EECE 5554 – Robotics: Sensing and Navigation

Lab 5 – NUance Navigation Report

Kamalnath Bathirappan 002084221

1. Introduction

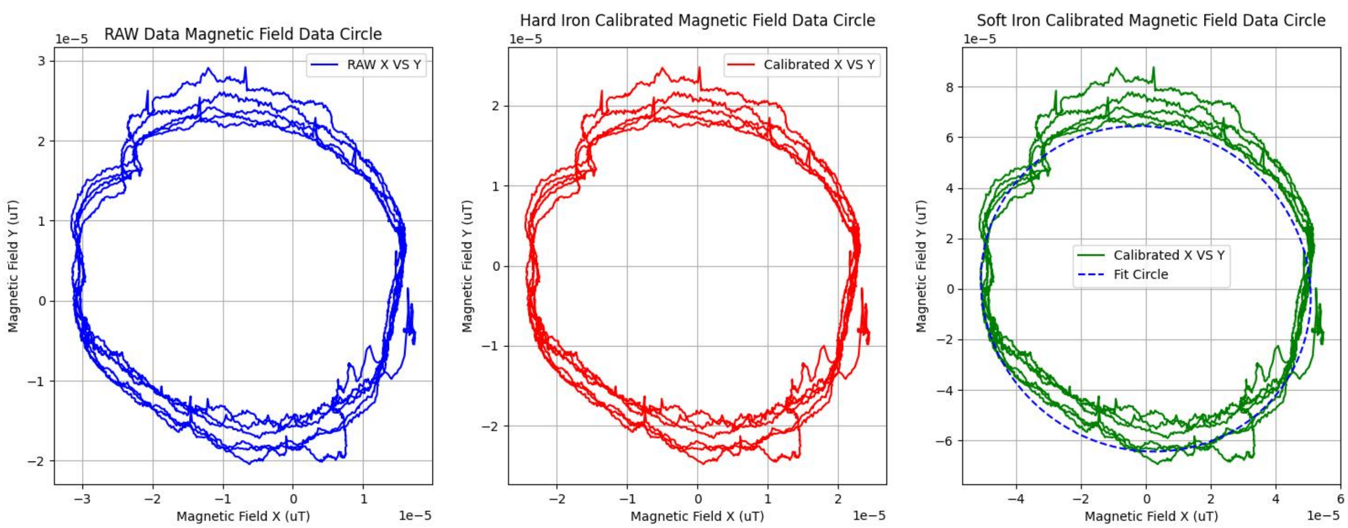
In modern navigation systems, integrating Inertial Measurement Unit (IMU) and Global Positioning System (GPS) data enhances accuracy and reliability.
GPS provides precise position information but is susceptible to signal loss in challenging environments such as urban canyons or dense foliage.
On the other hand, IMU sensors, including accelerometers and gyroscopes, enable continuous measurement of velocity, acceleration, and orientation, ensuring reliable position estimation during GPS outages.

This report addresses magnetometer calibration, yaw estimation using complementary filters, forward velocity computation, and trajectory estimation.
The focus is on analyzing the collected IMU and GPS data, applying calibration techniques, and comparing estimated trajectories. Notably, the data was collected on a rainy day, which may have introduced additional environmental noise into the sensor readings.

2. Output of the Analysis of IMU and GPS Data

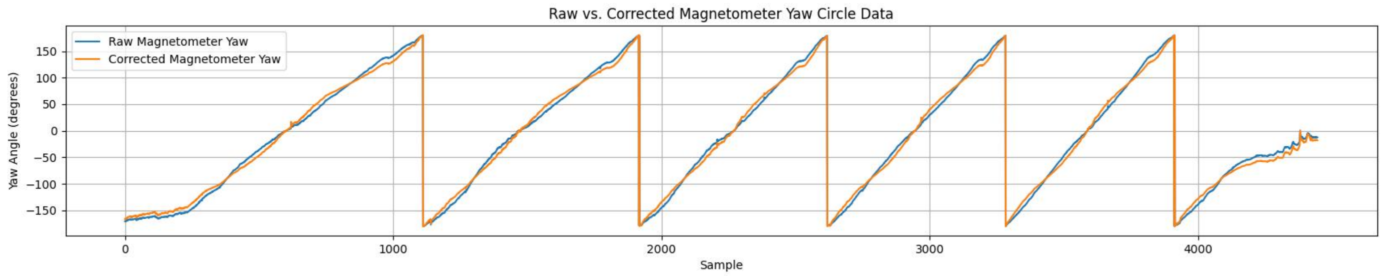
a. Magnetometer Data Before and After Correction

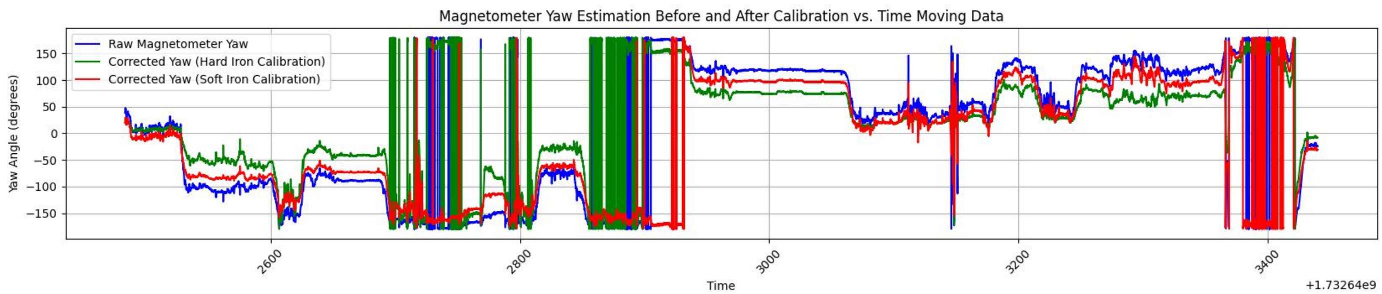
To improve magnetometer accuracy, we corrected hard iron and soft iron distortions. Hard iron corrections removed fixed biases caused by external magnetic sources, and soft iron corrections addressed distortions due to nearby ferromagnetic materials. After calibration, the magnetic field data was adjusted for both scale and orientation, resulting in a near-circular plot for soft iron-calibrated data.



b. Magnetometer Yaw Estimation Before and After Correction

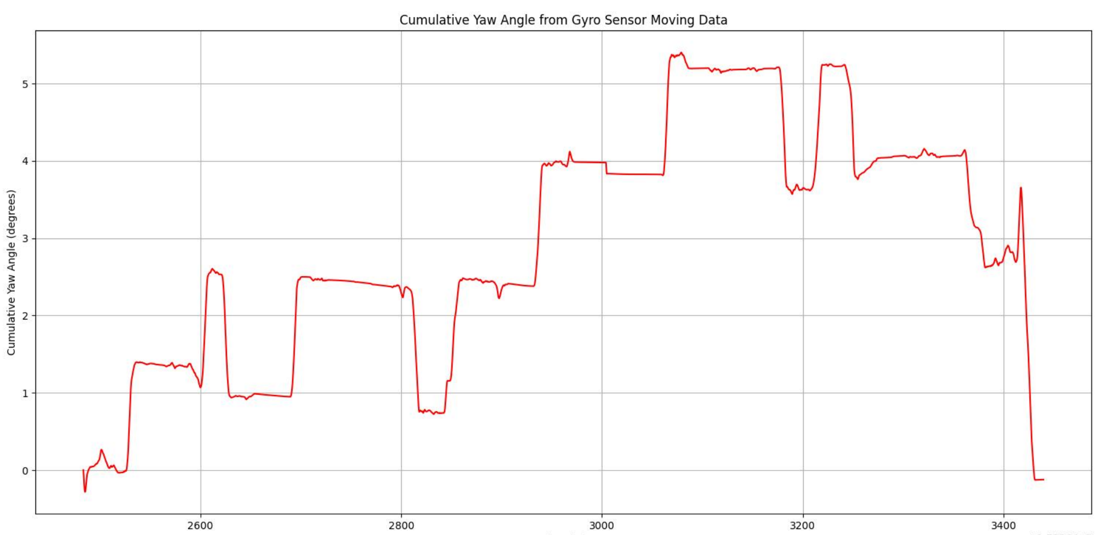
Yaw estimation from magnetometer data was performed by computing the yaw angle before and after calibration. Corrected data demonstrated reduced errors and improved consistency in heading measurements.





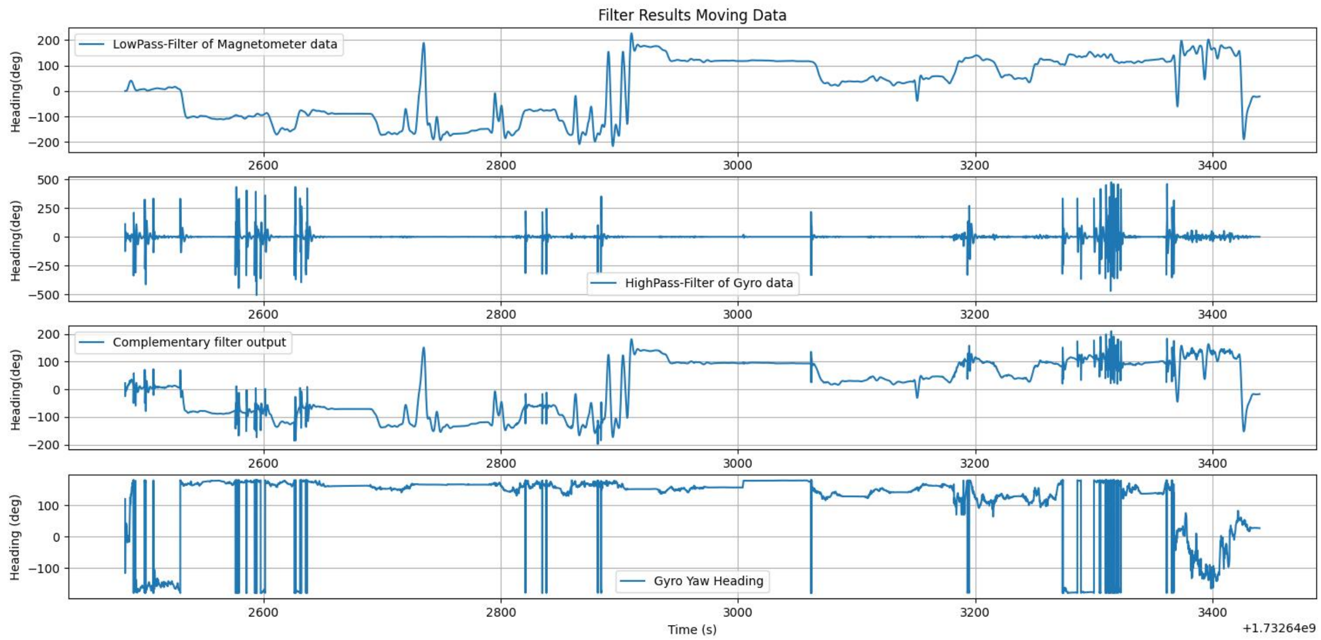
c. Gyro Yaw Estimation

Gyro yaw was derived by integrating angular velocity data from the IMU gyroscope. The cumulative yaw angle highlights the rotational behavior of the vehicle.



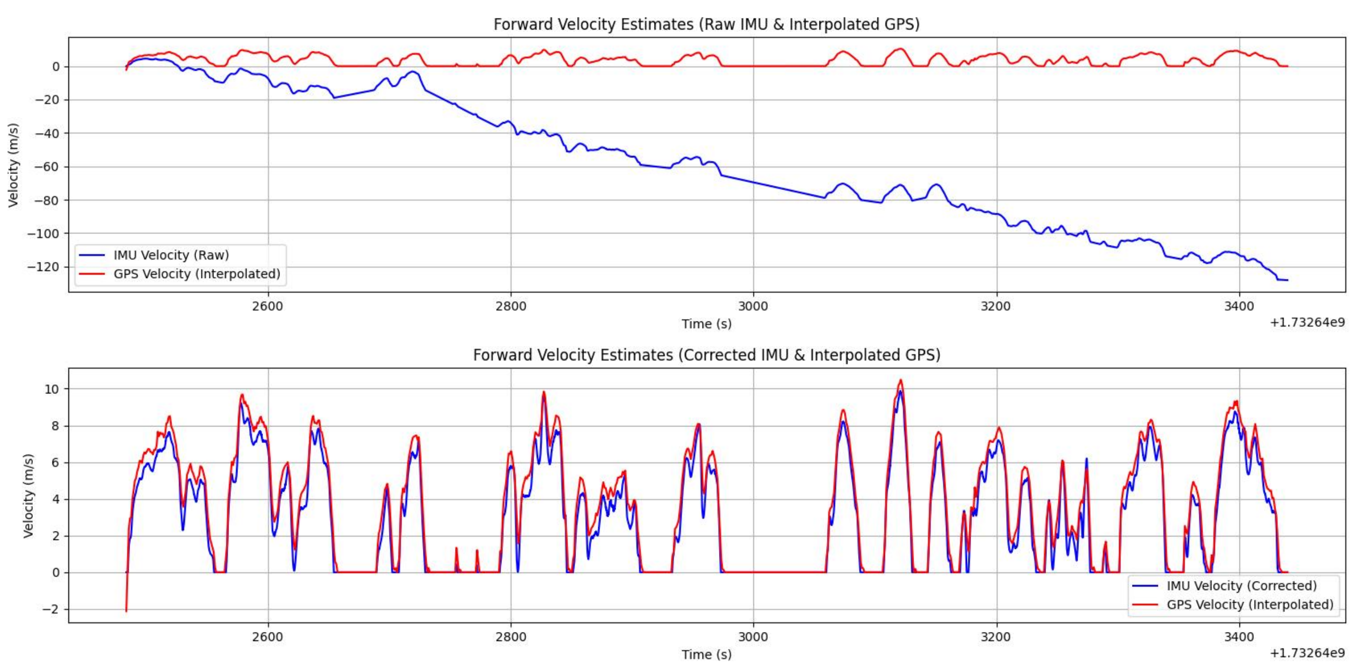
d. Filter Outputs and IMU Heading Estimate

Using a Butterworth filter, magnetometer data underwent low-pass filtering, and gyroscopic data underwent high-pass filtering. The complementary filter output combines these to produce a more accurate heading estimate.



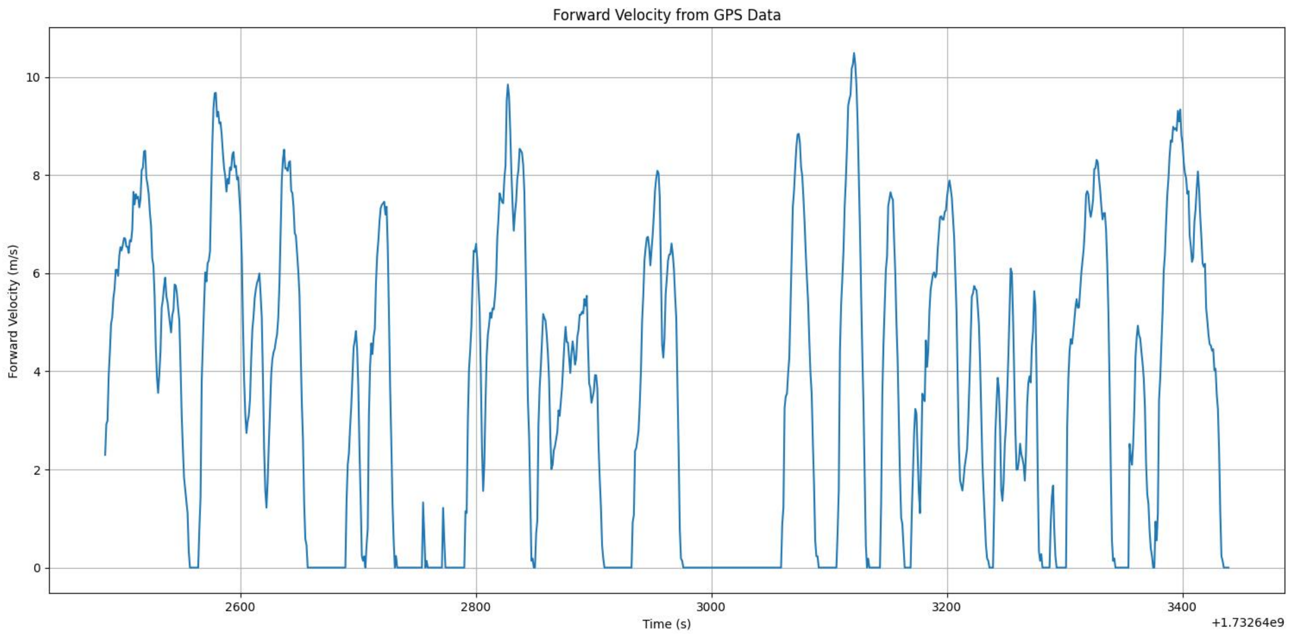
e. Forward Velocity from Accelerometer Before and After Correction

Forward velocity was estimated from accelerometer data by integrating acceleration over time. Adjustments to initial velocities and compensations for gravitational effects resulted in smoother and more accurate velocity estimates.



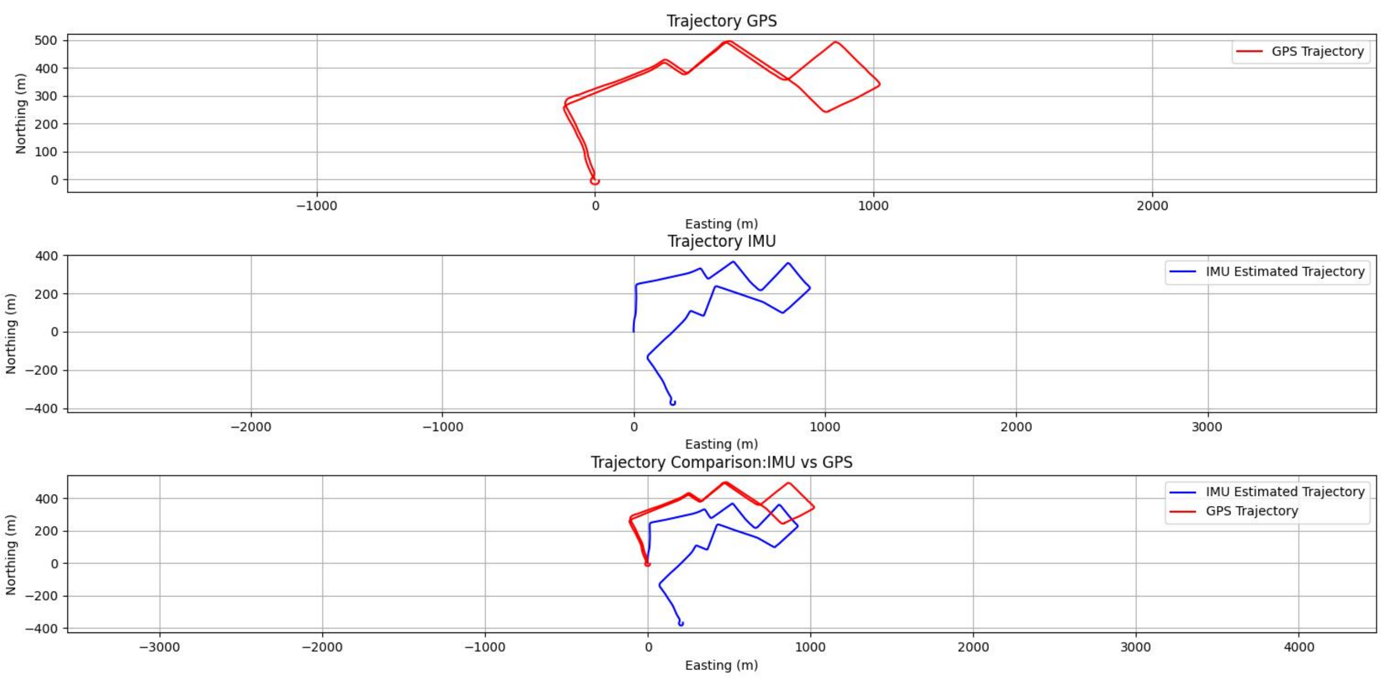
f. Forward Velocity from GPS

Velocity derived from GPS data was calculated based on the distance and time differences between consecutive data points, providing insights into the vehicle's speed dynamics.



g. Estimated Trajectory from GPS and IMU

Trajectories derived from GPS and IMU data were compared. The IMU trajectory was adjusted to align with the GPS heading. A scaling factor was applied to ensure consistency between the two datasets.



3. Questions and Answers

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

Magnetometer calibration involved correcting for both hard iron and soft iron distortions. Initially, we identified the sources of distortion by analyzing the raw magnetometer data. The presence of hard iron distortion was evident as an offset in the magnetic field values, causing the data points to deviate from the origin. Soft iron effects were identified by the elliptical shape of the magnetic field data, which indicated scaling and rotational distortions.

To address hard iron distortion, we calculated the mean offsets along the X, Y, and Z axes and subtracted them from the raw data. This realigned the magnetic field data to the origin. For soft iron calibration, we applied a least-squares fitting method to reshape the elliptical distortion into a circular pattern, ensuring the magnetometer's sensitivity axes were accurately aligned. The calibration process effectively neutralized both distortions, as evidenced by the circular shape of the corrected magnetic field data.

On the day of the data collection, rainfall may have introduced additional environmental noise, potentially affecting the consistency of magnetic field readings. However, the calibration process successfully mitigated these effects, as demonstrated by the improved data accuracy.

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 employed to combine low-frequency data from the magnetometer with high-frequency data from the gyroscope, leveraging the strengths of both sensors. The magnetometer provided stable orientation information over time, while the gyroscope offered responsive data for rapid changes in orientation.

We used a low-pass filter with a cutoff frequency of 0.1 Hz for the magnetometer data to suppress high-frequency noise and a high-pass filter with a cutoff frequency of 0.0001 Hz for the gyroscope data to eliminate low-frequency drift. The complementary filter formula integrated these filtered outputs using a weighted approach, with a tuning parameter (α) determining the contribution of each sensor. This method provided a robust and reliable yaw estimate, balancing stability and responsiveness.

The rainy conditions during data collection may have affected the magnetometer readings due to transient magnetic distortions caused by water interaction with nearby ferrous objects. The complementary filter effectively minimized such noise, ensuring accurate yaw estimation.

3. Which estimate or estimates for yaw would you trust for navigation? Why?

For navigation, the most reliable estimate is the output of the complementary filter. This estimate integrates the stability of the magnetometer with the dynamic responsiveness of the gyroscope, mitigating the weaknesses of each sensor individually. The magnetometer is prone to noise and distortion in dynamic environments, such as the rainy conditions on the day of data collection, while the gyroscope suffers from drift over time. By combining their strengths, the complementary filter provides a consistent and accurate yaw estimate suitable for navigation tasks.

4. What adjustments did you make to the forward velocity estimate, and why?

Stationary Zone Identification: We analyzed the acceleration data to detect stationary periods, during which velocity should remain constant. By identifying these periods, we corrected for any biases in the accelerometer readings.
Gravitational Component Correction: On slopes, gravitational forces influenced the acceleration readings, introducing errors in the velocity estimate. We calculated the pitch angle of the vehicle and subtracted the gravitational component from the forward acceleration data.
Baseline Adjustment: Initial velocity values were adjusted to align with known vehicle behavior, ensuring the estimates reflected realistic motion dynamics.

These adjustments were crucial for improving the reliability of the velocity estimate, particularly under the challenging conditions of rainfall, which may have affected sensor performance.

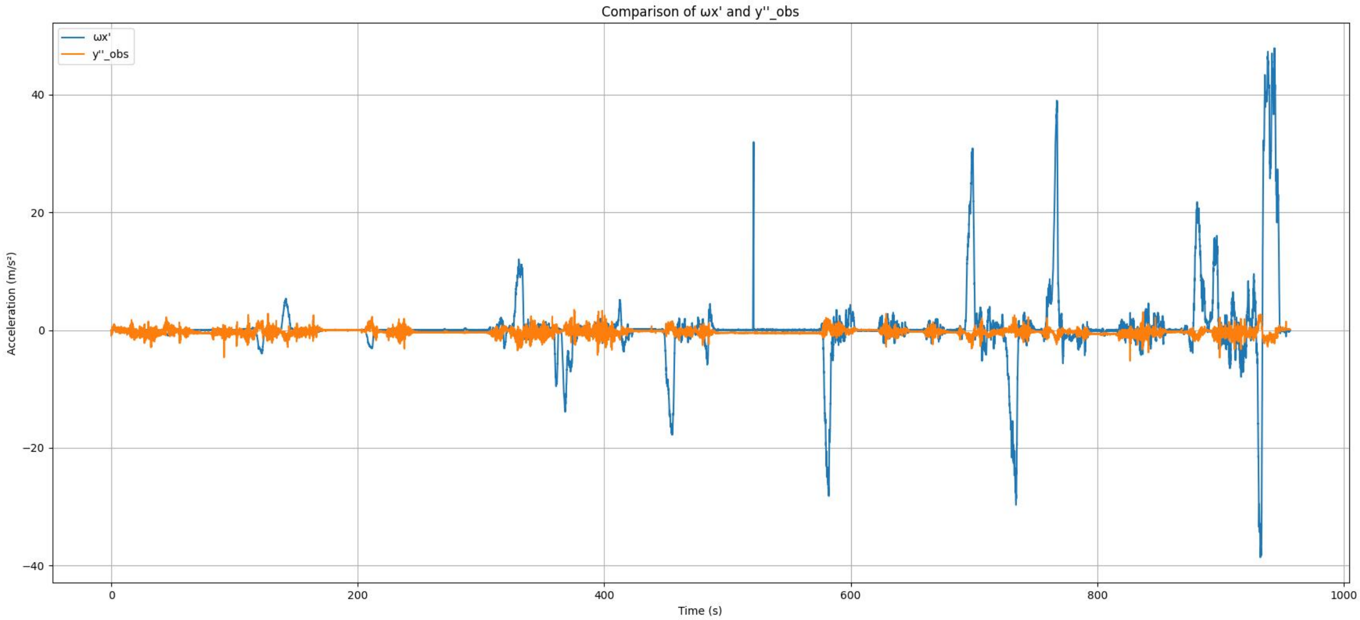
5. What discrepancies are present in the velocity estimate between accel and GPS? Why?

Discrepancies between accelerometer-based and GPS-based velocity estimates were observed, primarily due to the following factors:
Sensor Drift: Accelerometer readings exhibited drift over time, leading to cumulative errors in the velocity estimate.
Gravitational Effects: On inclines, uncorrected gravitational components introduced inaccuracies in the accelerometer-based velocity.
Noise and Vibrations: Rain-induced vibrations and environmental noise affected the accelerometer data, resulting in deviations from the GPS-derived velocities.

GPS, while less affected by such noise, is susceptible to signal degradation in poor weather conditions. The integration of both sensors provides a more reliable overall velocity estimate.

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 computed lateral acceleration (ωx′) was compared to the observed values (y″obs). The two measurements generally agreed, especially during steady-state motion. However, differences were noted during dynamic maneuvers, such as turns and rapid accelerations. These discrepancies were attributed to external forces, such as wet road conditions and sensor noise, which affected the accelerometer readings. Calibration improvements and more sophisticated noise reduction techniques could further enhance agreement.



7. Estimate the trajectory of the vehicle (χe,χn) from inertial data and compare it 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.

The vehicle's trajectory was estimated using inertial data from the IMU, corrected for orientation using yaw angle modifications. The heading was aligned with the GPS trajectory by adjusting the IMU data to match the initial straight-line direction of the GPS readings. A scaling factor of 0.2 was applied to normalize the trajectory lengths and ensure comparability.

While the IMU trajectory closely followed the GPS path initially, discrepancies emerged over time due to sensor drift and environmental noise. The rainy conditions may have contributed to these deviations by affecting sensor performance. Nevertheless, the alignment process highlighted the IMU's reliability for short-term trajectory estimation.

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 position estimates matched closely within a 2-meter range for approximately 350 seconds. This alignment demonstrates the effectiveness of the sensor fusion approach for short-term navigation. However, over longer durations, the IMU trajectory began to drift due to cumulative errors and environmental factors, such as rainfall-induced vibrations and noise.

Based on this performance, the navigation system could reliably operate without a GPS fix for a similar duration under comparable conditions. Extending this period would require additional measures, such as periodic recalibration or advanced error correction algorithms.

4. Conclusion

Magnetometer calibration and sensor fusion techniques significantly improved heading and velocity estimation.

While the IMU provides reliable short-term navigation, periodic GPS updates are essential for correcting drift and maintaining long-term accuracy.

Combining complementary filter outputs with calibrated data ensures robust navigation performance in diverse environments. The rainy conditions during data collection posed challenges but were effectively mitigated through careful calibration and filtering.