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Autonomous Trolley Localization

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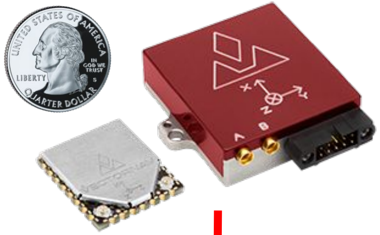
Outline

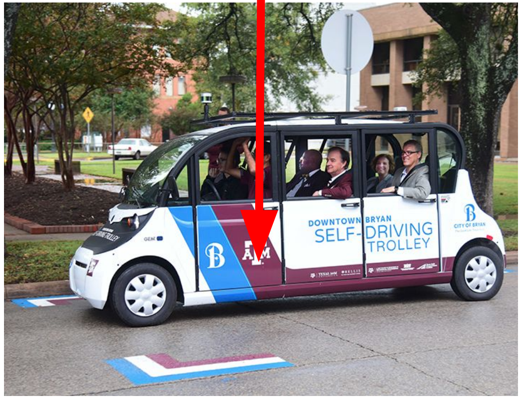
- Introduction
- Theory
- Data Collection
- Data Analysis
- Conclusions

Introduction

System

- Drive-by-wire 6 passenger Golf Cart
- Sensors for project 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

Issues with accelerometers and gyros

- Bias
- Scale Factor
- Noise
- Bias instabilities
- Temperature Effects
- Random Walk Error

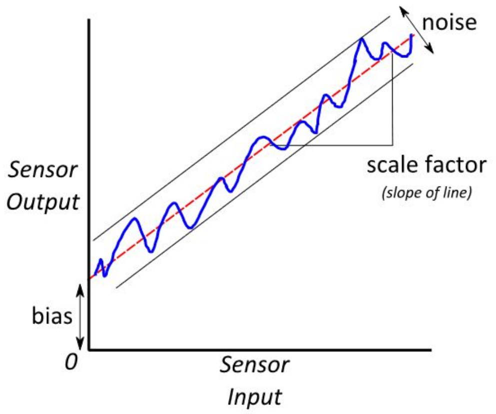


Figure 2: Common IMU Errors

Source: Novatel

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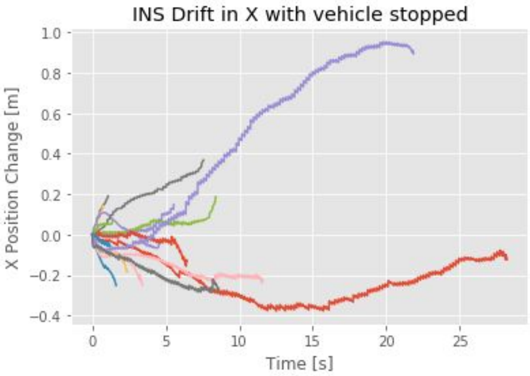
Introduction

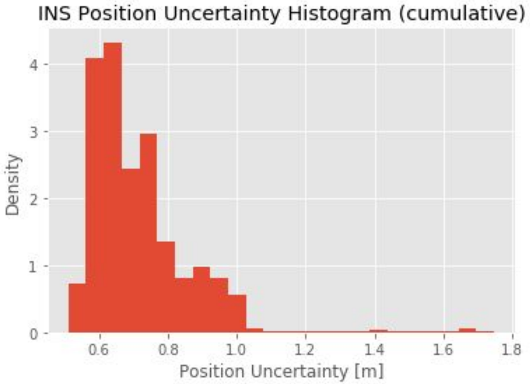
Problem Statement

- 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.



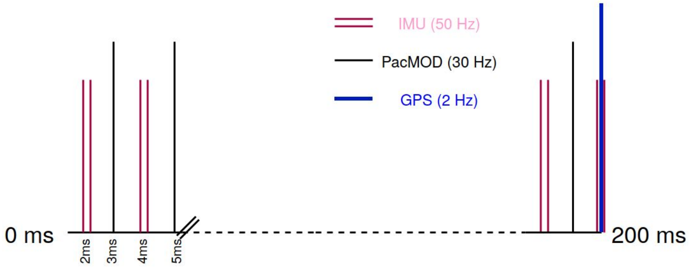


Methodology

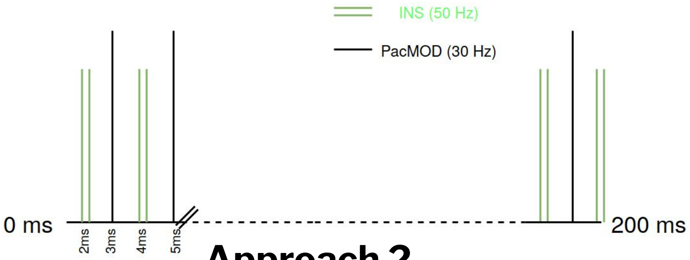
Approach

- Two different approaches are taken
  - **1st Approach:**
    Combine ***raw*** IMU, Gyro, GPS measurements with the vehicle model based on PacMOD measurements
  - **2nd Approach**
    Combine manufacturer fused (IMU, GPS) **INS** measurements with the vehicle model based on PacMOD measurements

Measurement Update Cycle



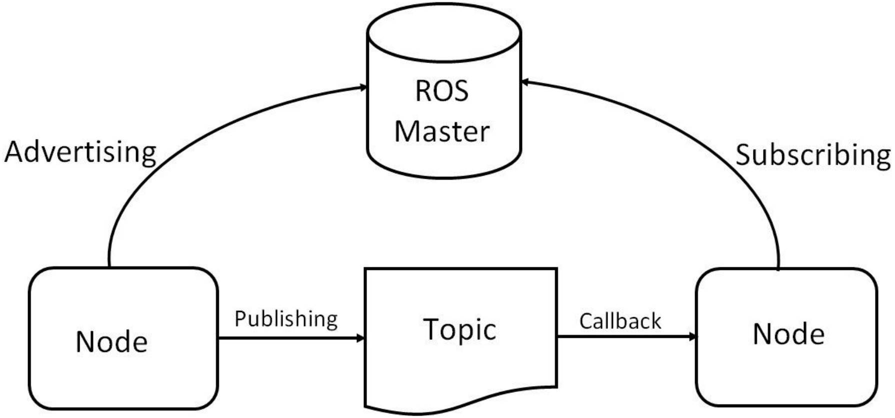
Approach 1



Approach 2

Data Collection

- Used Robot Operating System
- Standardized Messages for sensors
- Manages data messages between sources
- Can record and play back messages in real time



Theory - Kinematic “Bicycle” Model

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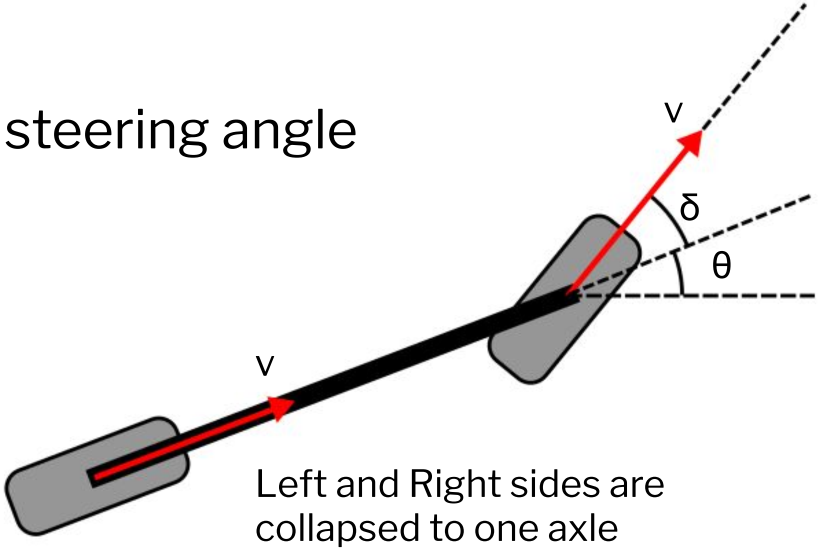
- Simplifies full vehicle
- Ignores slip and dynamics
- Depends only on velocity and steering angle

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

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

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



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:

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

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:

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

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

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

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

Measurement Step:

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

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

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

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

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

Differences in Approach

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1st Approach *Combine* ***raw*** *IMU, PACMod, GPS*

Harder to do, but good for exercise

1. Predict - IMU
   a. Integrate accelerometers to determine change in position and velocity
   b. Determine posterior distribution with state transition
2. Update - PACMod and GPS
   a. Linearize measurement models
   b. Use linearized models to calculate optimal Kalman gain
   c. Use this gain to find posterior state and distribution

2nd Approach *Combine fused* ***INS*** *measurements with PACMod*

Easier to do, and most implementable

1. Predict - INS
   a. Use ***manufacturer*** **filtered** (**INS**) data as posterior distribution
2. Update - PACMod
   a. Linearize measurement models
   b. Use linearized models to calculate optimal Kalman gain
   c. Use this gain to find posterior state and distribution

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

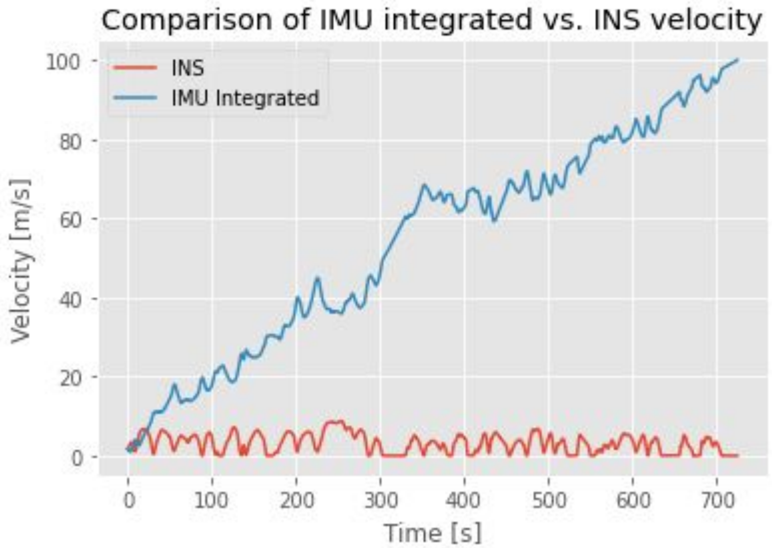
- The simplified calibration model

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

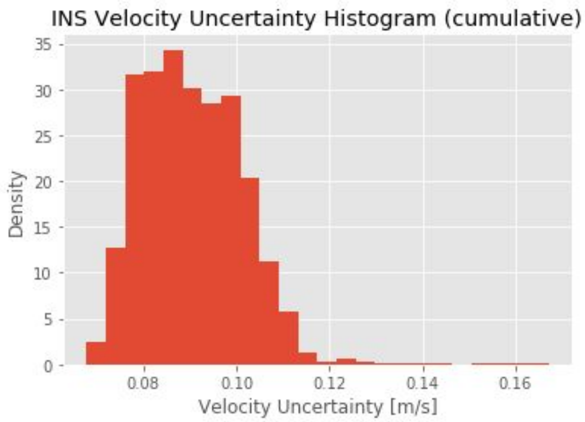
$$\omega = \begin{bmatrix} \frac{1}{S_X} & M_{XY} & M_{ZX} \\ M_{YX} & \frac{1}{S_Y} & M_{YZ} \\ M_{ZX} & M_{ZY} & \frac{1}{S_Z} \end{bmatrix} \left(\begin{bmatrix} B_X \\ B_Y \\ B_Z \end{bmatrix} + \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} \right)$$

Parameter Estimation - IMU Errors

- Integrating for velocity drifts due to misalignment and bias



Dataset 2



Parameter Estimation - IMU Errors

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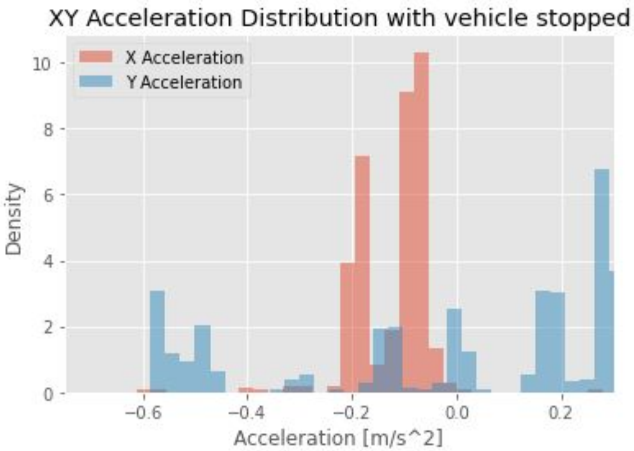
- Biases are multimodal and dependent on road geometry
- This is very difficult to measure



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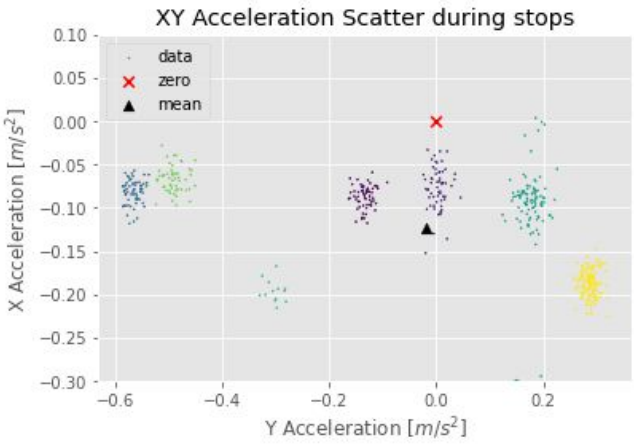

Dataset 2

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

Parameter Estimation - IMU Errors

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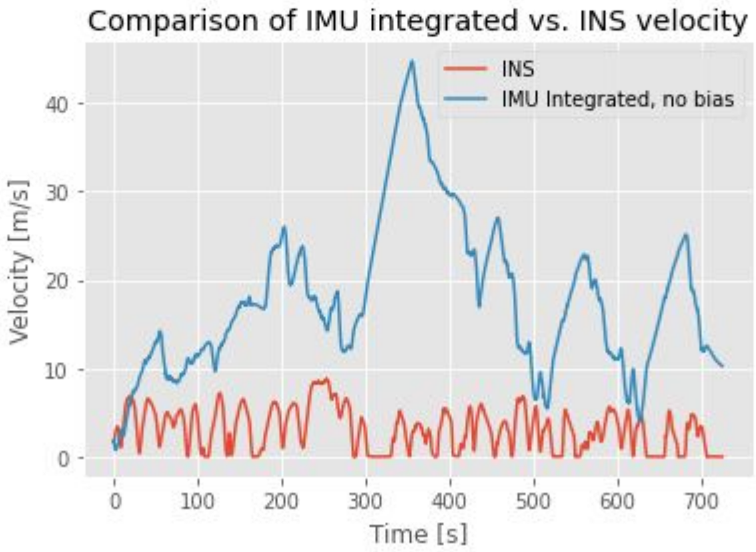
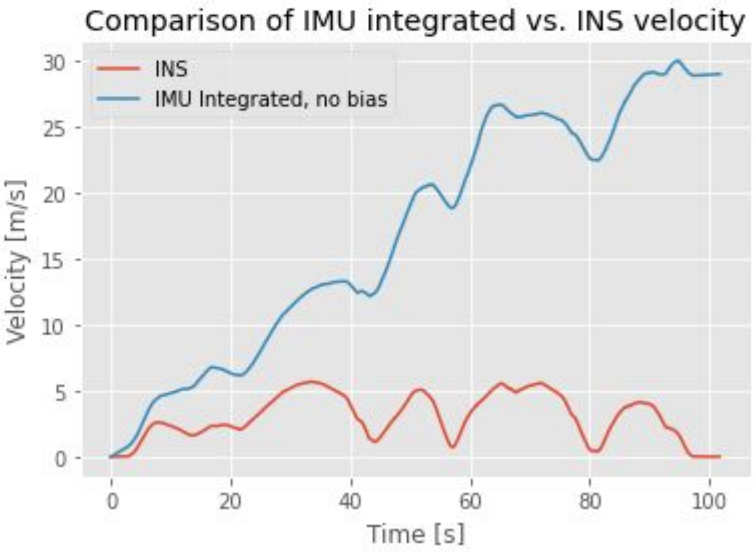
Removing average bias does improve integration



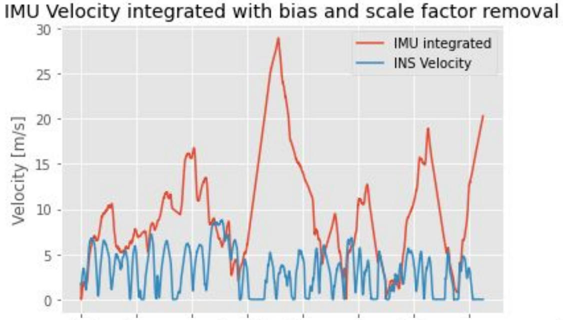
Dataset 2



Dataset 3

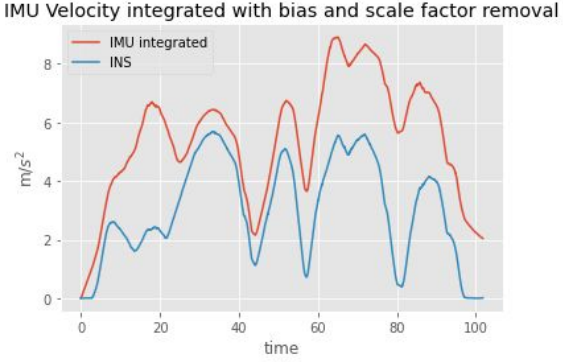
Parameter Estimation - IMU Errors

- Least Squares to minimize the velocity error



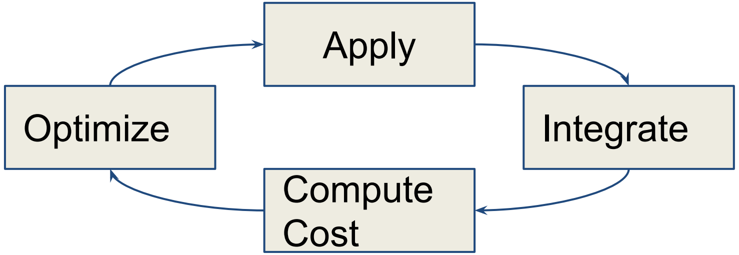
Dataset 2

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



Dataset 3

Optimize (scale_factor, bias)



Parameter Estimation - Why it's hard for the IMU

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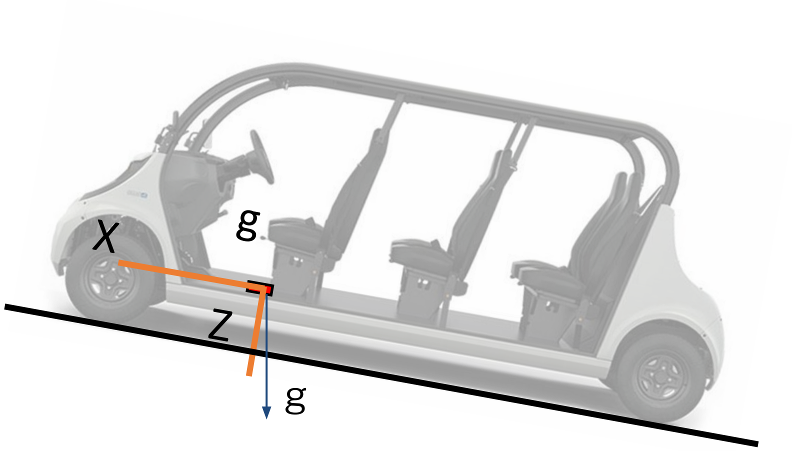
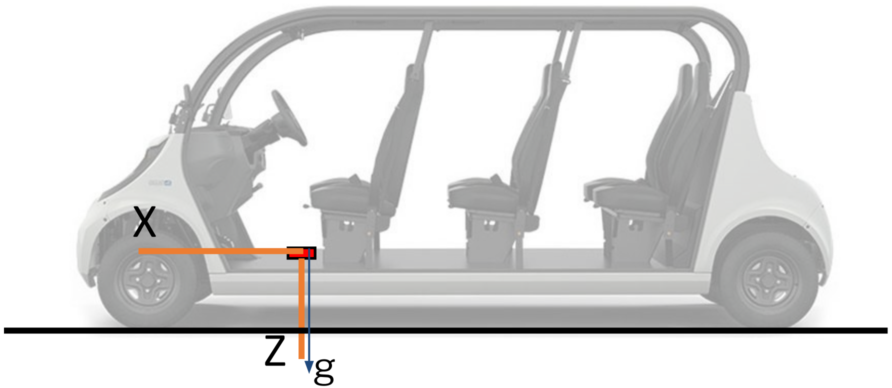
EX:
Golf Cart is pitched, gravity has components in X, Z

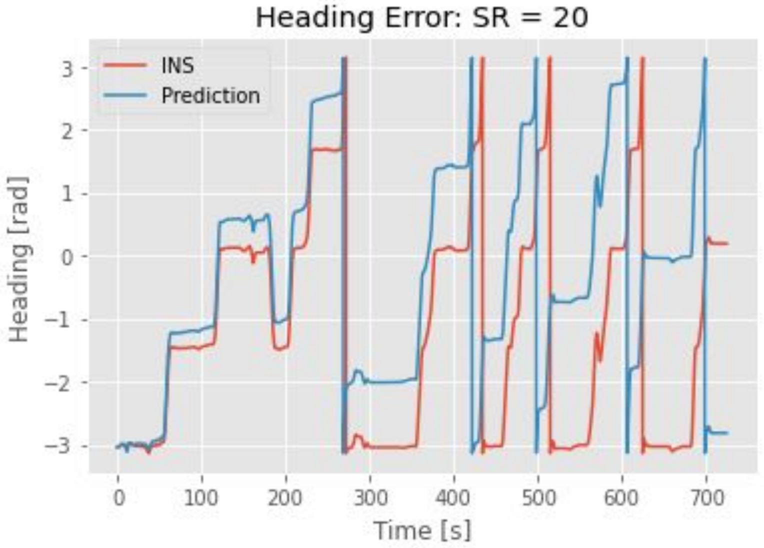


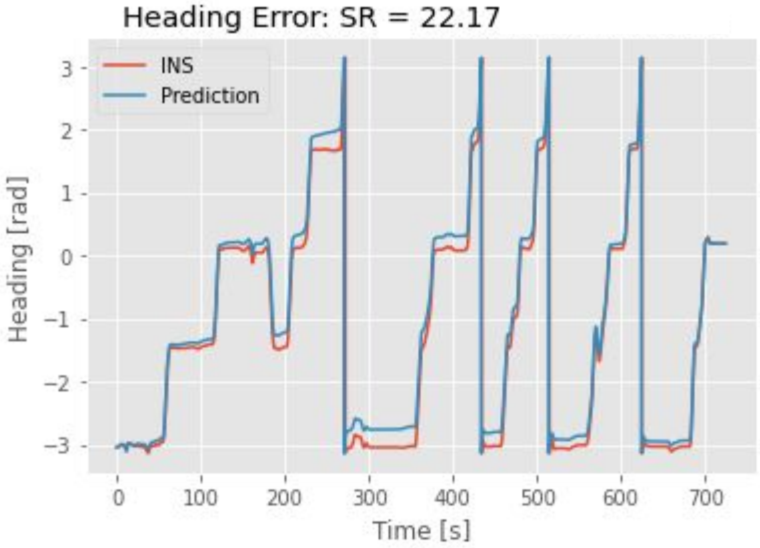
EX:
Golf Cart isn't pitched, gravity is entirely in Z axis



Parameter Estimation - Steering Ratio

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



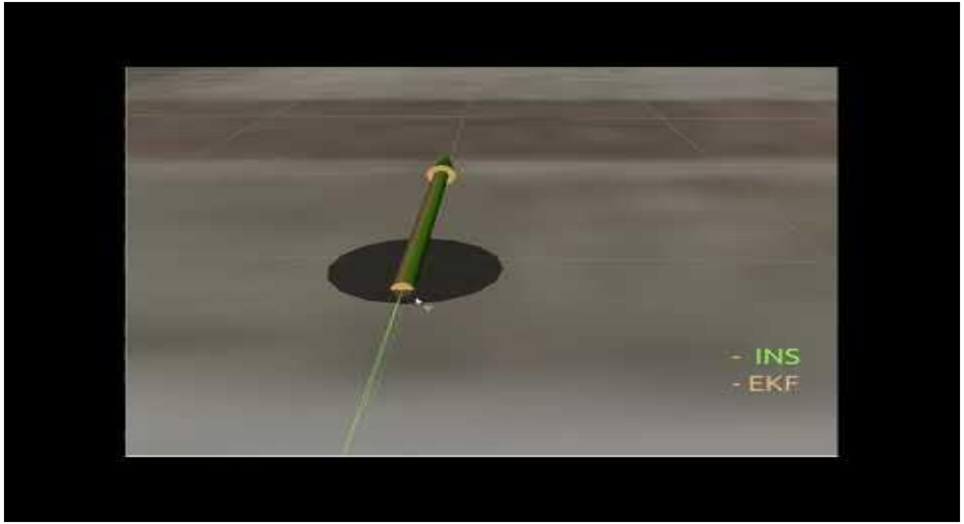


Real Time Implementation

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

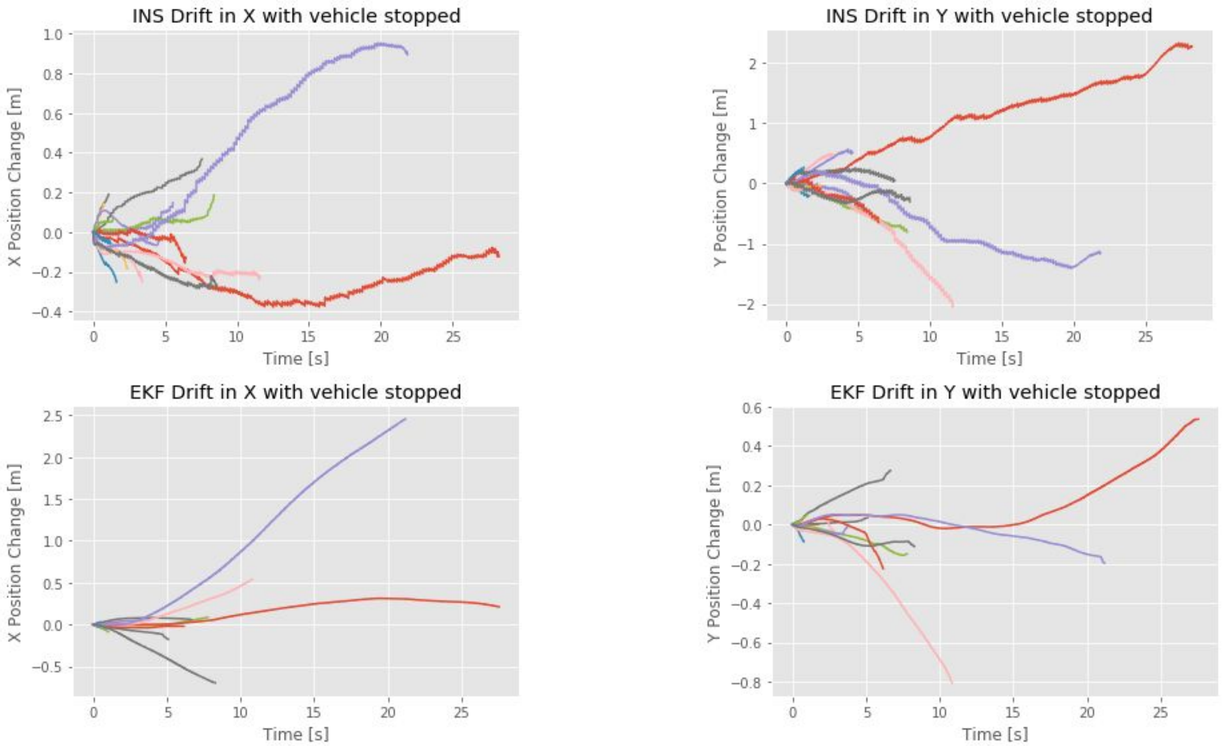
1st Approach

PacMOD + ***INS***



2nd approach

EKF results


INS Drift in X with vehicle stopped
X Position Change [m]
Time [s]
INS Drift in Y with vehicle stopped
Y Position Change [m]
Time [s]
EKF Drift in X with vehicle stopped
X Position Change [m]
Time [s]
EKF Drift in Y with vehicle stopped
Y Position Change [m]
Time [s]

Conclusions

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- Difficult to show accuracy improvements without proper calibration in the first approach

- Would like to run more tests with filter running in real time
- Able to filter in real time with golf cart data
- Smoother state estimate results
- Real time error estimation leads to filter instability
- Calibration and tuning is dataset dependent

References

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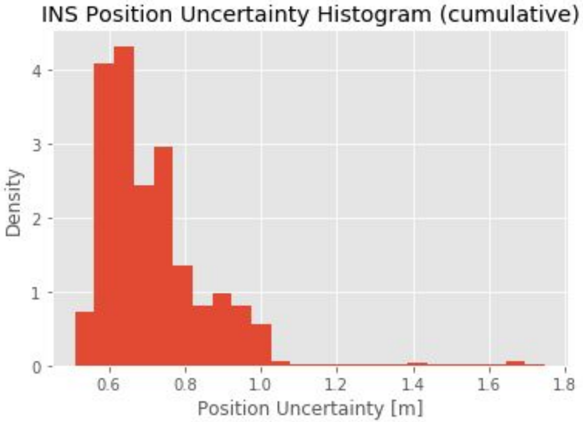
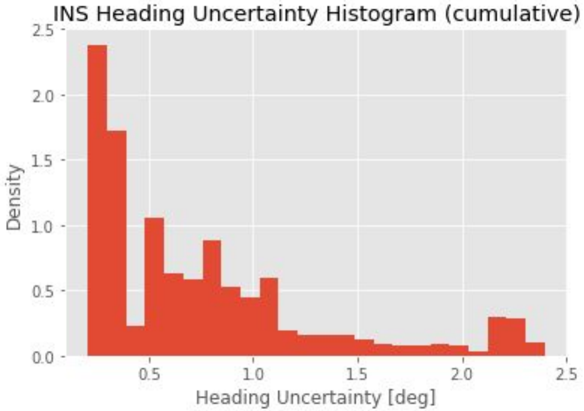
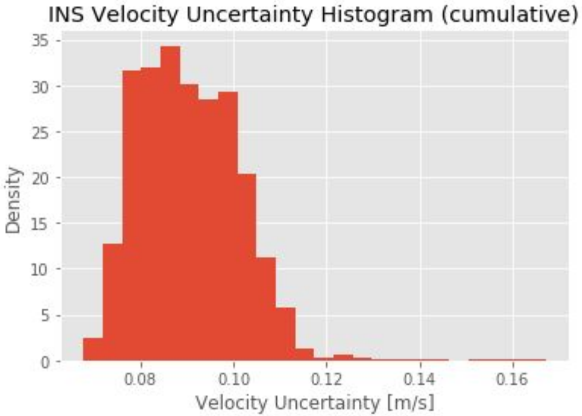
Autonomous Trolley Localization

Thank you for your time

Uncertainty Measurements

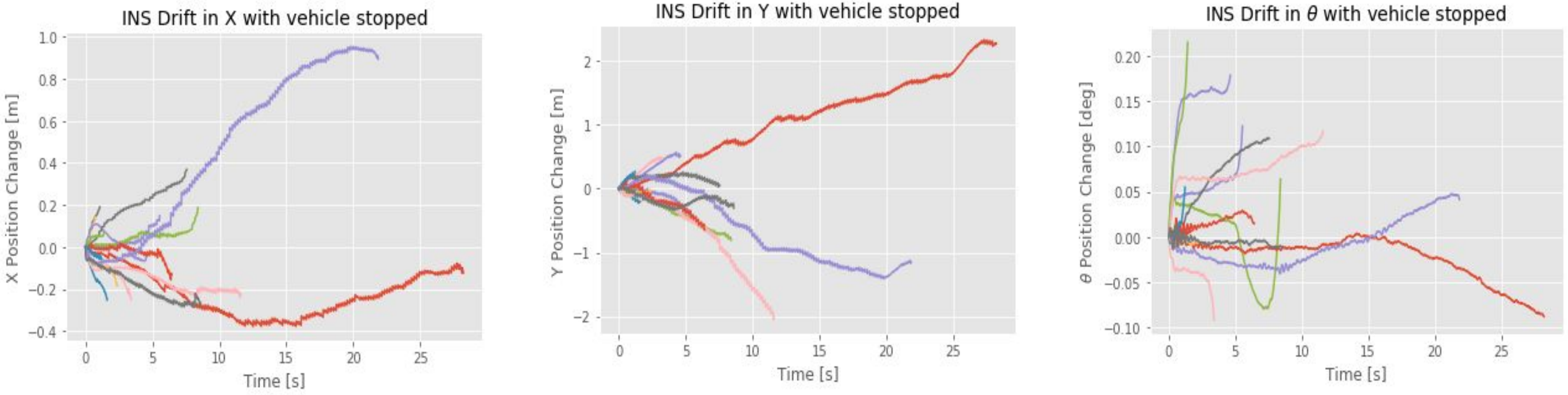






Data Analysis - INS Drift

- Even without motion, the INS tends to drift position



Parameter Estimation - IMU Errors