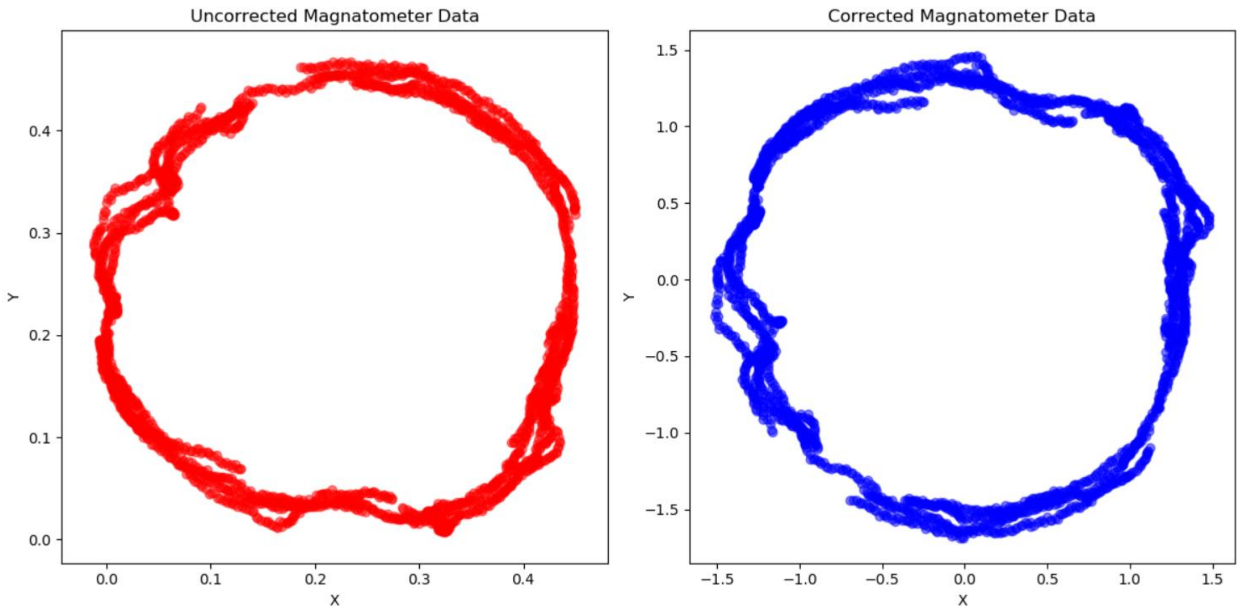
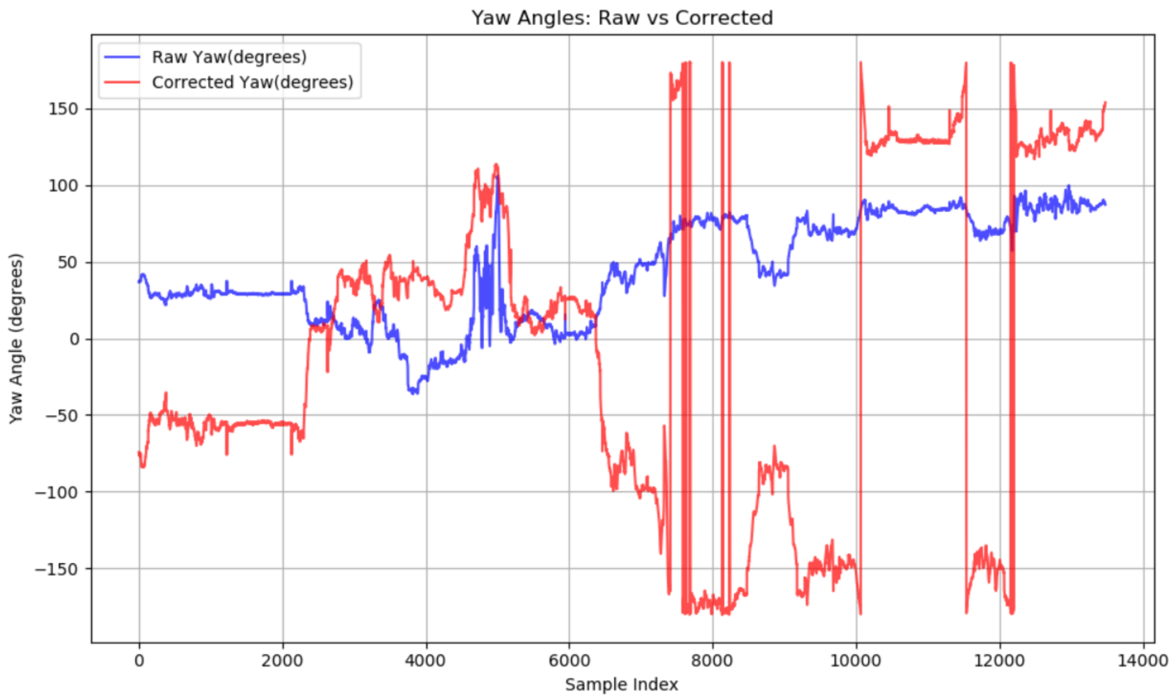
Lab 5

Robot Sensing and Navigation

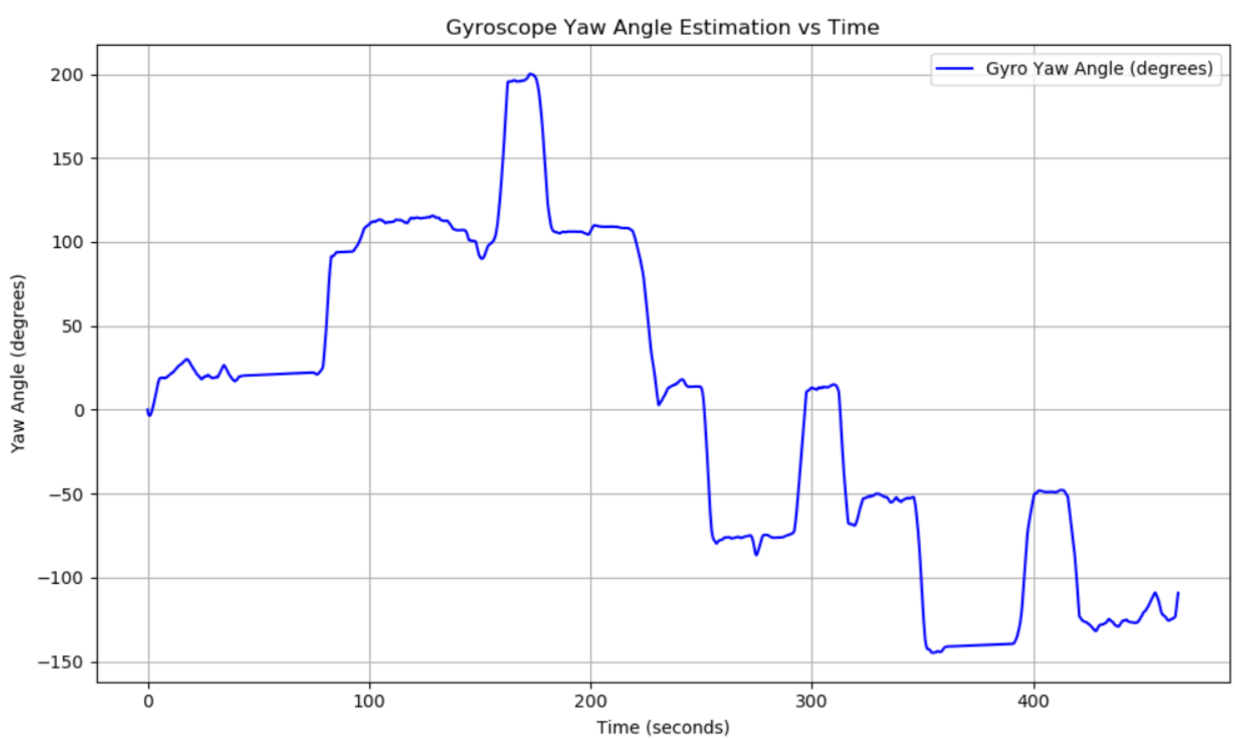
Plot 0: A plot showing the magnetometer data before and after the correction



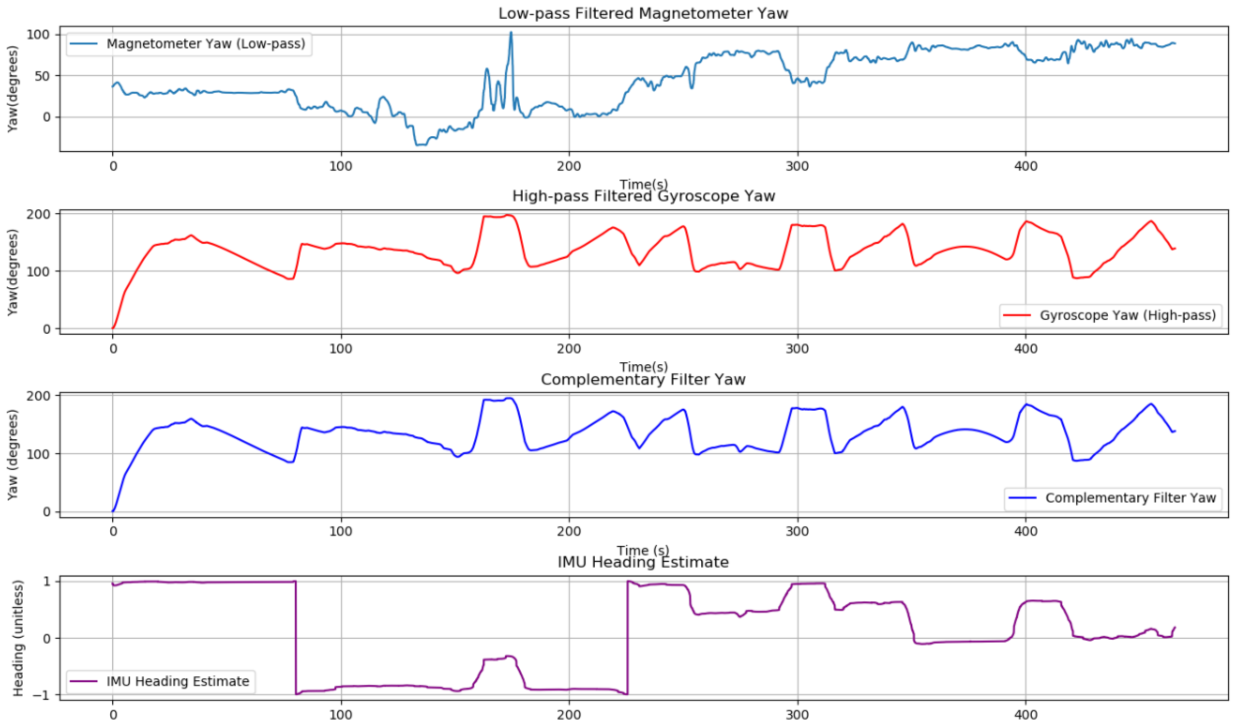
Plot 1: The magnetometer yaw estimation before and after hard and soft iron calibration vs. time



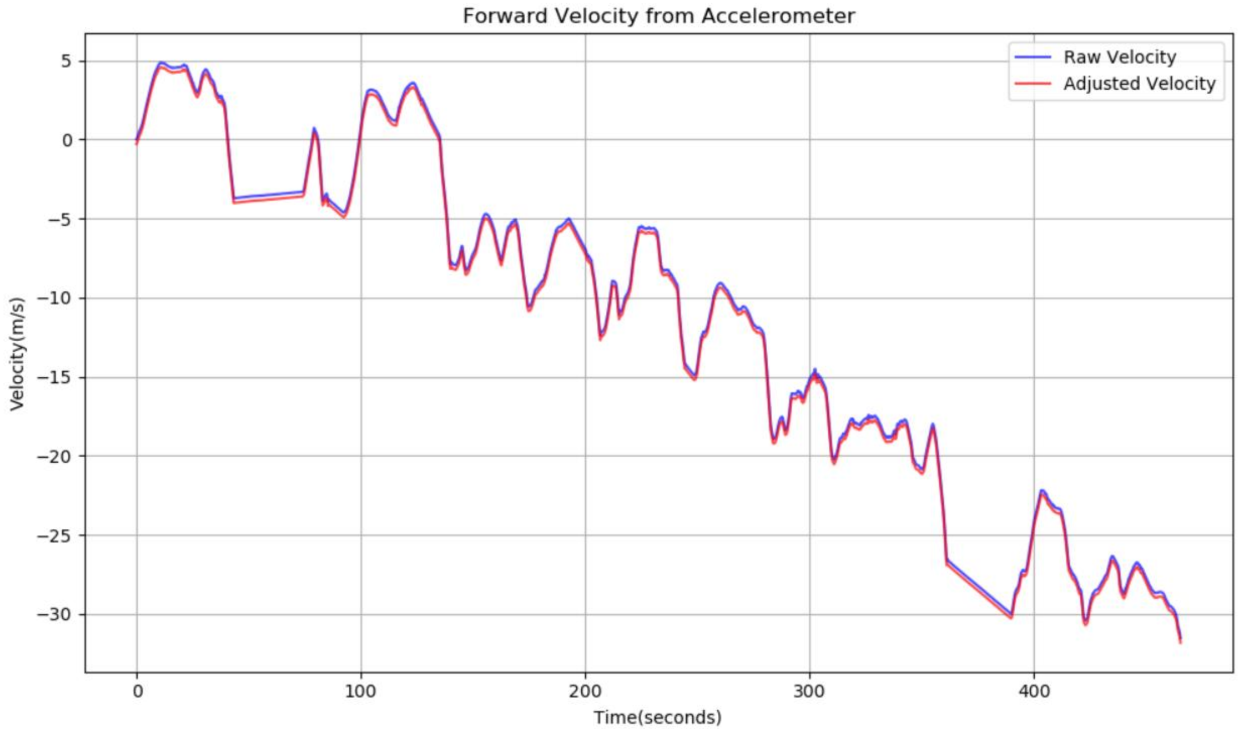
Plot 2: Plot of gyro yaw estimation vs. time



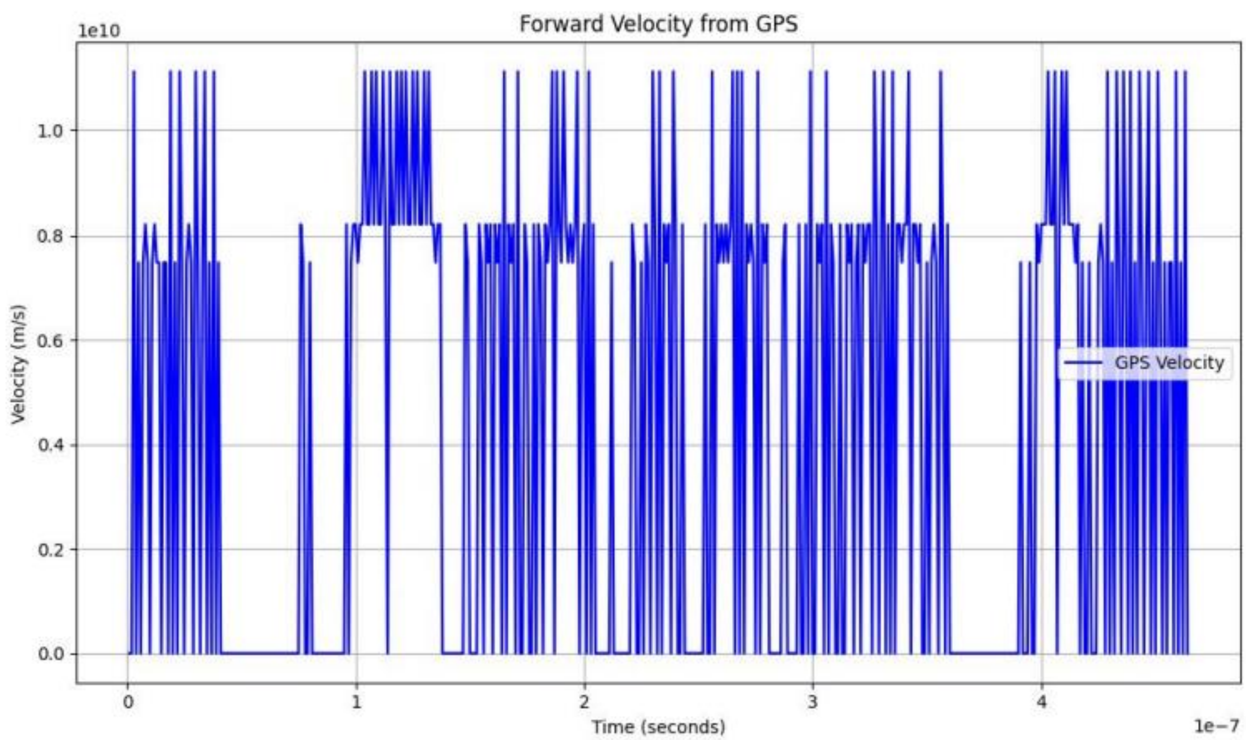
Plot 3: Low pass filter of magnetometer data, high pass filter of gyro data, complementary filter output, and IMU heading estimate



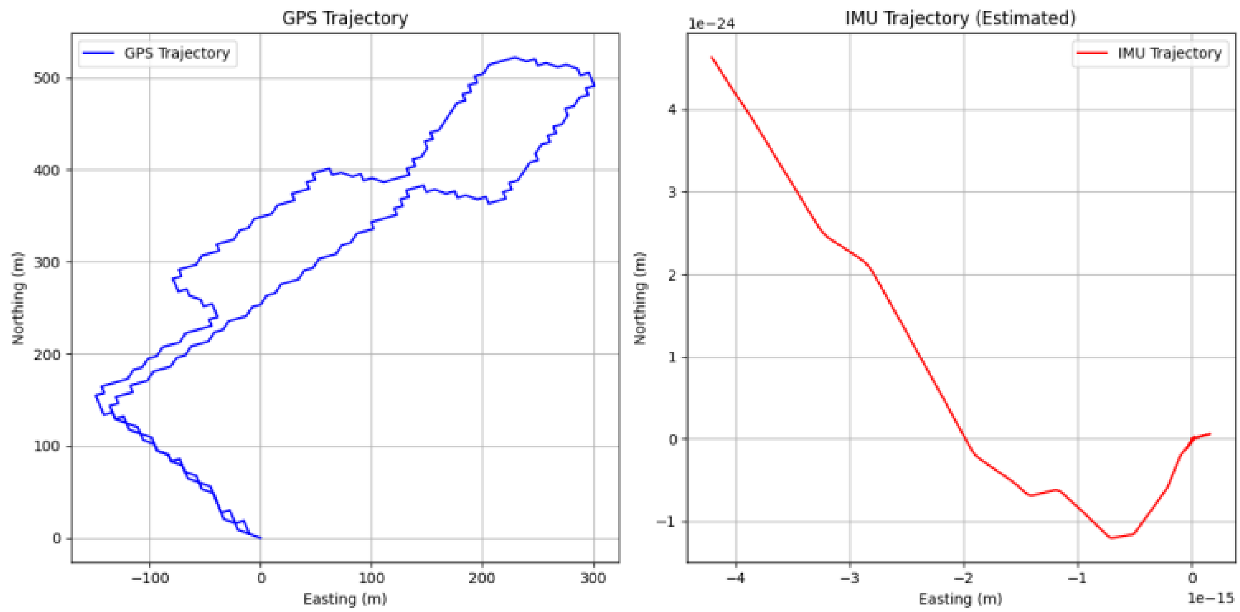
Plot 4: Plot of forward velocity from accelerometer before and after any adjustments



Plot 5: Plot of forward velocity from gps



Plot 6: Plot of estimated trajectory from GPS and from IMU velocity/yaw data



Questions:

1. How did you calibrate the magnetometer from the data you collected? What were the sources of distortion present, and how do you know?

Calibration is carried out by correcting two distortions, Hard Iron Distortion and Soft Iron Distortion.

Hard-Iron Distortion Correction

Hard-iron distortion creates constant bias or offset in the magnetic field measurements.

- Calculating the mean offset across all measurements
- Subtracting this offset from the raw data

Soft-Iron Distortion Correction

Soft-iron distortion causes scaling and rotation effects in the measurements.

- Computing the covariance matrix of the centered data
- Performing eigen decomposition to find principal axes and scaling factors
- Creating a correction matrix using the inverse square root of eigenvalues
- Applying this correction to the centered data

The presence of these distortions is evident in the plots:

- The uncorrected data (left plot) shows an offset from the origin (hard-iron effect) and an elliptical shape (soft-iron effect)
- The corrected data (right plot) is centered at the origin and forms a more circular pattern, indicating successful calibration

The effectiveness of the calibration can be seen in how the scattered points transform from an offset ellipse to a centered circle, which is the expected pattern when rotating a properly calibrated magnetometer in Earth's magnetic field.

2. How did you use a complementary filter to develop a combined estimate of yaw? What components of the filter were present, and what cutoff frequency(ies) did you use?
The complementary filter was used to combine yaw data from the magnetometer and gyroscope, leveraging their strengths:

- Magnetometer: Provides stable, long-term yaw measurements. A low-pass filter with a cutoff frequency of 0.5 Hz was applied to remove high-frequency noise.
- Gyroscope: Captures rapid short-term yaw changes. A high-pass filter with a cutoff frequency of 0.01 Hz was applied to remove low-frequency drift, and the yaw rate was integrated to estimate yaw.
- Filter Combination: The complementary filter formula:
    - $yawcombined=\alpha \cdot yawgyro+(1-\alpha) \cdot yawmag$
    - $\alpha=0.98$: Most weight was given to the gyroscope for responsiveness, with the magnetometer providing long-term stability.

Result: The combined yaw data achieves both short-term accuracy (from the gyroscope) and long-term stability (from the magnetometer), as shown in the plots. This approach successfully mitigates the weaknesses of each sensor, providing a robust yaw estimate.

3. Which estimate or estimates for yaw would you trust for navigation? Why?
The complementary Filter Yaw seems to be the most reliable estimate for navigation.
Comparison:
    - Low-pass Filtered Magnetometer Yaw (subplot 1):

Strength: Provides long-term stability since it uses Earth's magnetic field as a reference.
Weakness: Prone to noise and slow response to rapid changes in yaw, making it unsuitable for dynamic environments.

- High-pass Filtered Gyroscope Yaw (subplot 2):

Strength: Captures rapid, short-term changes in yaw, essential for responsiveness in dynamic situations.
Weakness: Suffers from drift over time due to integration errors, making it unreliable for long-term navigation

- Complementary Filter Yaw (subplot 3):

Strength: Combines the advantages of both sensors:
Uses the gyroscope for fast, short-term changes.
Leverages the magnetometer for long-term stability.
Outcome: Provides a balanced and robust yaw estimate suitable for both dynamic and static conditions.

- IMU Heading Estimate (subplot 4):

Strength: Directly from the IMU's onboard processing.

Weakness: May depend on proprietary algorithms and could lack the customizability or precision offered by the complementary filter.

The complementary filter delivers a robust, accurate, and dynamic yaw estimate, making it ideal for navigation in both static and dynamic conditions.

4. What adjustments did you make to the forward velocity estimate, and why?
    - Correction for Bias:

   The raw velocity was derived by integrating the acceleration data along the x-axis. However, accelerometers often introduce a constant bias due to sensor imperfections, which results in incorrect velocity values over time. To correct this, the bias is estimated by calculating the mean velocity over the first 50 samples, where the system was assumed to be stationary. This bias is subtracted from the raw velocity to produce an adjusted velocity.
    - Reason for the Adjustment:

   Without this correction, the integration process accumulates bias, leading to velocity drifting over time, where the velocity estimate deviates from the true value. The assumption that the system is stationary during the initial period provides a simple and effective way to estimate this bias.
    - Outcome:

   The plot highlights the improvement:
   The raw velocity (blue) shows clear signs of drift due to bias. The adjusted velocity (red) is more stable and aligns with the expected behavior, providing a more accurate representation of the system's forward motion.

5. What discrepancies are present in the velocity estimate between accel and GPS. Why?
   Observed Discrepancies:
    - Accelerometer Velocity:

   The velocity estimate (blue: raw, red: adjusted) from the accelerometer is smooth and continuous, as shown in the first plot.
   This is because the accelerometer integrates acceleration to derive velocity, and adjustments (e.g., bias removal) ensure gradual changes.
    - GPS Velocity:

   The GPS-derived velocity (second plot) is highly noisy and jumpy, with abrupt changes and frequent spikes.
   This is due to inaccuracies in GPS signal processing, especially when updates are sparse, or signal quality is poor.

The discrepancies between accelerometer and GPS velocity estimates arise due to differences in measurement methods and limitations:

- Measurement Sources:

Accelerometers derive velocity through integration, which can drift over time if biases aren't corrected.

GPS calculates velocity from position updates, which are prone to errors from signal quality.

- Noise and Update Rates:

GPS has lower update rates and suffers from signal noise, causing jumpy and abrupt velocity changes.

Accelerometers provide higher-frequency data, resulting in smoother estimates.

- Environmental Factors:

GPS is affected by poor satellite visibility (e.g., in tunnels or urban areas).

Accelerometers are unaffected by the environment but require proper calibration to avoid drift.

6. Compute ωx' and compare it to y''obs. How well do they agree? If there is a difference, what is it due to?

   The comparison between ωx' and y''obs shows differences due to three main factors:

   - Vehicle Motion
     - Sideslip during turns
     - Cornering forces
     - Road angles
   - Sensor Issues
     - IMU not exactly at vehicle's center
     - Sensor alignment errors
     - Measurement noise
   - Model Simplifications
     - Assumes no sideways motion
     - Ignores suspension effects
     - Doesn't account for road conditions

   These differences matter because they affect how accurately we can track the vehicle's movement. To improve accuracy, we need proper sensor calibration and should consider the vehicle's actual dynamics rather than just using simplified assumptions. The discrepancies between these measurements actually help us understand how the vehicle is moving in real conditions versus our idealized model.

7. Estimate the trajectory of the vehicle (xe,xn) from inertial data and compare with GPS. (adjust heading so that the first straight line from both are oriented in the same direction). Report any scaling factor used for comparing the tracks

    - GPS Trajectory:

    Converted GPS latitude/longitude to local Cartesian coordinates (xe, xn)
    Normalized starting position to (0,0)
    Used Earth radius of 6,371,000 meters for conversion

    - IMU Trajectory:

    Calculated forward velocity by integrating acceleration
    Used heading from complementary filter (magnetometer + gyro)
    Projected velocity into East/North components

    Key Observations

    - IMU Errors:

    The IMU trajectory diverges due to sensor drift, integration errors, and the lack of external corrections (e.g., GPS fixes).
    Small errors in acceleration or yaw measurements accumulate over time, causing the trajectory to deviate significantly.

    - GPS Accuracy:

    GPS provides a more reliable global position estimate, albeit with noise and lower update rates

8. For what period of time did your GPS and IMU estimates of position match closely? (within 2 m) Given this performance, how long do you think your navigation approach could work without another position fix?

    The GPS and IMU trajectories begin to diverge quickly after the start of the motion. The GPS provides accurate global positioning, while the IMU accumulates errors over time due to sensor noise, drift, and biases in the measurements. These factors cause the IMU-based trajectory to deviate from the actual path.

    To determine when the GPS and IMU positions match closely (within 2 meters), I computed the distance between corresponding points on the two trajectories over time. For example, if the difference in both the x (Easting) and y (Northing) coordinates between the GPS and IMU is small (less than 2 meters), they are considered to match. This close match likely happens only during the initial few seconds of the motion because the IMU drift hasn't accumulated significantly yet.

From the plots, the divergence is noticeable, suggesting that without GPS corrections, the IMU's trajectory becomes increasingly inaccurate. Given this performance, the IMU-based navigation system would require frequent GPS updates—likely every 5- 10 seconds—to recalibrate and correct the drift. Without these updates, the IMU data alone would lead to large positional errors, especially over longer distances or timeframes.

In summary, the GPS and IMU agree closely for only a few seconds, and regular GPS fixes are essential to maintain accurate navigation. Beyond 5-10 seconds without a position fix, the IMU alone cannot reliably estimate the vehicle's trajectory.