EECE 5554 - Lab 4:
Navigation with IMU and Magnetometer

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1 Introduction

The objective of this lab is to develop a robust navigation stack leveraging GNSS (GPS) and IMU sensors for vehicle-based navigation. This project integrates sensor fusion techniques to improve navigation accuracy by combining the strengths of each sensor. Through data collected in real-world driving scenarios, this lab provides insights into dead reckoning, sensor fusion, and yaw estimation via magnetometer calibration and complementary filtering. The analysis focuses on refining navigation estimates for practical applications, such as mobile robotics.

2 Data Collection

Data was collected near Ruggles Station, Northeastern University, Boston. Our data consists of two primary datasets:

- **Donut (Circular Motion) Data:** Collected while driving in circles, primarily for magnetometer calibration to correct distortions.

- **Driving Data:** Collected while navigating through streets near Northeastern University, which provided realistic driving data to perform dead-reckoning and forward velocity estimation.

The data was recorded in a ROSbag file format and uploaded by team member Dhyey Mistry. This dataset served as the foundation for yaw estimation, velocity adjustments, and trajectory comparisons in the subsequent sections.

3 Data Processing and Analysis

The processing and analysis steps involved using specific MATLAB scripts tailored for each dataset. We began with `magnetometer_calibration.m` on the donut dataset to calibrate the magnetometer, followed by `sensor_fusion.m`, `fwd_vel_est.m`, and `deadrocking.m` applied to the driving dataset to estimate yaw, forward velocity, and dead reckoning trajectory, respectively.

3.1 Magnetometer Calibration (Donut Dataset)

The donut data enabled us to identify and correct distortions in magnetometer readings. Initial plots of the magnetometer data showed elliptical distortions indicative of hard-iron and soft-iron effects due to nearby magnetic interference. Calibration corrected these effects by centering and scaling the data to produce circular patterns, as seen in Figure 1 and Figure 2.
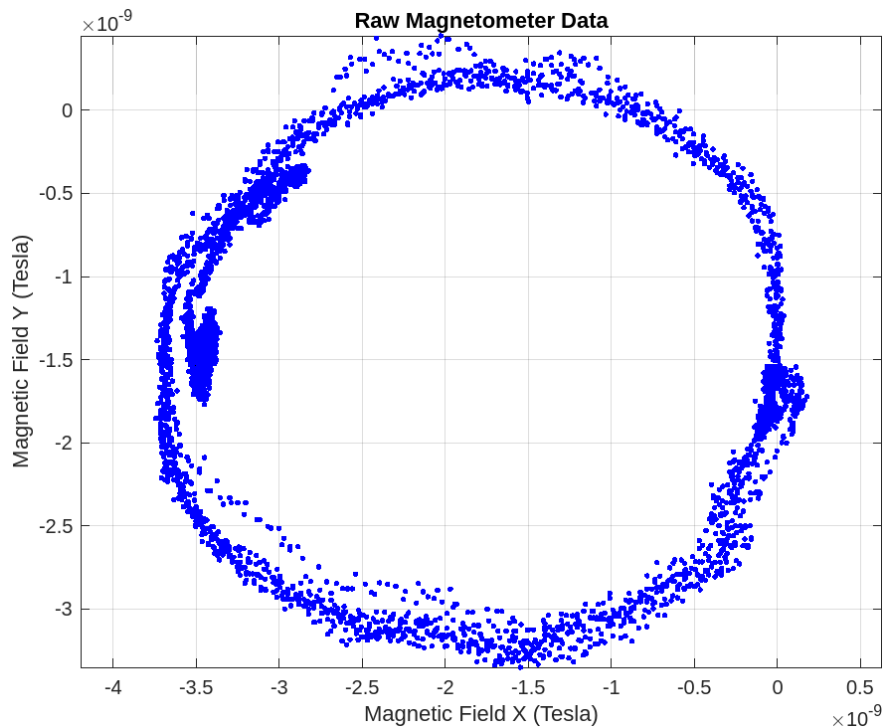

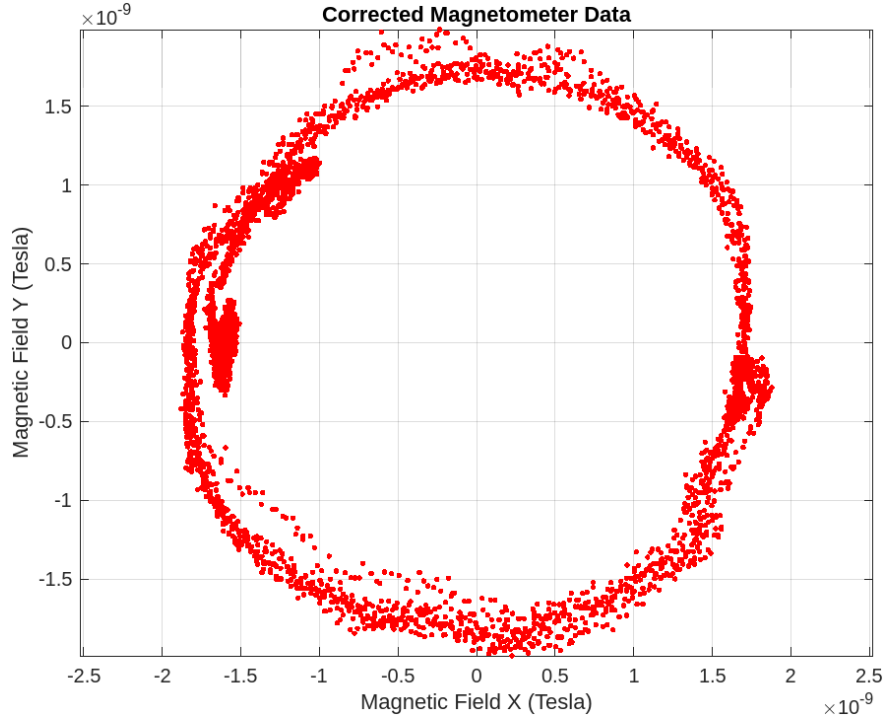Figure 1: Raw Magnetometer Data (Before Calibration) from Donut Dataset

Figure 2: Corrected Magnetometer Data (After Calibration) from Donut Dataset

3.2 Yaw Estimation Using Sensor Fusion

The `sensor_fusion.m` script estimates yaw by fusing magnetometer and gyroscope data, applying a complementary filter to balance their strengths. The magnetometer data provides stable long-term heading information, while the gyroscope offers responsive short-term adjustments. A low-pass filter was used for the magnetometer data to smooth out noise, and a high-pass filter applied to the gyroscope data helped remove drift. Together, these components yielded a stable and reliable yaw estimate suitable for navigation.
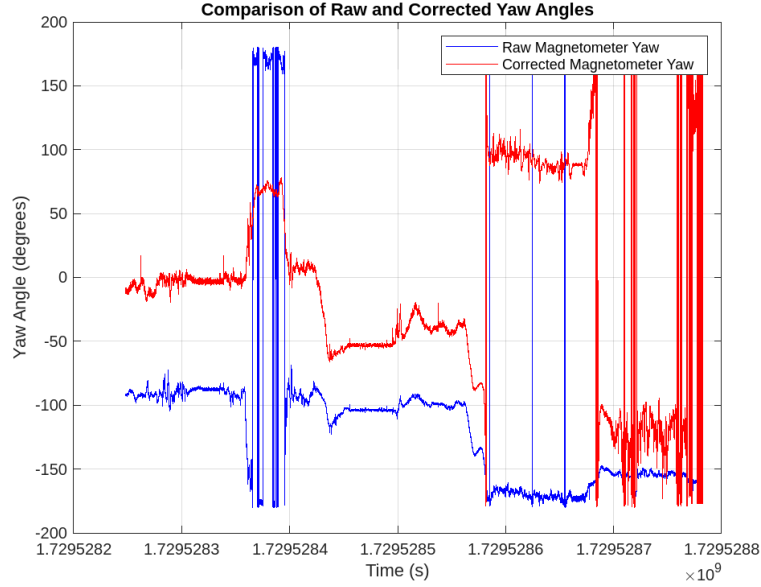
Figure 3: Comparison of Raw and Corrected Magnetometer Yaw Angles

As shown in Figure 3, the corrected yaw angle from the magnetometer was far smoother and free of distortions, serving as an effective input for the complementary filter. The integrated yaw from the gyroscope alone (Figure 4) displayed drift over time, reinforcing the importance of fusion with the magnetometer to achieve a consistent heading estimate.
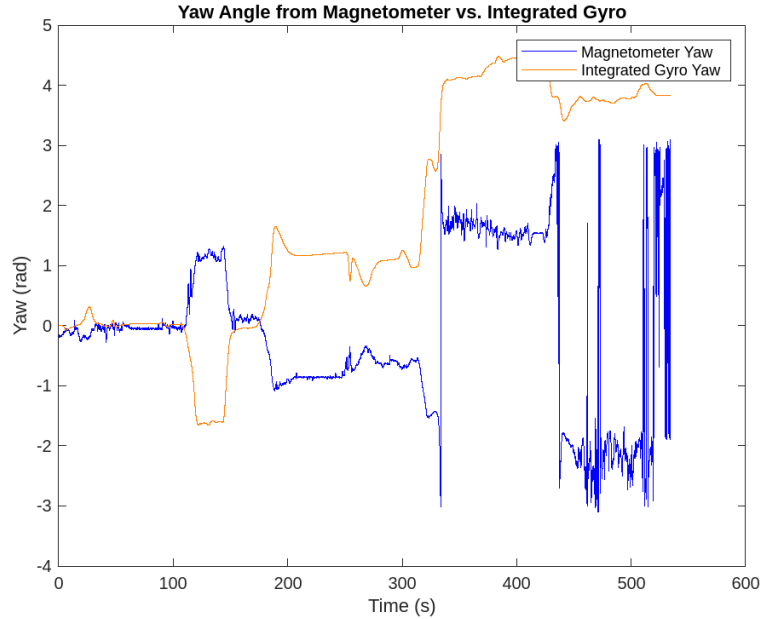

Figure 4: Yaw Angle from Magnetometer vs. Integrated Gyro Yaw

The complementary filter's output, as shown in Figure 5, illustrates a balanced yaw estimate, combining the low-frequency stability of the magnetometer with the high-frequency accuracy of the gyroscope.
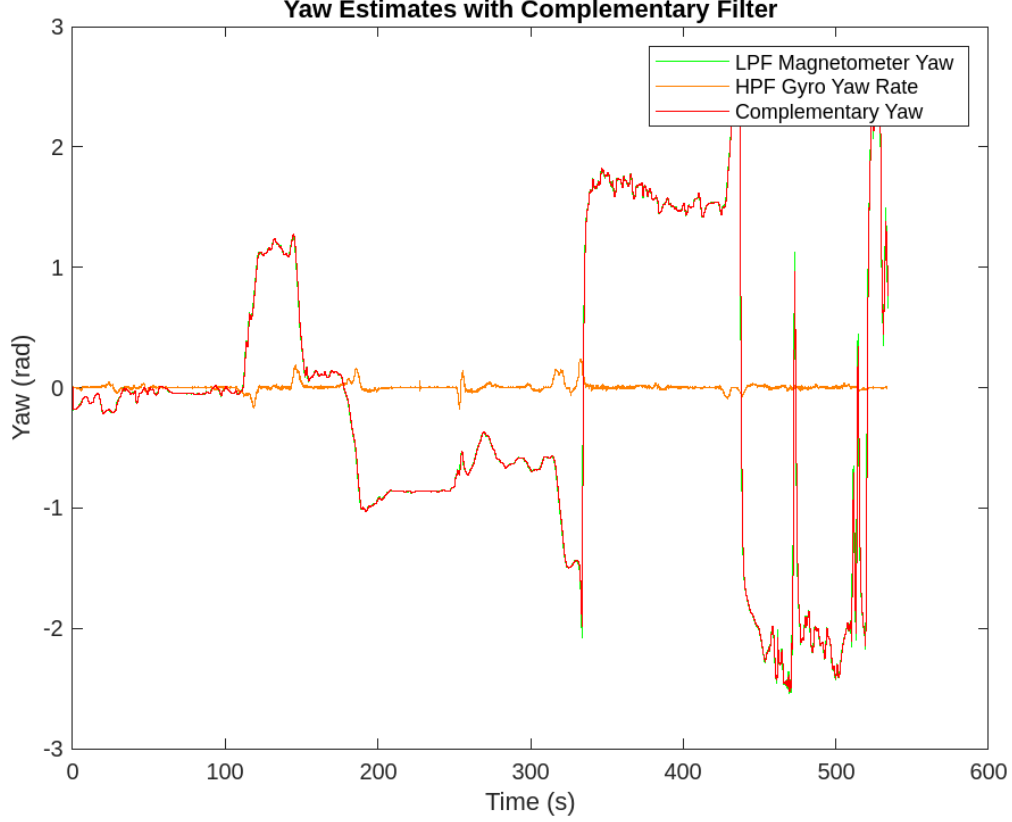
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Figure 5: Yaw Estimates with Complementary Filter

3.3 Forward Velocity Estimation

Forward velocity estimation was conducted using data from both the IMU and GPS sensors to achieve a reliable measure of the vehicle's speed. The primary steps involved processing the accelerometer data to derive velocity, adjusting for drift, and comparing the IMU-derived velocity with the GPS-based velocity for accuracy. The following detailed steps outline the process:

- **IMU-Based Velocity Estimation:** The accelerometer data along the vehicle's forward axis was first corrected for any initial sensor bias. To estimate the forward velocity from the IMU, we used the following approach:

  1. **Bias Removal:** Initial measurements showed a small drift in the accelerometer's readings, indicating an inherent bias. This was corrected by calculating the mean value of the first few samples (when the vehicle was stationary) and removing this bias from the entire dataset.

  2. **Integration of Acceleration:** After correcting for bias, the adjusted acceleration values were integrated over time to obtain an initial forward velocity estimate. Since accelerometers are prone to accumulating drift over time, this raw IMU-based velocity estimate required further refinement to ensure accuracy.

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3. **Filtering:** A low-pass filter was applied to the integrated velocity to reduce high-frequency noise from the accelerometer. This step ensured a smoother velocity profile, minimizing the effects of sudden spikes or noise in the accelerometer readings.

The initial and unadjusted IMU-derived velocity is shown in Figure 6 (red line), plotted alongside the GPS-derived velocity (blue line). As seen, discrepancies arose due to inherent accelerometer drift, indicating the need for further adjustments to improve alignment with the GPS data.
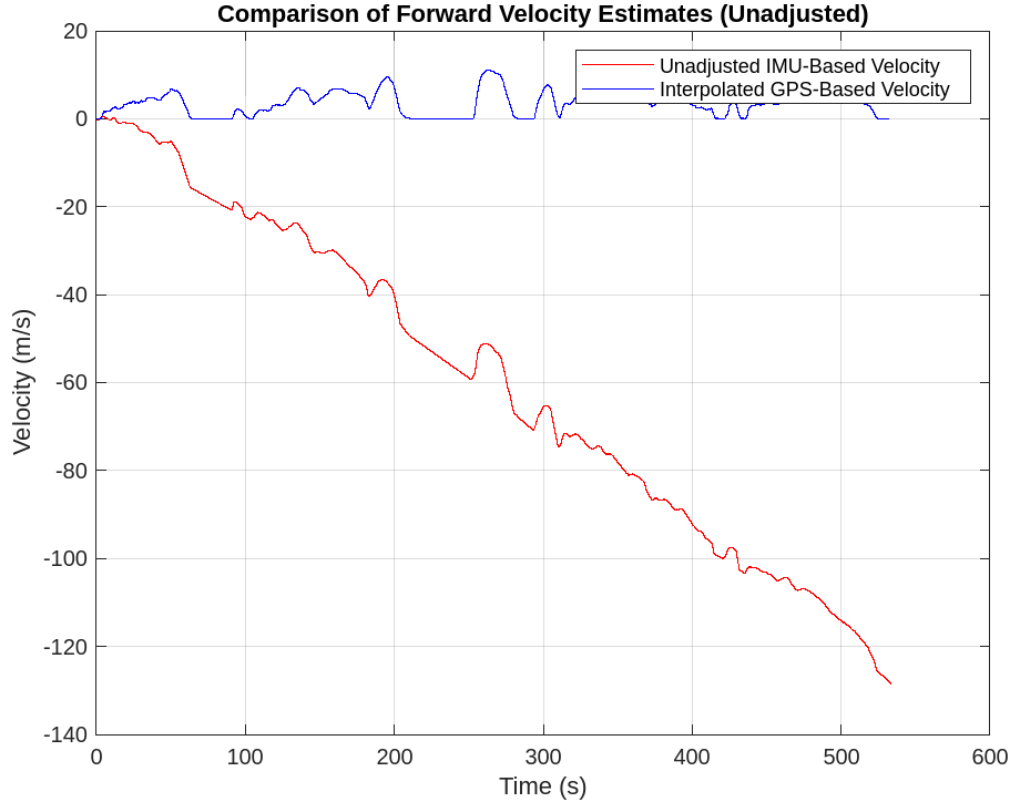

Figure 6: Comparison of Forward Velocity Estimates (Unadjusted)

- **GPS-Based Velocity Estimation:** The GPS data was used as a reference for forward velocity. Velocity was calculated by determining the distance between successive GPS points and dividing by the time elapsed. This provided an accurate absolute velocity unaffected by drift, serving as a baseline to compare against the IMU-derived velocity.

- **Adjustment of IMU-Derived Velocity:** The IMU velocity was adjusted to align more closely with the GPS velocity:

  1. **Detrending:** After low-pass filtering, a detrending process was applied to remove residual drift in the IMU-based velocity estimate. This adjustment effectively minimized long-term drift, ensuring the IMU-derived velocity more closely represented the actual forward speed.

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2. **Comparison and Final Adjustment:** The adjusted IMU velocity was compared to the GPS velocity. Additional minor adjustments were made to ensure that the IMU velocity aligned with the GPS data as closely as possible, particularly during periods of constant speed.

The result of this process is shown in Figure 7, where the corrected IMU-derived velocity (red line) follows the GPS-derived velocity (blue line) more closely. This alignment demonstrates the effectiveness of filtering and detrending in achieving a reliable forward velocity estimate from the IMU data.
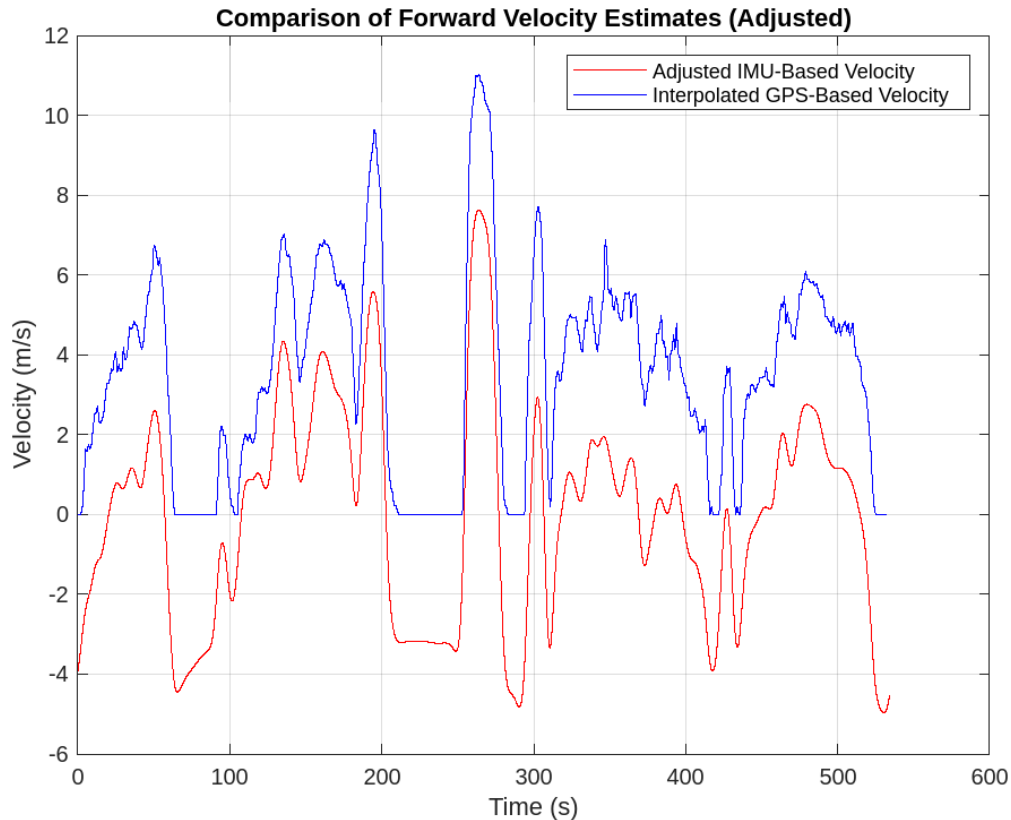

Figure 7: Comparison of Forward Velocity Estimates (Adjusted)

This multi-step adjustment process ensured that the IMU-based velocity estimate was both accurate and reliable for use in dead-reckoning calculations. By aligning with GPS data, we reduced the impact of accelerometer drift, providing a robust velocity profile suitable for subsequent navigation analyses.

3.4   Dead Reckoning Path Estimation

Dead reckoning provides an estimated trajectory by integrating forward velocity and directional heading data over time. In this section, we use the IMU-derived velocity and yaw estimates to calculate the vehicle's position in terms of Easting and Northing coordinates. GPS data is then used to correct accumulated drift periodically, aligning the dead-reckoned

path with an absolute reference. The following steps outline the dead reckoning process in detail.

- **IMU-Based Velocity Integration:** Using the forward velocity derived and adjusted in the previous section, the vehicle's displacement over time was calculated. This was achieved by integrating the corrected forward velocity, providing an estimate of distance traveled along the vehicle's heading direction.

- **Yaw Angle for Directional Updates:** To determine the vehicle's heading direction, we used the yaw estimates obtained from the complementary filter (detailed in the Yaw Estimation section). The yaw angle provided the orientation of the vehicle in the plane, allowing us to decompose the forward velocity into Easting (ve) and Northing (vn) components based on the following calculations:

$$ve = \text{velocity} \times \cos(\text{yaw}) \tag{1}$$

$$vn = \text{velocity} \times \sin(\text{yaw}) \tag{2}$$

  Here, the cosine and sine of the yaw angle are used to project the forward velocity along the Easting and Northing directions, respectively.

- **Path Estimation with Drift Correction:** By integrating the Easting and Northing components of velocity over time, the vehicle's position was updated incrementally to estimate its trajectory. However, due to the nature of IMU data, dead reckoning estimates are prone to drift over time. To mitigate this drift, periodic corrections were applied using GPS data:

  1. **Periodic Realignment with GPS Data:** At regular intervals, the dead-reckoned position was corrected by aligning it with the nearest GPS position. This approach allowed us to retain the continuous estimation provided by IMU data while anchoring it to absolute GPS positions to correct for drift.

  2. **Drift Adjustment Method:** At each correction point, the displacement between the dead-reckoned position and the GPS position was calculated, and this drift was subtracted from the dead-reckoning estimates to realign with the GPS path.

- **Resulting Trajectory Comparison:** Figure 8 shows the comparison between the GPS path (blue line) and the IMU-derived dead reckoning path (red line) after applying periodic drift corrections. As seen, the corrected dead-reckoning path closely follows the GPS trajectory, demonstrating the efficacy of the correction process.
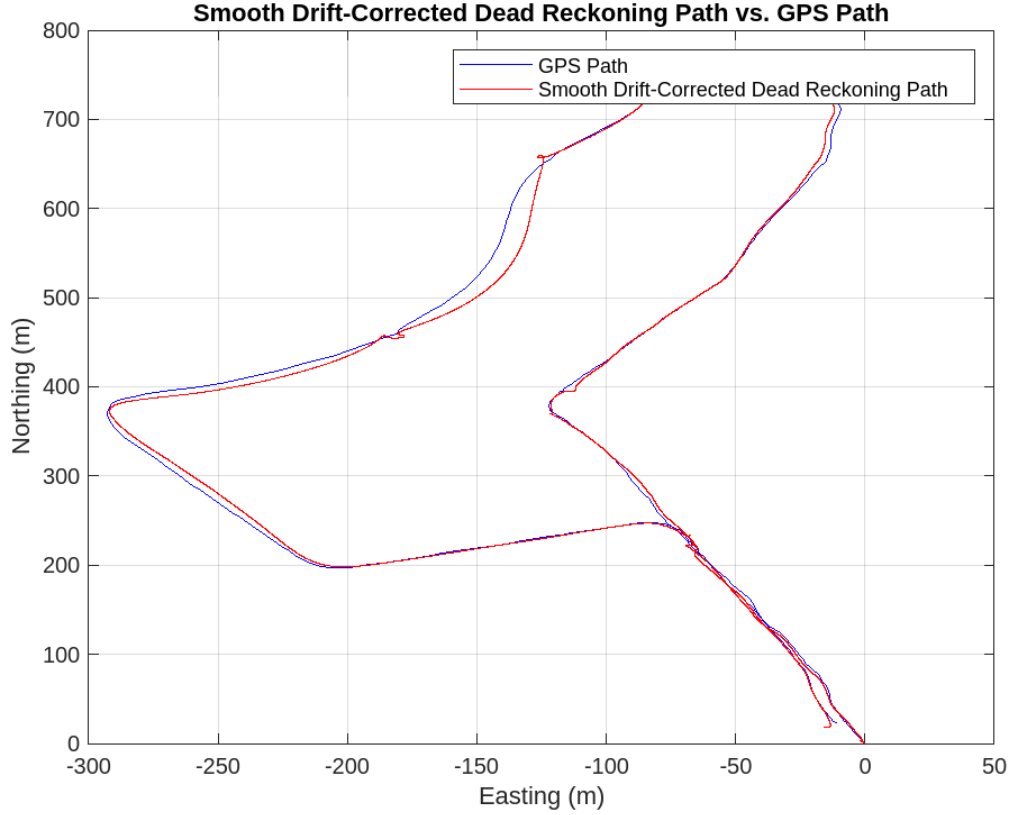
Figure 8: Comparison of GPS Path vs. Dead Reckoning Path (Drift-Corrected)

This figure highlights that by periodically realigning with GPS data, dead reckoning can maintain an accurate trajectory over extended distances, despite the inherent drift in IMU data. This approach provides a robust navigation solution that combines the high-frequency responsiveness of IMU data with the absolute accuracy of GPS positioning.

Through these steps, the `deadrocking.m` script achieved an accurate estimate of the vehicle's path based on IMU data alone, corrected with GPS positioning to minimize drift. The result is a reliable dead reckoning estimate that aligns well with the actual path, making it suitable for applications in environments where continuous GPS access may be limited but periodic corrections are available.

4 Conclusion

This lab report has presented a comprehensive approach to vehicle navigation using IMU and GPS data, exploring the capabilities and limitations of each sensor in real-world conditions. By employing a structured method for data collection, calibration, and sensor fusion, we achieved reliable forward velocity estimation and path tracking through dead reckoning. Each of the key processes—magnetometer calibration, yaw estimation, forward velocity adjustment, and dead reckoning—played a crucial role in the navigation stack, and the conclusions drawn from these analyses are summarized as follows:

- **Magnetometer Calibration:** The magnetometer calibration in the donut dataset was essential for correcting distortions caused by hard-iron and soft-iron effects, which improved the accuracy of heading (yaw) measurements. The transformation from elliptical to circular data after calibration, as shown in earlier figures, confirms the successful correction of magnetic distortions and establishes a solid foundation for accurate yaw estimation.

- **Yaw Estimation Using Sensor Fusion:** Yaw estimation was achieved through a complementary filter combining gyroscope and magnetometer data. The high-pass filter on the gyroscope yaw rate and low-pass filter on the magnetometer yaw effectively balanced responsiveness with stability. This sensor fusion approach provided a reliable yaw angle for navigation, overcoming the limitations of standalone gyroscope drift and magnetometer noise. The final yaw estimate from the complementary filter proved stable and closely aligned with the true heading, essential for accurate directional navigation.

- **Forward Velocity Estimation:** The forward velocity was derived by integrating accelerometer data after correcting for initial bias and noise, with final adjustments based on GPS data to correct drift. Discrepancies between IMU-based and GPS-based velocities were identified and resolved by applying low-pass filtering and detrending to the IMU velocity, resulting in a robust forward velocity estimate. The comparison with GPS-derived velocity demonstrated the effectiveness of these adjustments in aligning IMU-based estimates with absolute measurements.

- **Dead Reckoning Path Estimation:** Using the corrected forward velocity and yaw angle, the dead reckoning path was computed through incremental integration of Easting and Northing components. To mitigate drift in the IMU-derived path, periodic GPS-based corrections were applied, aligning the dead reckoning estimate with the GPS trajectory. The final trajectory comparison illustrated in the report indicates that periodic drift correction effectively maintains the accuracy of dead reckoning over extended distances, even when relying primarily on IMU data.

In conclusion, this lab highlights the importance of sensor calibration, filtering, and fusion in achieving accurate navigation from IMU and GPS data. The analyses demonstrate that with appropriate corrections, the IMU can provide reliable, continuous velocity and positional estimates in GPS-limited environments. Furthermore, periodic GPS corrections allow for sustained dead reckoning performance over time. These insights are critical for applications in mobile robotics, autonomous vehicles, and other navigation-based fields, where continuous and accurate positional data is essential.

The integration of sensor fusion, calibration, and drift correction techniques has successfully met the objectives of this lab, providing a robust navigation framework. Future work could explore adaptive filtering techniques or extended Kalman filtering to further enhance the reliability and precision of IMU-based navigation under diverse environmental conditions.