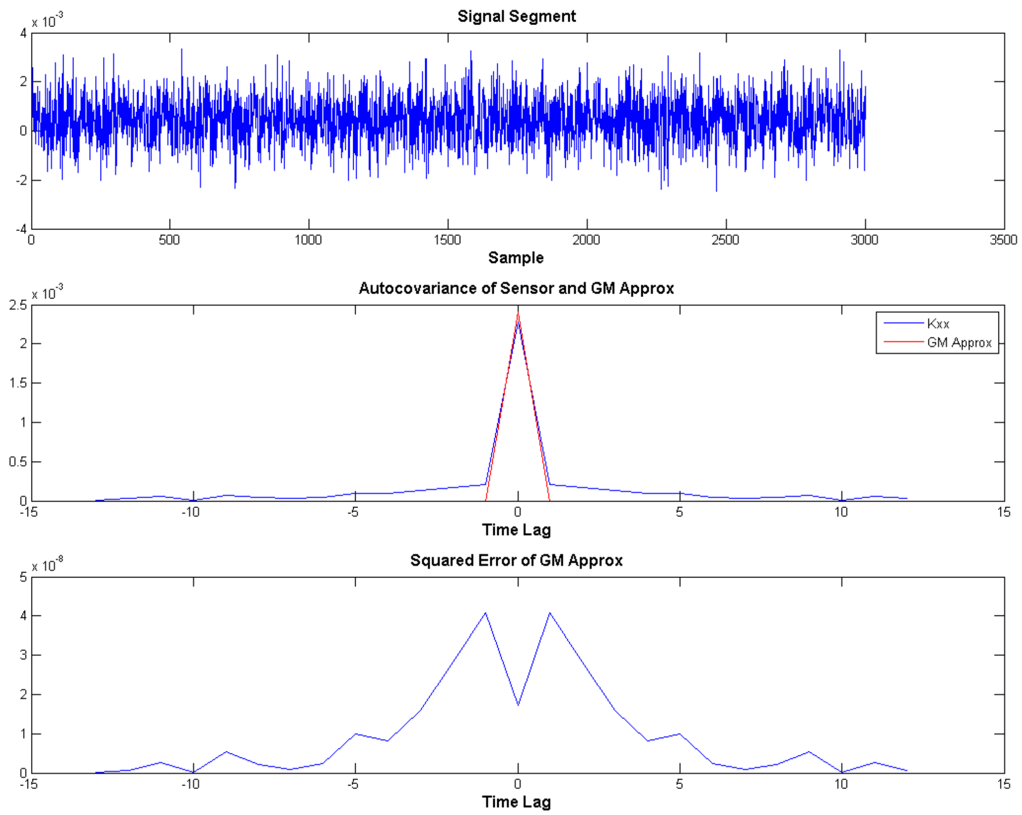


State Equations

$$\dot{\boldsymbol{p}} = \boldsymbol{v}$$

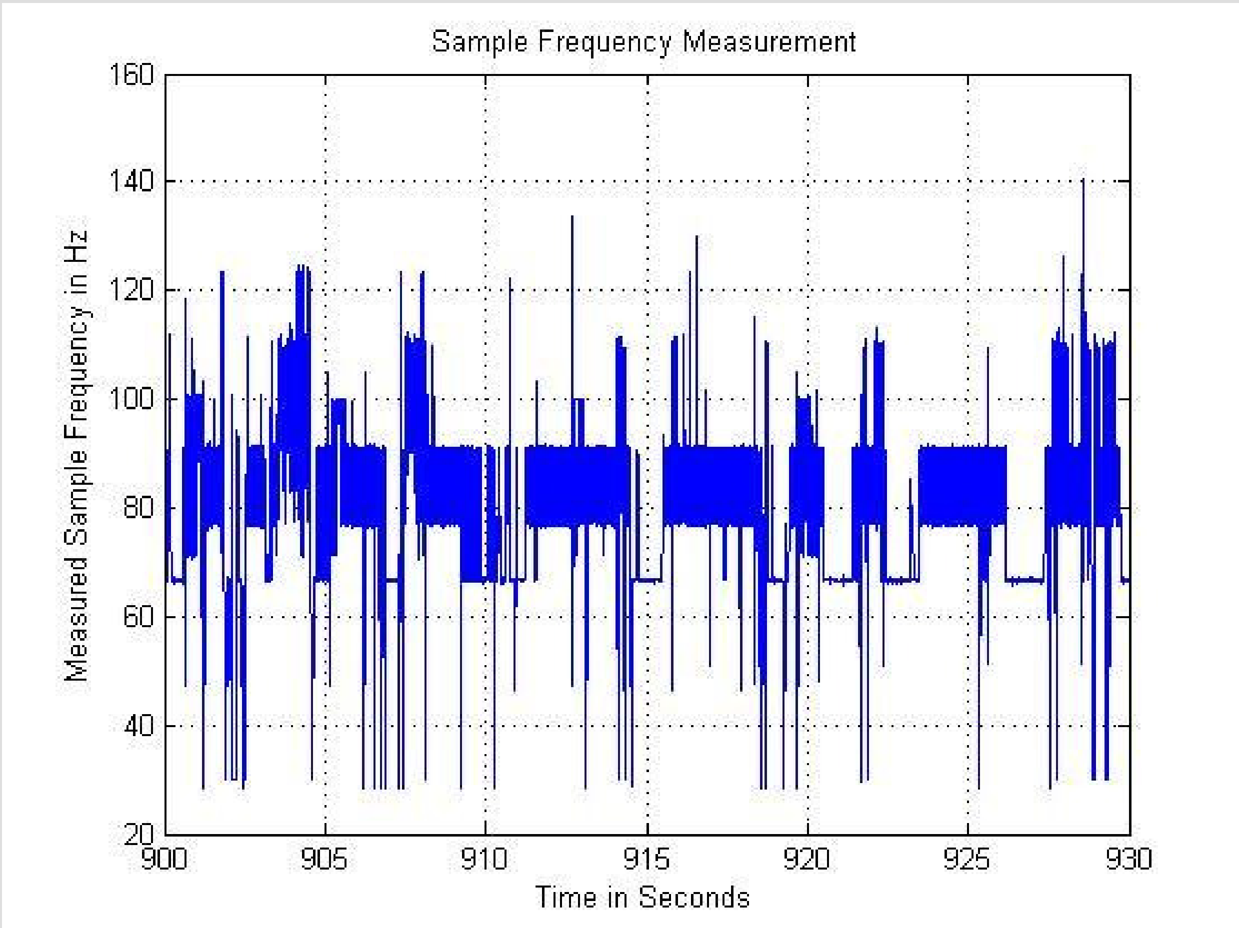
$$\dot{\boldsymbol{v}} = \boldsymbol{C}(\boldsymbol{f} - \boldsymbol{f}_{\boldsymbol{bias}}) - [0 \quad 0 \quad g(h, \lambda)]^T$$

$$\dot{\boldsymbol{f}}_{\boldsymbol{bias}} = diag(\boldsymbol{\alpha})\boldsymbol{f}_{\boldsymbol{bias}} + \boldsymbol{n}_f$$

$$\dot{\boldsymbol{q}} = \frac{1}{2}\boldsymbol{q} \otimes \boldsymbol{p}$$

$$\dot{\boldsymbol{\omega}}_{\boldsymbol{bias}} = diag(\boldsymbol{\beta})\boldsymbol{\omega}_{\boldsymbol{bias}} + \boldsymbol{n}_\omega$$

Interfacing Issues



Interfacing Issues