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Engineering

Autonomous Trolley Localization

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MEEN 689: Robotic Perception - 22 April 2020

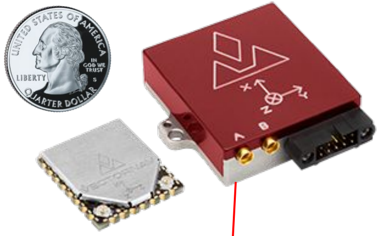
Outline

- Introduction
- Theory
- Data Collection
- Data Analysis
- Conclusions

Introduction

System

- Drive-by-wire 6 passenger Golf Cart
- Sensors include:
  - Vectornav Navigation System (VN300)
    - Raw GPS - 5 Hz
    - Raw Accelerometer/Gyro (IMU) - 50 Hz
    - **Fused Solution (INS) (50 Hz)**
  - PacMOD drive-by-wire module
    - Steering Wheel Angle - 30 Hz
    - Wheel Velocity - 30 Hz



Introduction

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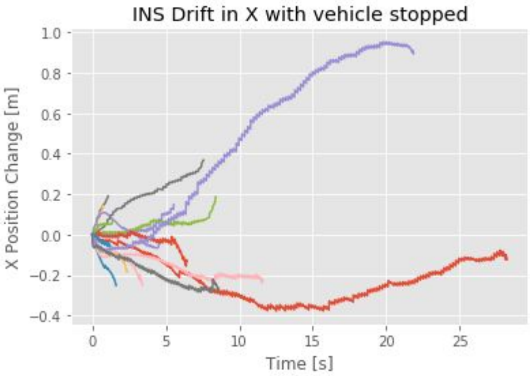
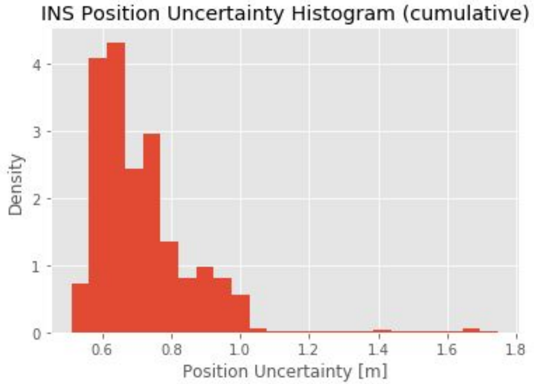
Problem Statement

- Current localization methods are limited to the **INS** solution uncertainty **(0.2-1.5 m)**
- **INS** solution accuracy is very susceptible to atmospheric conditions, trees, buildings, and overpasses.
- **INS** solutions can “jump”, particularly while at rest, and can cause improper control actions.

Objective

Combine Vectornav measurements with a physics based vehicle model to avoid these susceptibilities.



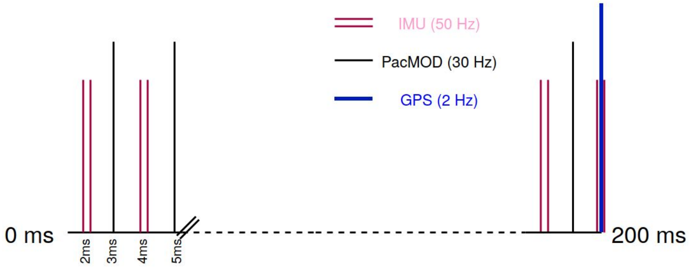


Methodology

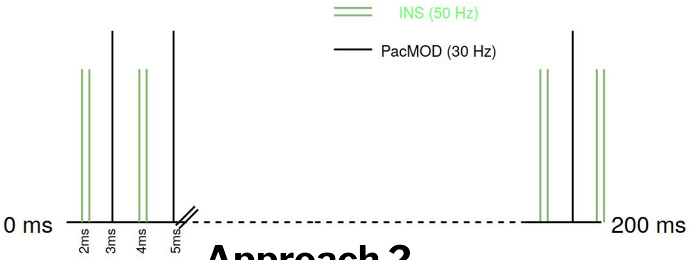
Approach

- Two different approaches are taken
  - Combine ***raw*** IMU, Gyro, GPS measurements with the vehicle model based on PacMOD measurements
  - Combine manufacturer fused (IMU, Gyro, GPS) **INS** measurements with the vehicle model based on PacMOD measurements
- Robotic Operating System (ROS) & Python for real time implementation
- MATLAB for 3D version

Measurement Update Cycle



Approach 1



Approach 2

Theory - Kinematic "Bicycle" Model

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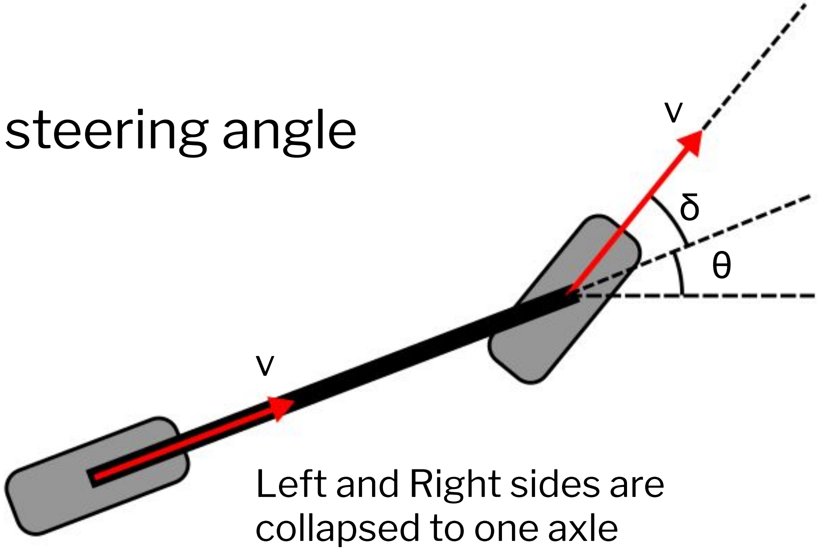
- Simplifies full vehicle
- Ignores slip and dynamics
- Depends only on velocity and steering angle

$$\dot{x}_r = v\cos\theta$$

$$\dot{y}_r = v\sin\theta$$

$$\dot{\theta} = \frac{v}{L}\tan\delta$$



Left and Right sides are collapsed to one axle

Theory - Kalman Filter

- Also known as Linear Quadratic Estimation (LQE)
- A two-step, recursive, real-time algorithm
- Equals the MAP in linear systems
- Assumes errors are Gaussian

State:

$$\boldsymbol{x} = \begin{bmatrix} x\ position\ p_x \\ y\ position\ p_y \\ heading\ \theta \\ x\ velocity\ v_x \\ y\ velocity\ v_y \\ heading\ rate\ \dot{\theta} \end{bmatrix}$$

Prediction Step:

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{F}_k \hat{\boldsymbol{x}}_{k-1|k-1} + \boldsymbol{B}_k \boldsymbol{u}_k$$

$$\boldsymbol{P}_{k_k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1|k-1} \boldsymbol{F}_k^T + \boldsymbol{Q}_k$$

Measurement Step:

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - \boldsymbol{H}_k \hat{\boldsymbol{x}}_{k|k-1}$$

$$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T \boldsymbol{S}_k^{-1}$$

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k \tilde{\boldsymbol{y}}_k$$

$$\boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_{k|k-1}$$

Theory - Extended Kalman Filter

- Nonlinear systems can be linearized about current state
- More computationally expensive
- Extends to most dynamic systems

Prediction Step:

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{f}(\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_k)$$

$$\boldsymbol{P}_{k_k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1|k-1} \boldsymbol{F}_k^T + \boldsymbol{Q}_k$$

$$\boldsymbol{F}_k = \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{x}}|_{\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_k}$$

$$\boldsymbol{H}_k = \frac{\partial \boldsymbol{h}}{\partial \boldsymbol{x}}|_{\hat{\boldsymbol{x}}_{k-1|k-1}}$$

Measurement Step:

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - \boldsymbol{h}(\hat{\boldsymbol{x}}_{k|k-1})$$

$$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T \boldsymbol{S}_k^{-1}$$

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k \tilde{\boldsymbol{y}}_k$$

$$\boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_{k|k-1}$$

Sensors - Calibration

Accelerometer calibration model:

$$A = \begin{bmatrix} 1 & M_{XY} & M_{XZ} \\ M_{YX} & 1 & M_{YZ} \\ M_{ZX} & M_{ZY} & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{S_X} & 0 & 0 \\ 0 & \frac{1}{S_X} & 0 \\ 0 & 0 & \frac{1}{S_X} \end{bmatrix} \left(\begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix} + \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} \right)$$

Gyroscope calibration model:

$$\omega = \begin{bmatrix} 1 & M_{XY} & M_{XZ} \\ M_{YX} & 1 & M_{YZ} \\ M_{ZX} & M_{ZY} & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{S_X} & 0 & 0 \\ 0 & \frac{1}{S_X} & 0 \\ 0 & 0 & \frac{1}{S_X} \end{bmatrix} \left(\begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix} + \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} + \begin{bmatrix} H_{XX} & H_{XY} & H_{XZ} \\ H_{YX} & H_{YY} & H_{YZ} \\ H_{ZX} & H_{ZY} & H_{ZZ} \end{bmatrix} \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \right)$$

Sensors - Simplified Calibration

Assume the system is properly calibrated, just misaligned

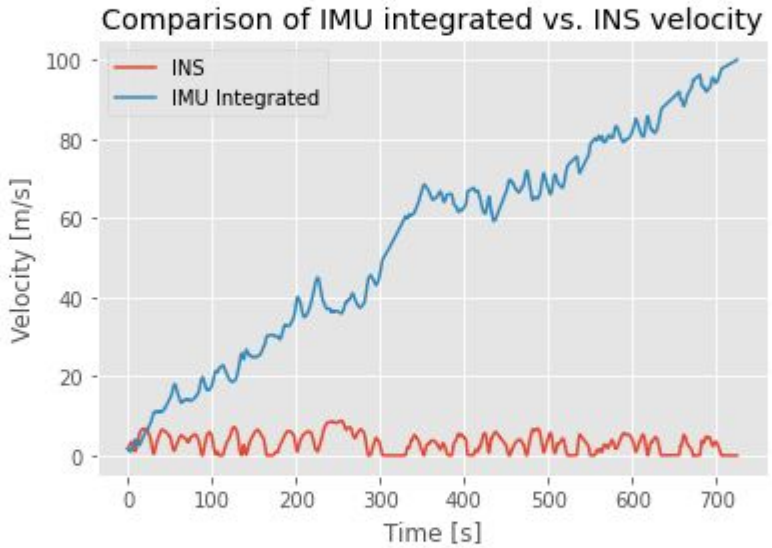
- Removes scaling factors
- Orthogonal misalignment matrix

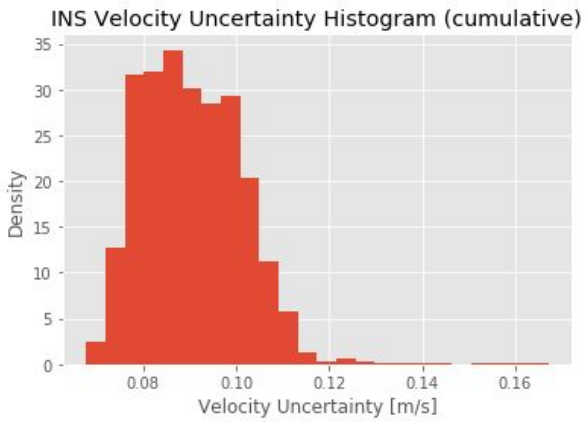
$$A = \begin{bmatrix} 1 & M_{XY} & M_{ZX} \\ M_{XY} & 1 & M_{YZ} \\ M_{ZX} & M_{YZ} & 1 \end{bmatrix} \left(\begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix} + \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} \right)$$

$$\omega = \begin{bmatrix} 1 & M_{XY} & M_{ZX} \\ M_{XY} & 1 & M_{YZ} \\ M_{ZX} & M_{YZ} & 1 \end{bmatrix} \left(\begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix} + \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} \right)$$

Parameter Estimation - IMU Errors

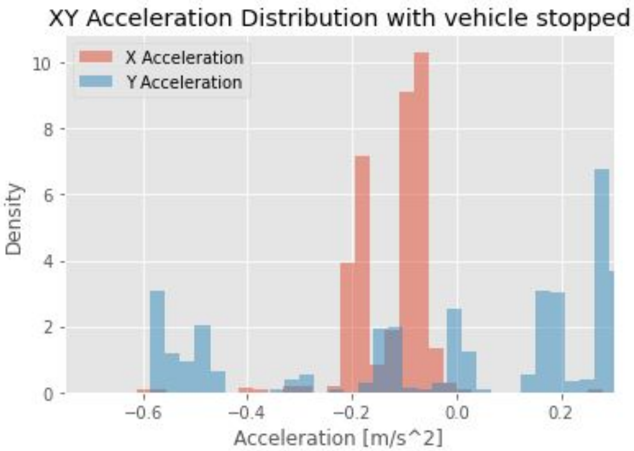
- Integrating for velocity drifts due to misalignment and bias

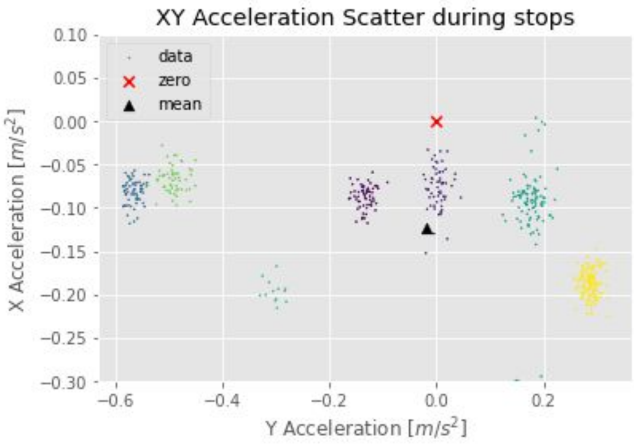




Parameter Estimation - IMU Errors

- Biases are multimodal and dependent on road geometry
- This is very difficult to measure

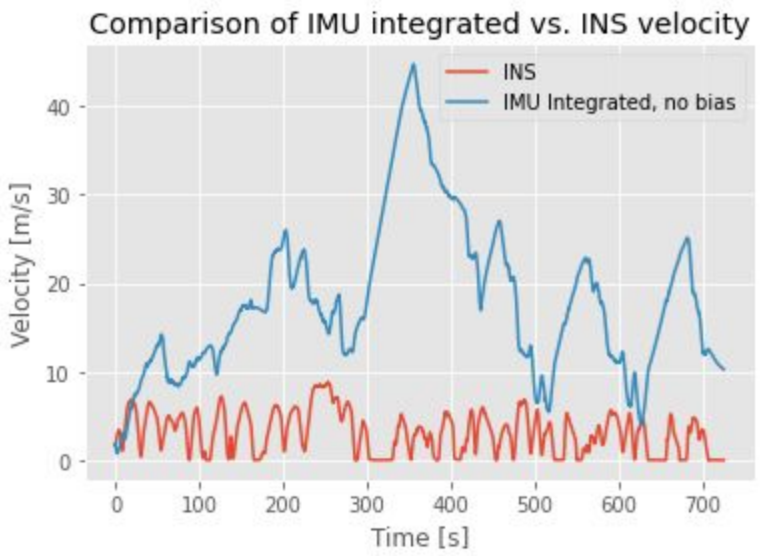




MEAN
x: $-0.122\ m/s^2$
y: $-0.02\ m/s^2$

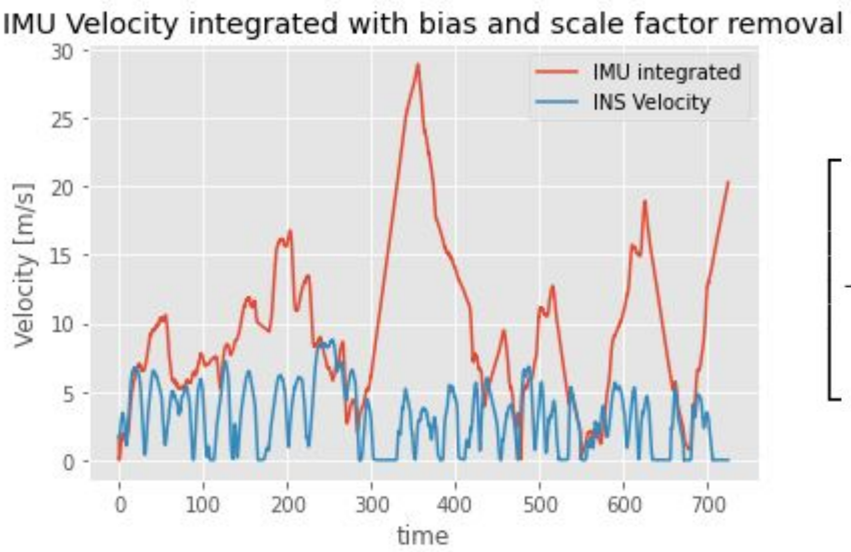
Parameter Estimation - IMU Errors

Removing average bias does improve integration



Parameter Estimation - IMU Errors

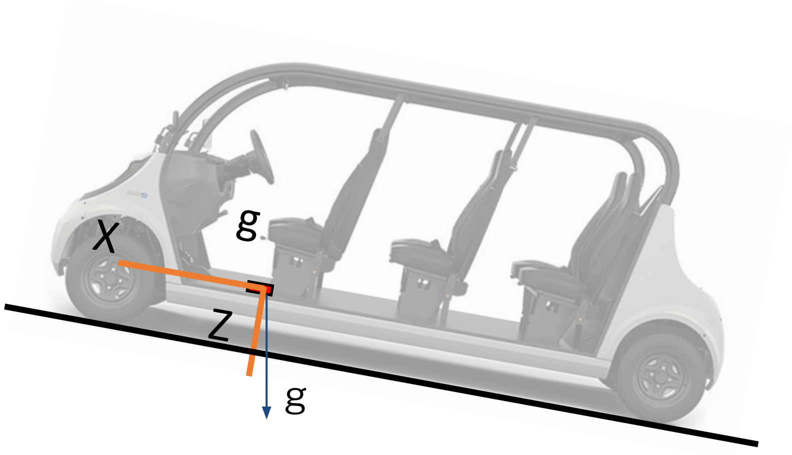
- Least Squares to minimize the velocity error



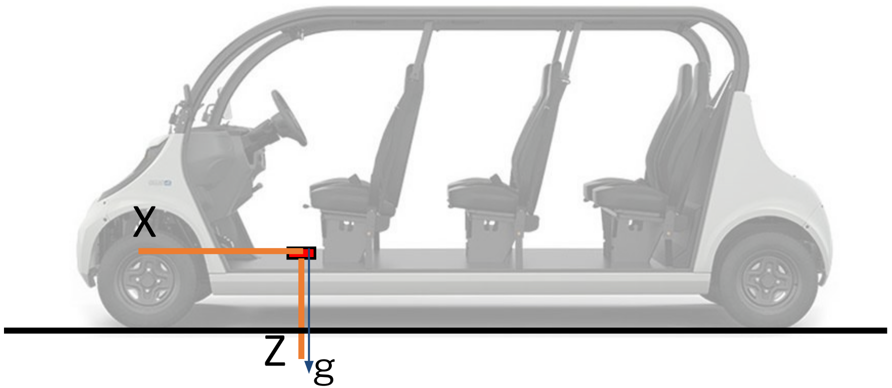
$$\begin{bmatrix} 0.9107 & 0.084 & -0.0053 \\ -0.0356 & 0.900 & -0.0016 \\ 0.0265 & -0.0435 & 0.9818 \end{bmatrix} \begin{bmatrix} V_X + 0.056 \\ V_Y + 0.1009 \\ V_Z - 0.200 \end{bmatrix}$$

Parameter Estimation - Biases Example

EX:
Golf Cart is pitched, gravity has components in X, Z

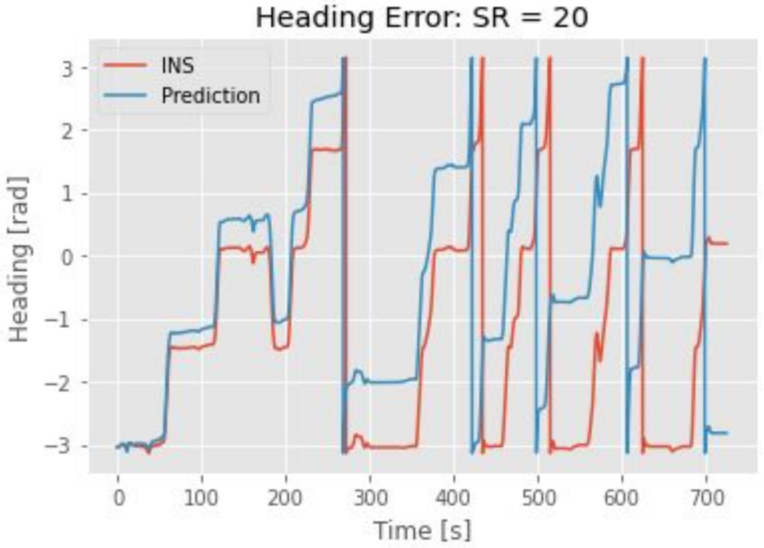


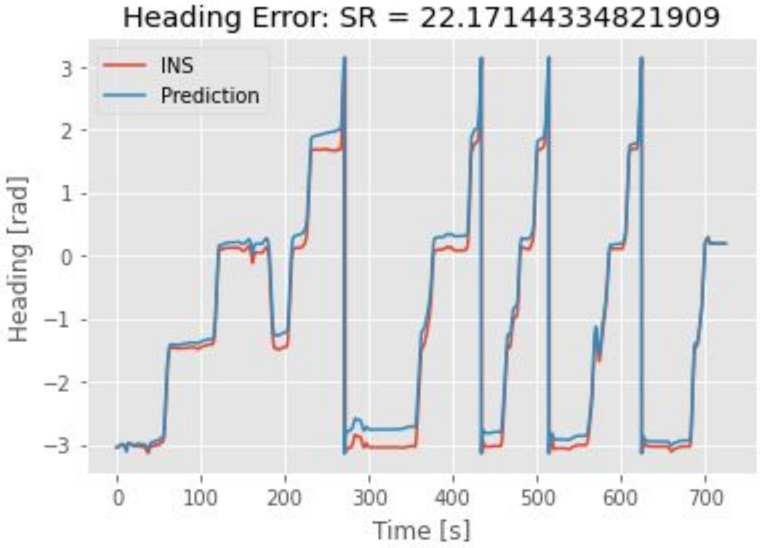
EX:
Golf Cart isn't pitched, gravity is entirely in Z axis



Parameter Estimation - Steering Ratio

- Calibration of Steering Ratio
- Integrated Kinematic Bicycle Model vs INS
- Minimized final heading error

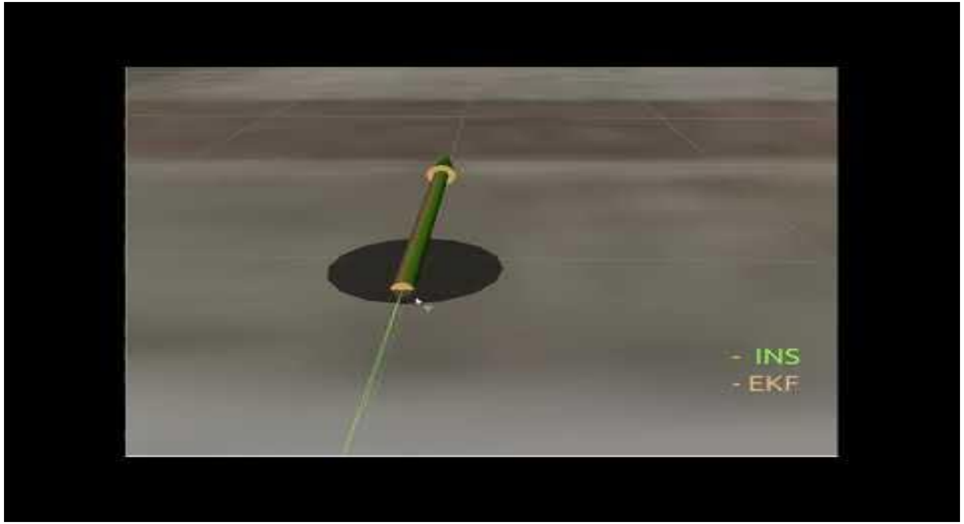




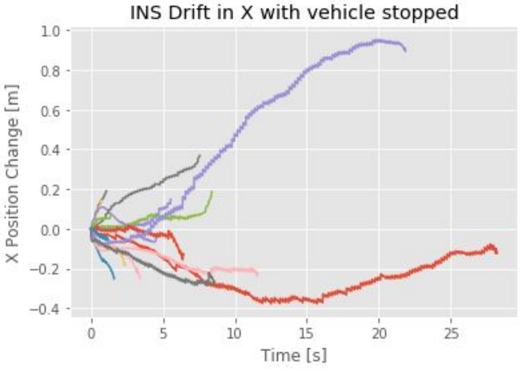
Real Time Implementation

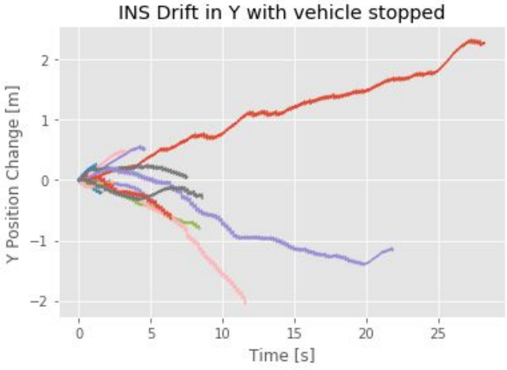
PacMOD + ***(processed)*** GPS, IMU

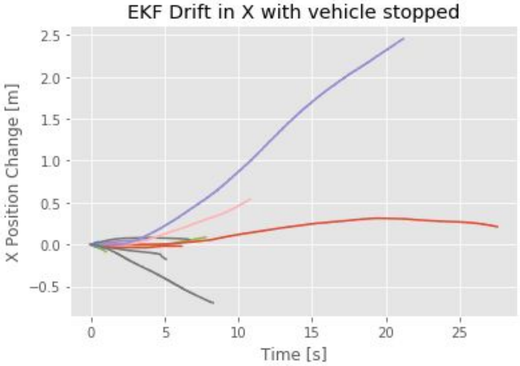
PacMOD + ***INS***

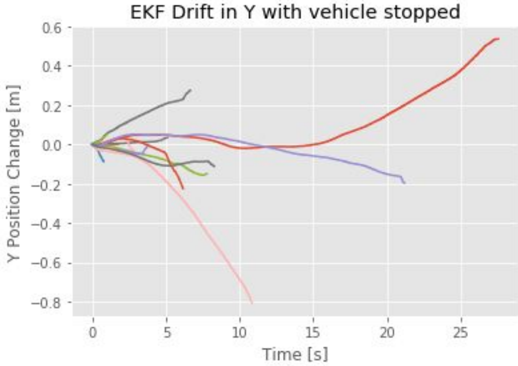


EKF results


INS Drift in X with vehicle stopped
X Position Change [m]
Time [s]
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
0
5
10
15
20
25


INS Drift in Y with vehicle stopped
Y Position Change [m]
Time [s]
2
1
0
−1
−2
0
5
10
15
20
25


EKF Drift in X with vehicle stopped
X Position Change [m]
Time [s]
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
0
5
10
15
20
25


EKF Drift in Y with vehicle stopped
Y Position Change [m]
Time [s]
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
0
5
10
15
20
25

State Estimation in 3D

Accelerometer data

$$u_k = [a^b_{x_k}, a^b_{y_k}, a^b_{z_k}, p_k, q_k, r_k]^T$$

Transform acceleration to world frame and offset gravity

$$a^{NED} = R_z R_y R_z \begin{bmatrix} a^b_{x_k} \\ a^b_{y_k} \\ a^b_{z_k} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix}$$

Convert body rates to euler angle rates

$$\begin{bmatrix} \dot{\phi}_k \\ \dot{\theta}_k \\ \dot{\psi}_k \end{bmatrix} = \begin{bmatrix} cos\theta_k cos\psi_k & -sin\psi_k & 0 \\ cos\theta_k sin\psi_k & cos\psi_k & 0 \\ -sin\theta_k & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} p_k \\ q_k \\ r_k \end{bmatrix}$$

Prediction

$$\hat{x}_k = f(x_{k-1}, u_k) = \begin{bmatrix} x_{k-1} + dt \times v_{x_{k-1}} + 0.5 \times dt^2 \times a_{x_k}^{NED} \\ y_{k-1} + dt \times v_{y_{k-1}} + 0.5 \times dt^2 \times a_{y_k}^{NED} \\ z_{k-1} + dt \times v_{z_{k-1}} + 0.5 \times dt^2 \times a_{z_k}^{NED} \\ v_{x_{k-1}} + dt \times a_{x_k}^{NED} \\ v_{y_{k-1}} + dt \times a_{y_k}^{NED} \\ v_{z_{k-1}} + dt \times a_{z_k}^{NED} \\ \phi_{k-1} + dt \times \dot{\phi}_k \\ \theta_{k-1} + dt \times \dot{\theta}_k \\ \psi_{k-1} + dt \times \dot{\psi}_k \end{bmatrix}$$

$$F_k = \left. \frac{\partial f}{\partial x} \right|_{(\hat{x}_{k-1}, u_k)}$$

$$B_k = \left. \frac{\partial f}{\partial u} \right|_{(\hat{x}_{k-1}, u_k)}$$

$$\hat{P}_k = F_k P_k F_k^T + B_k Q_k B_k^T$$

Correction

$$H_k = \begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{0}_{3\times6} \\ \mathbf{0}_{3\times6} & \mathbf{I}_{3\times3} \end{bmatrix}$$

GPS+Orientation Measurement

$$z_k = [x_k, y_k, z_k, \phi_k, \theta_k, \psi_k]^T$$

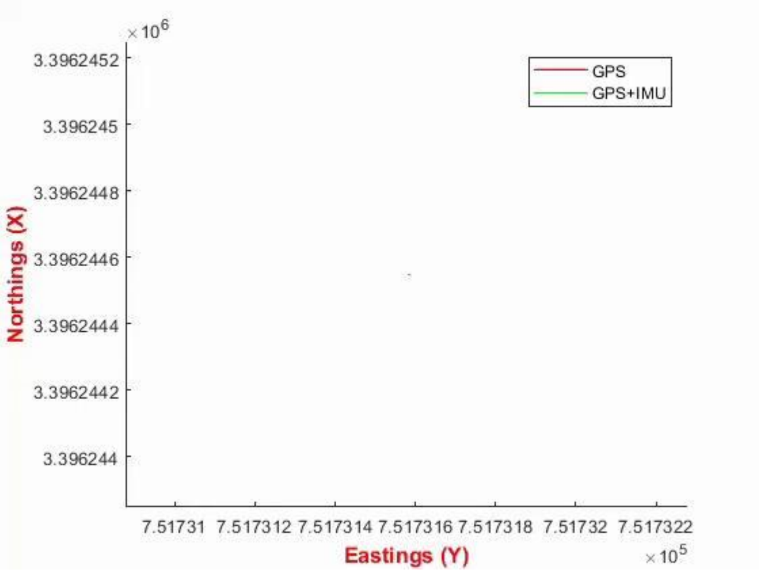
State Correction

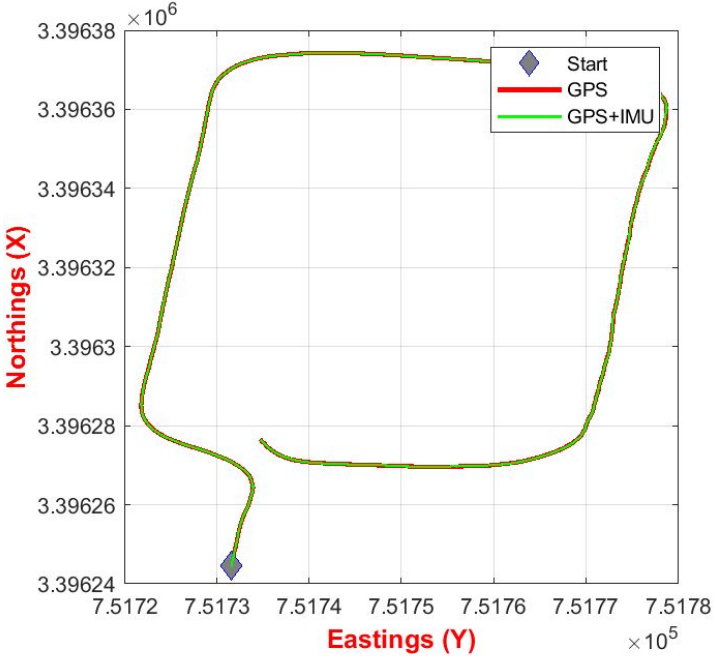
$$X_k = \hat{X}_k + K_k(z_k - H_k\hat{X}_k)$$

Covariance Correction

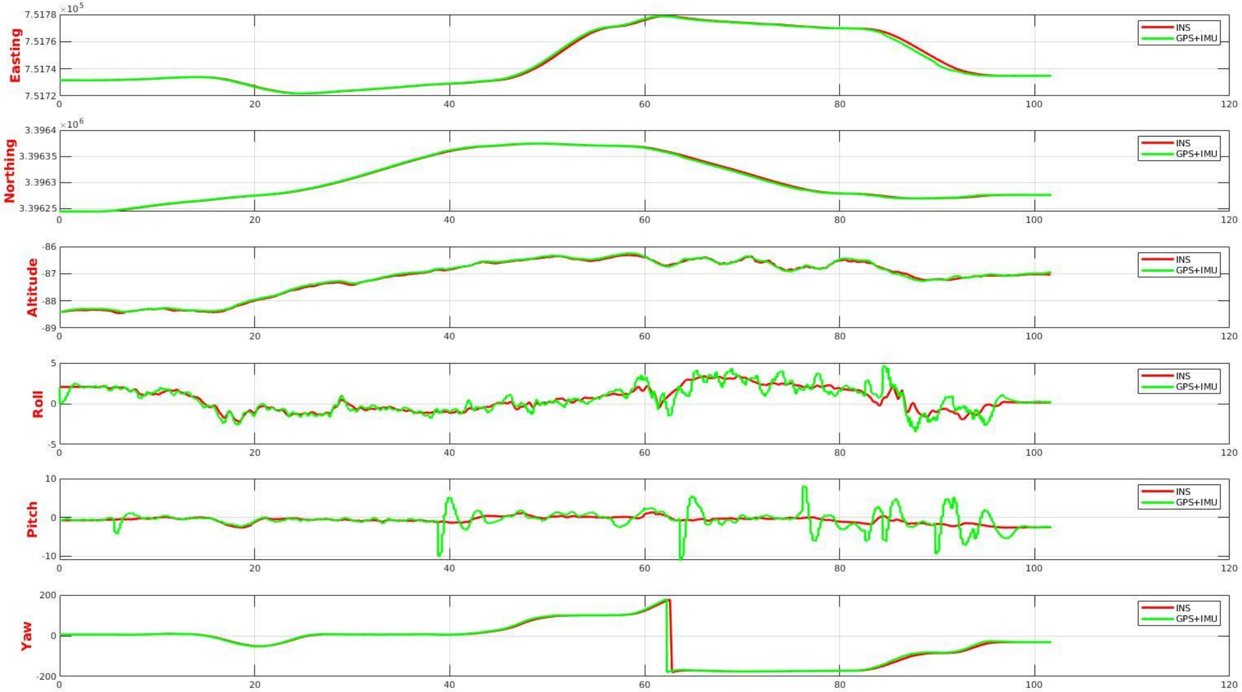
$$P_k = \hat{P}_k - K_k H_k \hat{P}_k$$

3D Results


$\times 10^6$
3.3962452
3.396245
3.3962448
3.3962446
3.3962444
3.3962442
3.396244
Northings (X)
7.51731
7.517312
7.517314
7.517316
7.517318
7.51732
7.517322
Eastings (Y)
$\times 10^5$
GPS
GPS+IMU

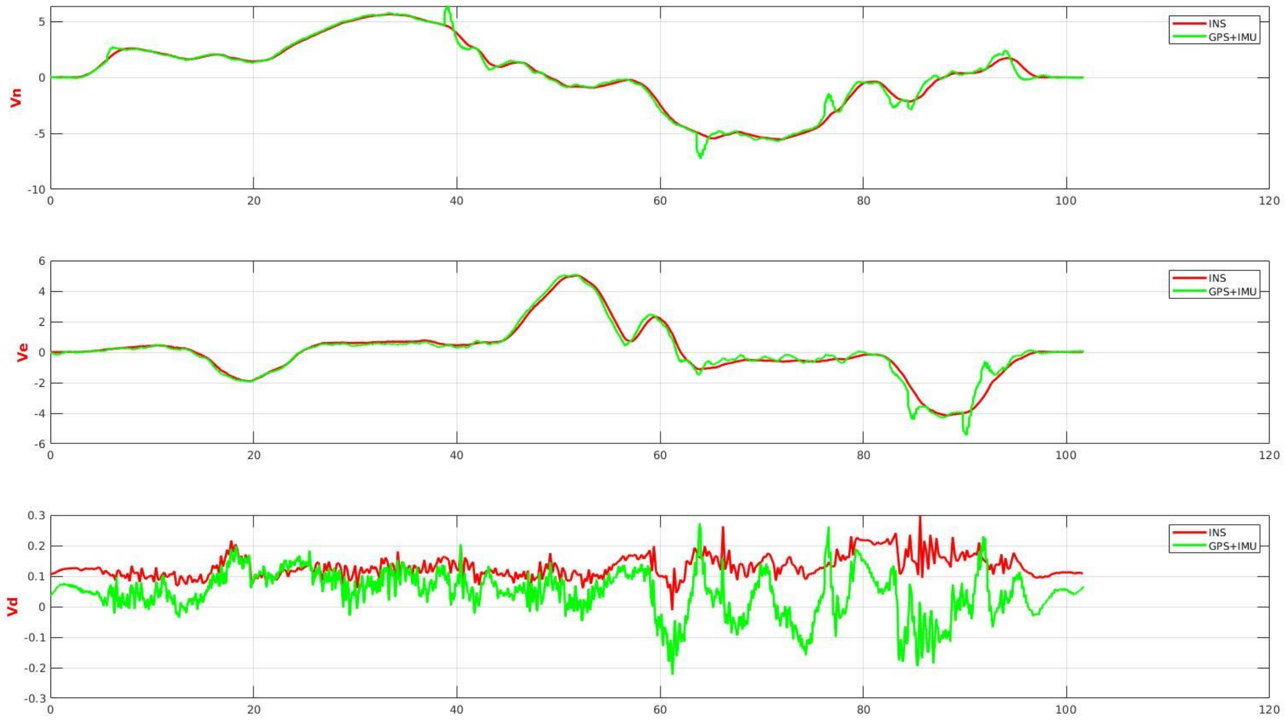

$\times 10^6$
3.39638
3.39636
3.39634
3.39632
3.3963
3.39628
3.39626
3.39624
Northings (X)
7.5172
7.5173
7.5174
7.5175
7.5176
7.5177
7.5178
Eastings (Y)
$\times 10^5$
Start
GPS
GPS+IMU

3D Results



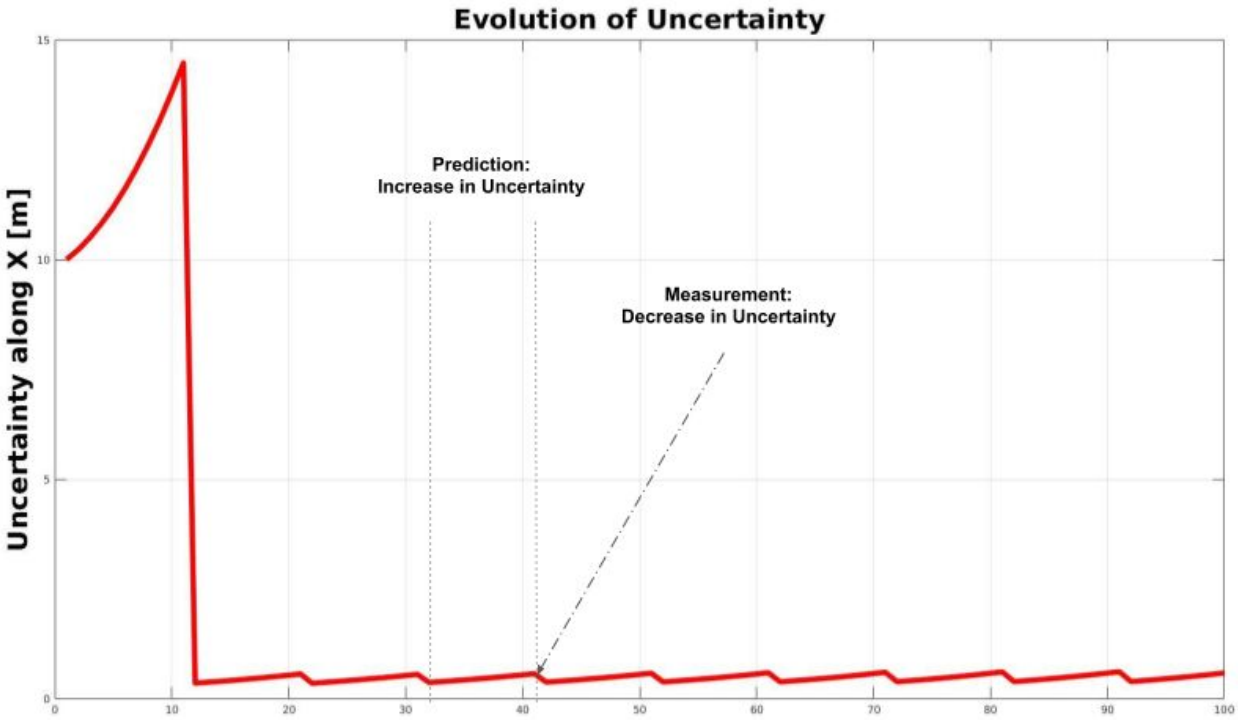
Easting
$\times10^5$
7.5178
7.5176
7.5174
7.5172
Northing
$\times10^6$
3.3964
3.39635
3.3963
3.39625
Altitude
-86
-87
-88
-89
Roll
5
0
-5
Pitch
10
0
-10
Yaw
200
0
-200
0
20
40
60
80
100
120
INS
GPS+IMU

3D Results



Vn
INS
GPS+IMU
5
0
-5
-10
0
20
40
60
80
100
120
Ve
INS
GPS+IMU
6
4
2
0
-2
-4
-6
0
20
40
60
80
100
120
Vd
INS
GPS+IMU
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
0
20
40
60
80
100
120

Evolution of State Uncertainty



Conclusions

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- Difficult to show accuracy improvements
- Would like to run more tests with filter running in real time
- Overall has lower covariance due to PACMod integration
- Able to filter in real time with golf cart data
- Smoother state estimate results
- Real time error estimation leads to filter instability

References

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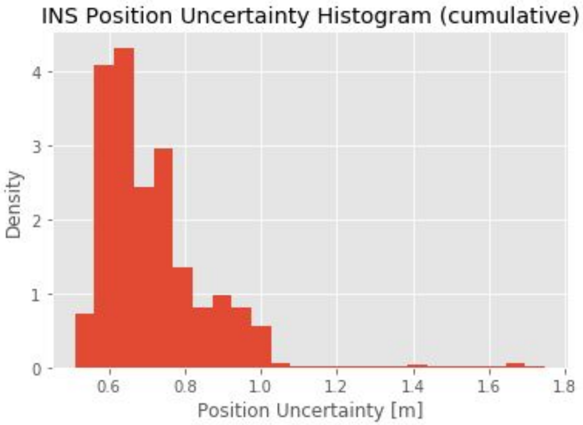
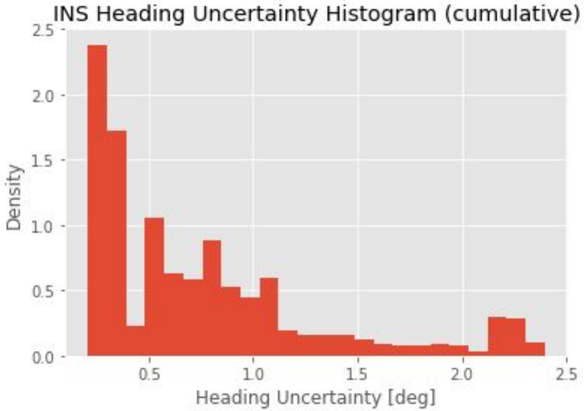
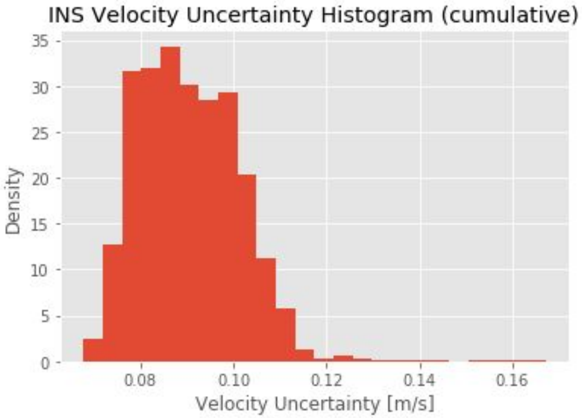
Thank you for your time

Uncertainty Measurements







vectornav EKF results

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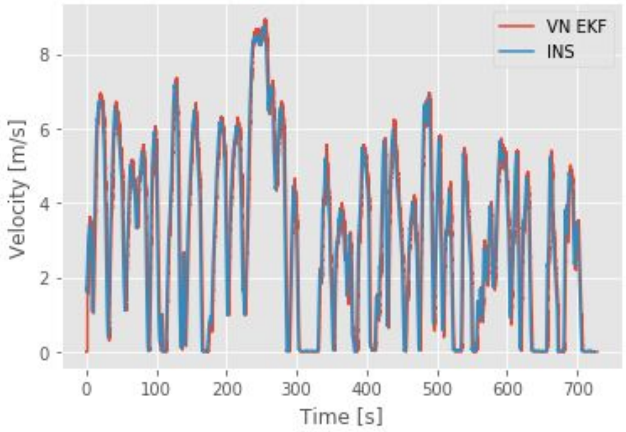

Data Collection

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ROS

- Used Robot Operating System
- Robotics middleware
- Manages data messages between sources
- Can record and play back messages in real time

Data Analysis - INS Drift

- Even without motion, the INS tends to drift position