Lab 4 Report: Navigation with IMU and Magnetometer

Group 9: Data uploaded by Varun Raghavendra (@raghavendra.va)

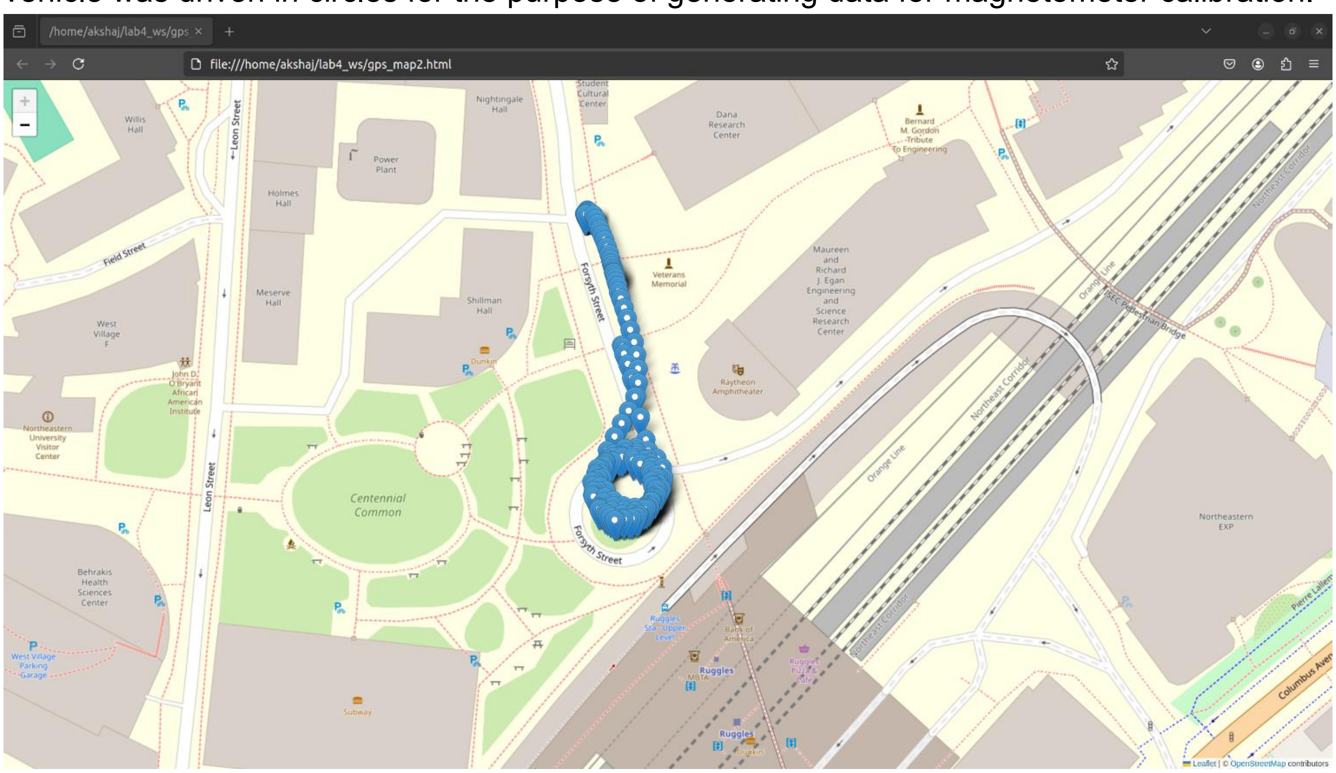
Introduction:

The specific purpose of the laboratory exercise was to create a navigation system but with the two sensors which are the GPS and an IMU sensor by understanding the advantages and disadvantages of each sensor in the application of dead reckoning systems. In such cases where GPS data may not be available, the lab studies used sensor fusion techniques to provide robust estimation of heading (or yaw) and velocity, and to formulate a strong navigation solution. In particular, the emphasis of this project was detailed towards the calibration of magnetometer data, yaw estimation using various techniques, integration of forward velocity, and dead-reckoning that was used to find out the IMU approximated trajectories as compared to GPS trajectories.

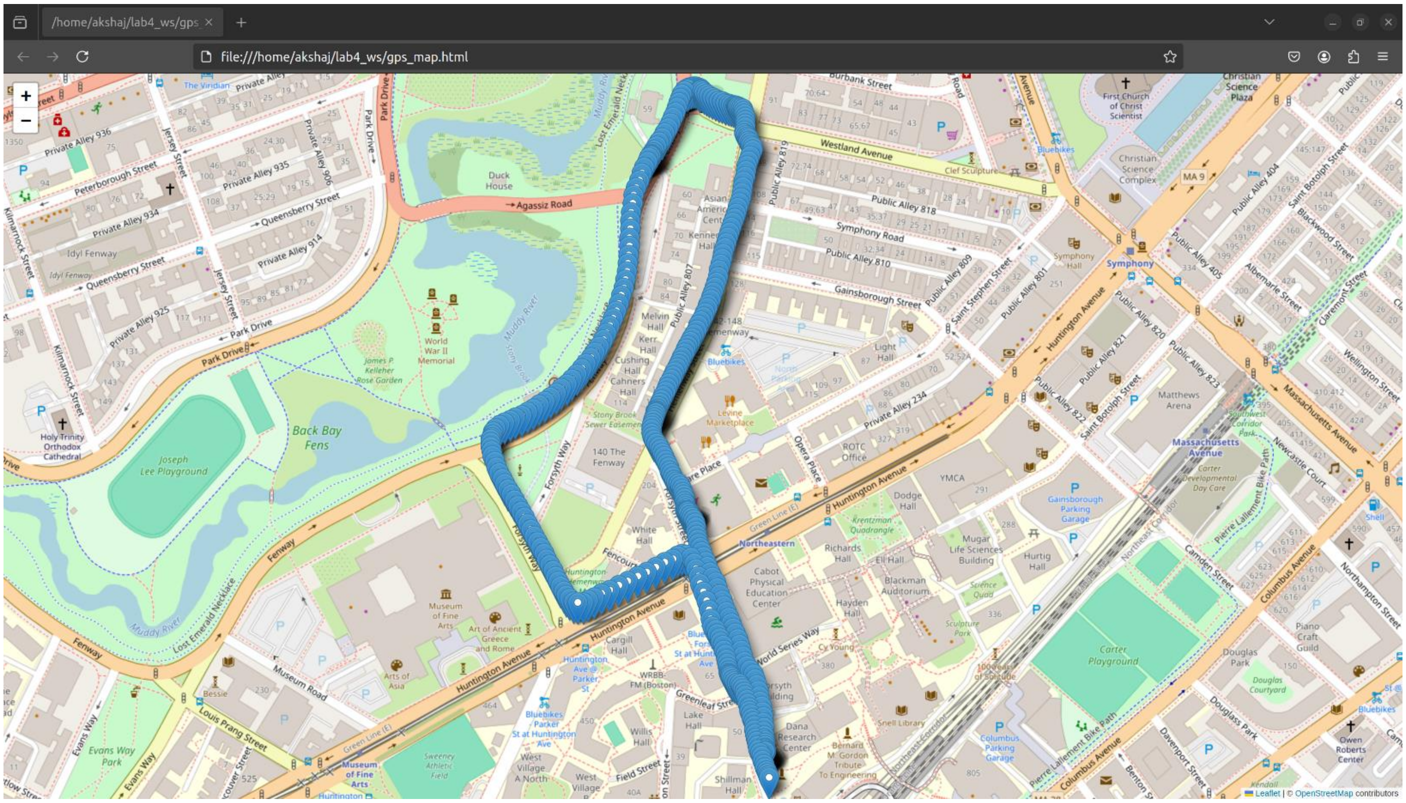
Data Collection Process:

To collect the data, an arrangement was made such that the GPS puck was fixed on the roof of the car and the IMU was mounted in the middle of the dashboard with its X axis pointing forwards. Two routes were taken in terms of data collecting:

Data Going in Circles: In this data, the hard-iron and soft-iron distortions were captured when the vehicle was driven in circles for the purpose of generating data for magnetometer calibration.



Mini Boston Tour: In this dataset, we collected GPS and IMU data in a car while making turns and completing a distance of 2-3 kilometers.

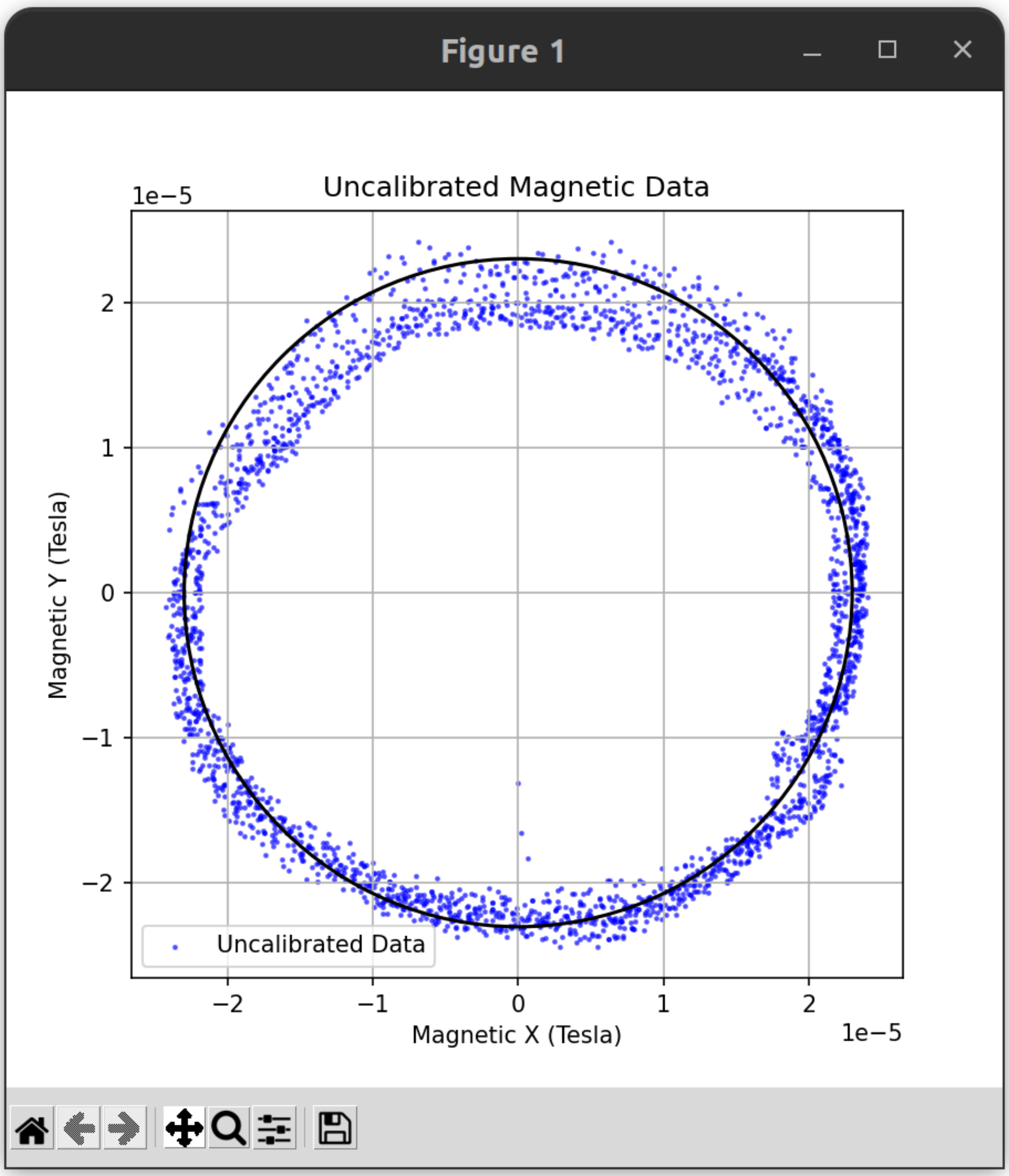


Magnetometer Calibration

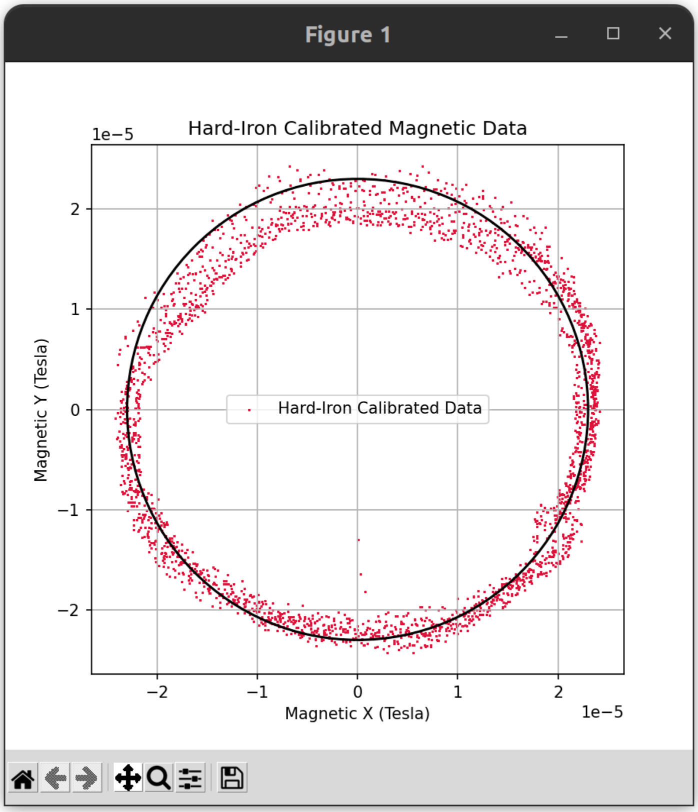
The collected data from the “Data Going in Circles” route was used to correct for hard-iron and soft-iron effects on the magnetometer readings. Hard-iron distortion, typically caused by the vehicle’s permanent magnetic fields, shifts the center of the magnetometer data away from the origin. Soft-iron distortion, on the other hand, skews the shape of the data. The calibration procedure adjusted the magnetometer data by applying transformations to realign it with a centered, circular pattern.

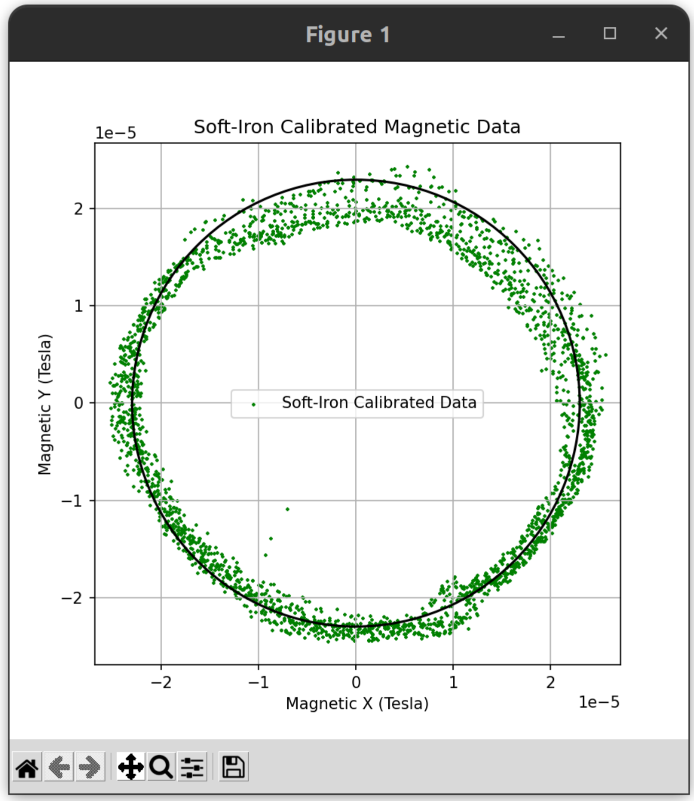
The following figures show the data obtained from the magnetometer:

Magnetometer X-Y plot (Before Calibration) – The original magnetometer readings contained an offset and an elongated-u shape indicating hard and soft iron distortions.



Magnetometer X-Y plot (After Calibration) – First hard iron corrections were applied and then soft iron corrections.





In our case, the uncalibrated data was almost making a circle with the center at origin so the calibration did not affect the plot by much.

These distortions were, however, demonstrated by the non circular outline of plots, which is usually the case in undistorted plots. The corrections enhanced the accuracy of the yaw measurements derived from the magnetometer.

Heading (Yaw) Estimation

The calibrated magnetometer data was then used to estimate the yaw angle. The raw magnetometer yaw was first calculated and then corrected using the hard and soft iron corrections. Following this, gyro sensor was integrated over time to obtain a yaw angle. Both methods of estimation were plotted together to illustrate any differences.

To improve the yaw angle further, a complementary filter was applied, fusing the magnetometer-based and gyro-based yaw estimates. This filter utilized a low-pass filter on the magnetometer's yaw to handle low-frequency data and a high-pass filter on the gyro's yaw for high-frequency responsiveness. After tuning the filter parameters, the fused yaw estimate provided smoother and more accurate heading information.

Complementary Filter for Yaw Estimation

To develop a robust yaw estimate, a complementary filter was used to fuse yaw measurements from both the magnetometer and gyroscope. The magnetometer provides long-term stability but is susceptible to noise, while the gyroscope has high responsiveness but can drift over time.

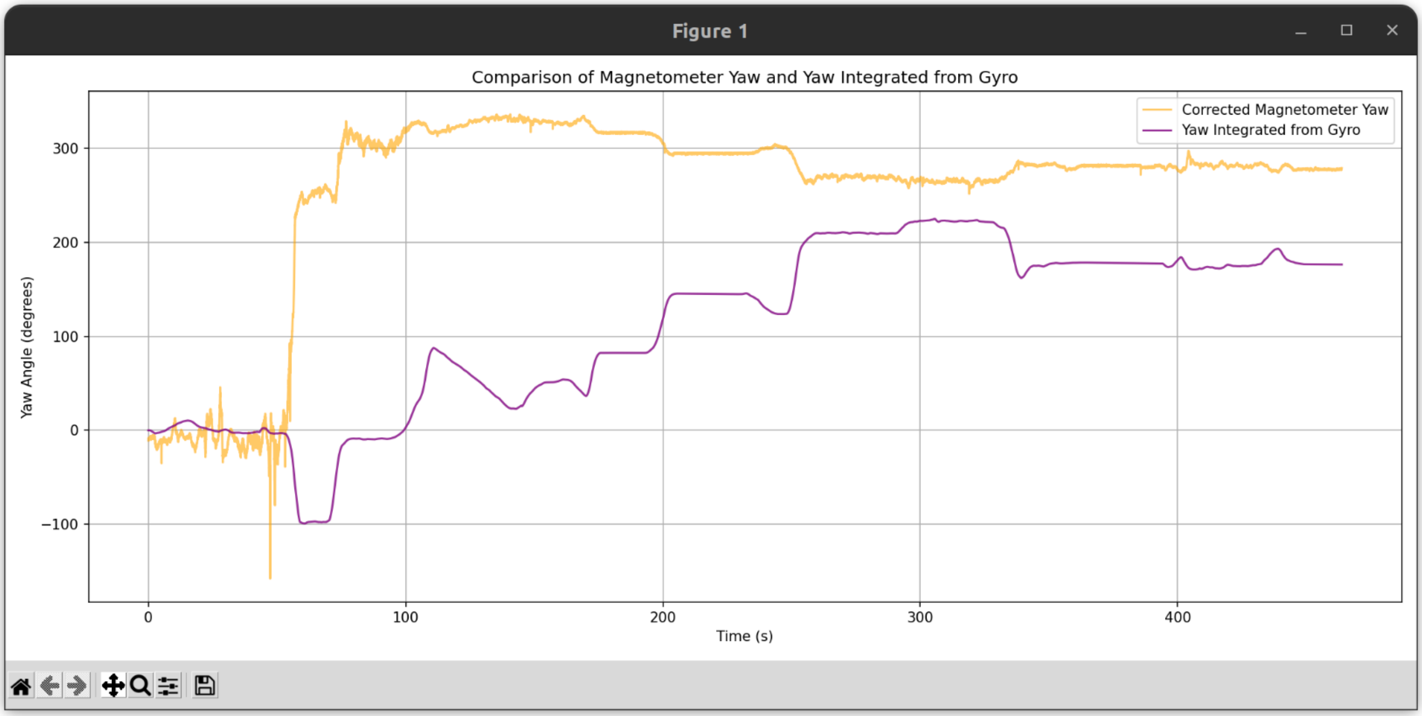
$Yaw_{combined} = \alpha\ (Yaw_{gyro}) + (1-\alpha)\ (Yaw_{mag})$

The variable α is set to 0.88.

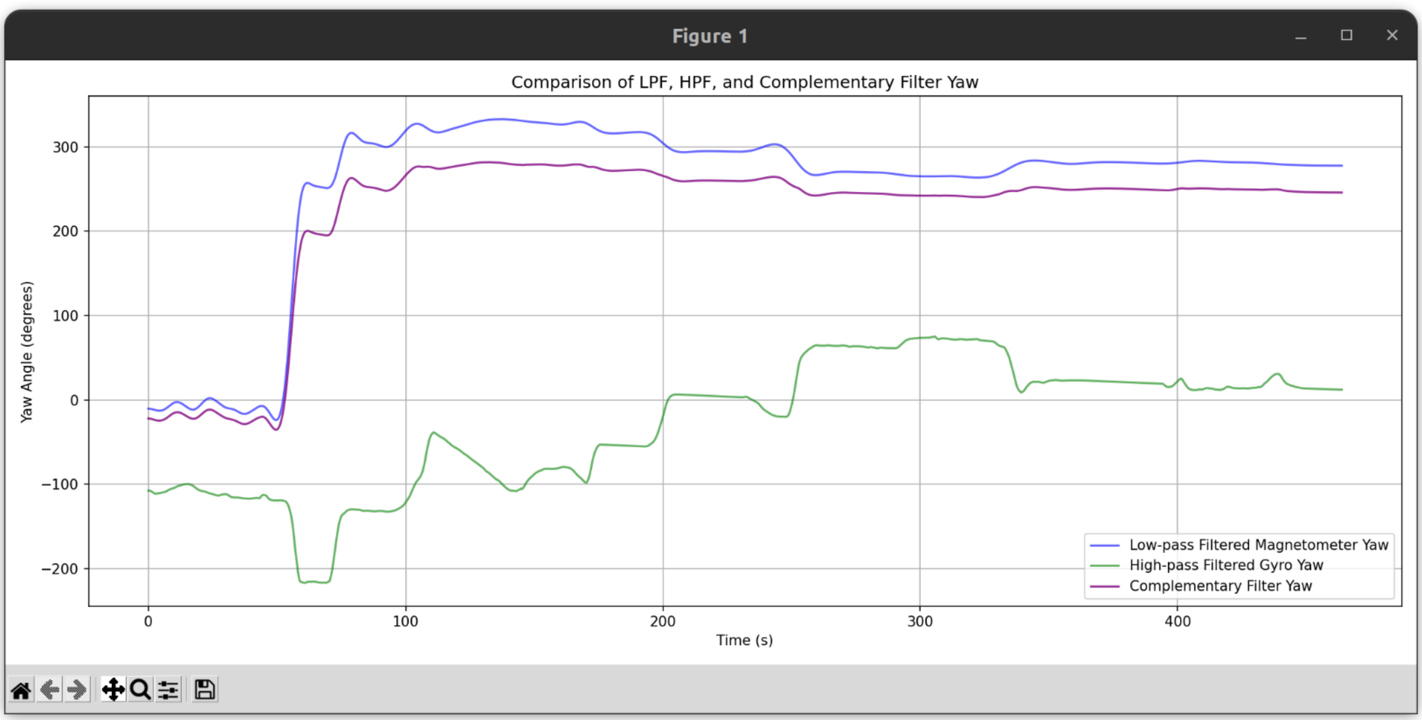
Filter Components The complementary filter combines the low-frequency data from the magnetometer with the high-frequency data from the gyroscope using the following approach:

1. **Low-Pass Filter for Magnetometer:** The magnetometer data was filtered through a low-pass filter to handle long-term orientation data. This filter helps to smooth out high-frequency noise that may affect magnetometer readings, making it ideal for capturing the stable, low-frequency component of the yaw. The cutoff frequency for the low-pass filter applied to the magnetometer yaw is set to 0.1 Hz.
2. **High-Pass Filter for Gyroscope:** The gyroscope's yaw rate data was integrated over time and passed through a high-pass filter to capture rapid, short-term changes in yaw. This prevents the slow drift inherent to gyroscopic data from affecting the estimate, making it suitable for capturing quick directional changes. The cutoff frequency for the high-pass filter applied to the integrated gyroscope yaw is set to 0.0001 Hz.

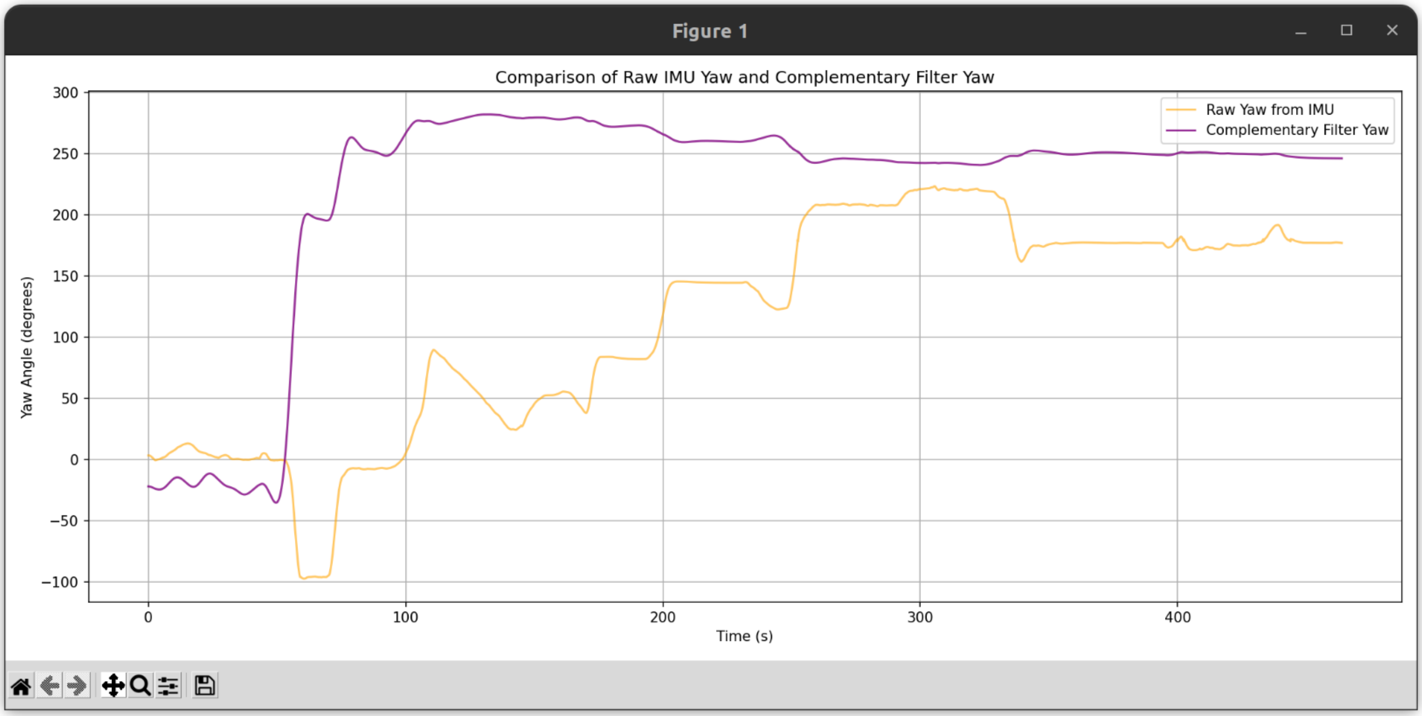
Magnetometer Yaw & Yaw Integrated from Gyro



LPF, HPF, and CF plots



Yaw from the Complementary filter & Yaw angle computed by the IMU



Forward Velocity Estimation

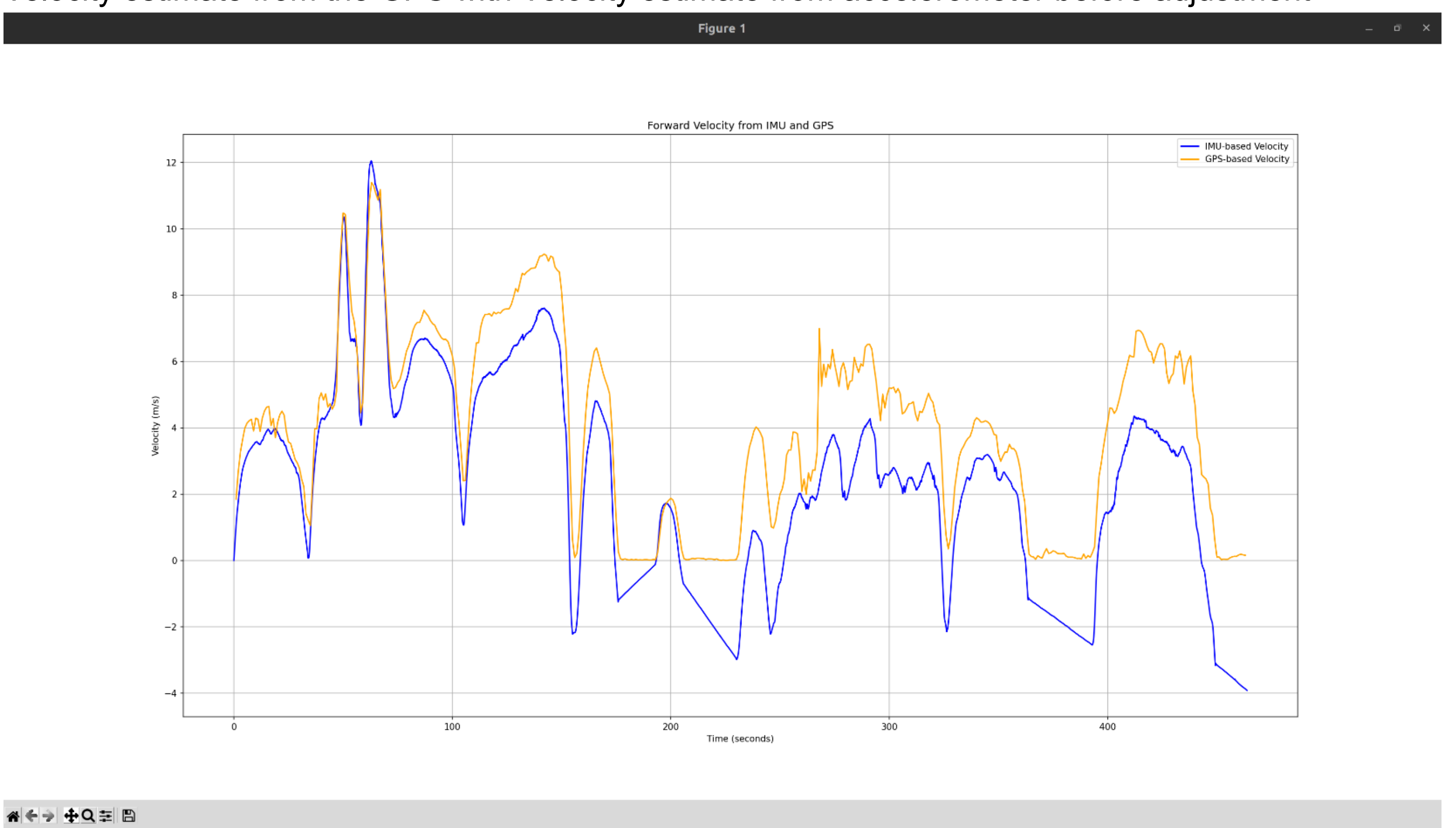
Forward velocity was estimated by integrating forward acceleration readings from the IMU. This acceleration-derived velocity was then compared with GPS velocity estimates.

There are discrepancies present in the velocity estimates of the accelerometer and GPS data.

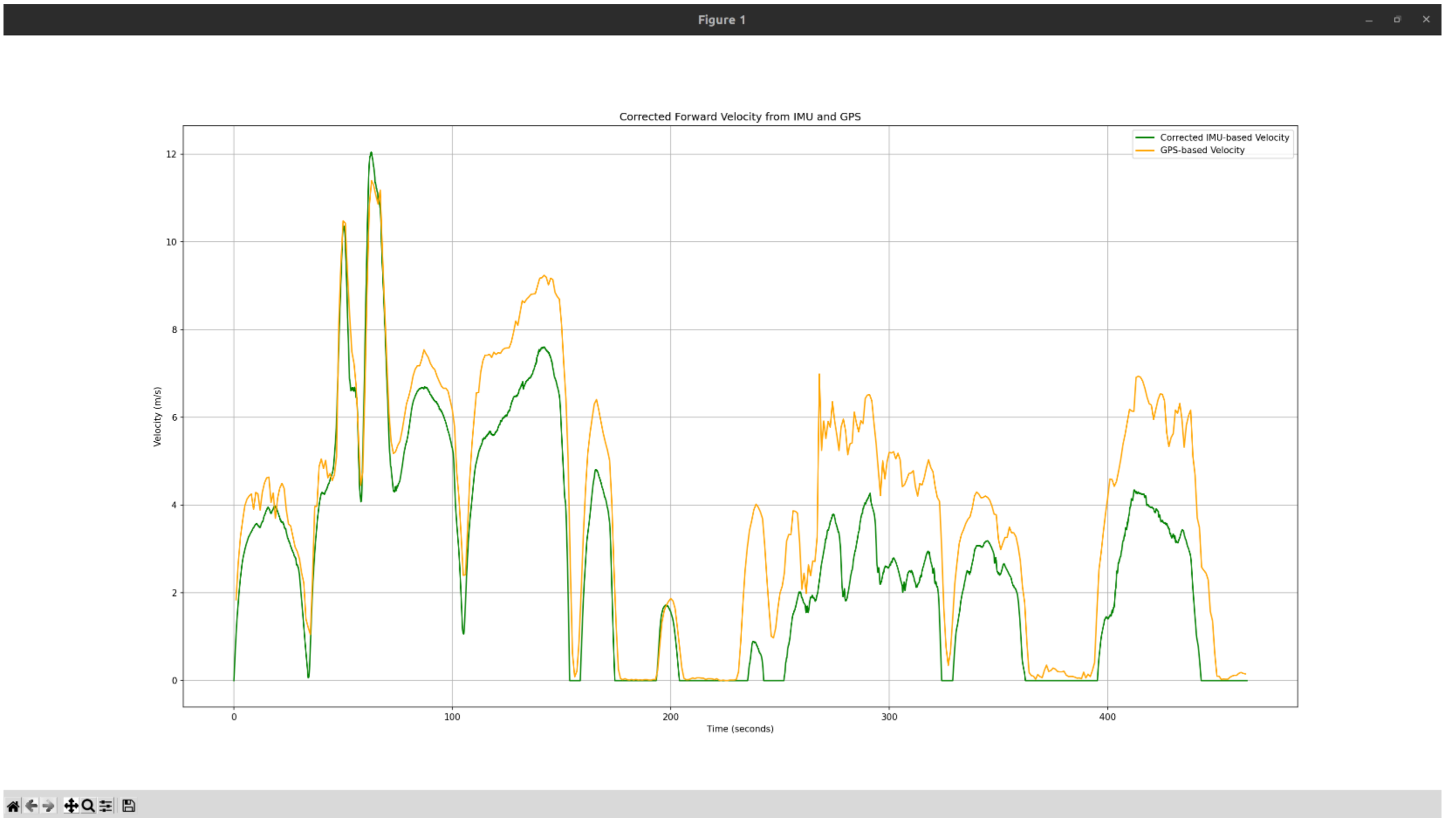
- The accelerometer data tends to drift away from the true value when the car is stationary or moving at a constant speed. In the plots it can be observed that when the car is stationary, the velocity derived from the accelerometer is constantly drifting.
- The GPS updates at a lower rate as compared to the IMU so the GPS speed is less responsive to rapid changes whereas the accelerometer captures much more data.
- Accelerometers are sensitive to high-frequency vibrations and other transient forces acting on the vehicle, such as road bumps or minor shocks.
- The accelerometer based velocity estimate requires a reliable heading direction to compute forward velocity. Errors in yaw estimation can cause inaccuracies in the accelerometer derived forward velocity, especially during turns or changes in orientation, while GPS inherently accounts for direction in its velocity estimate.

To address this, adjustments were applied to the forward acceleration to correct for any biases and drift over time. I have set the forward velocity to 0 when the GPS velocity is 0.

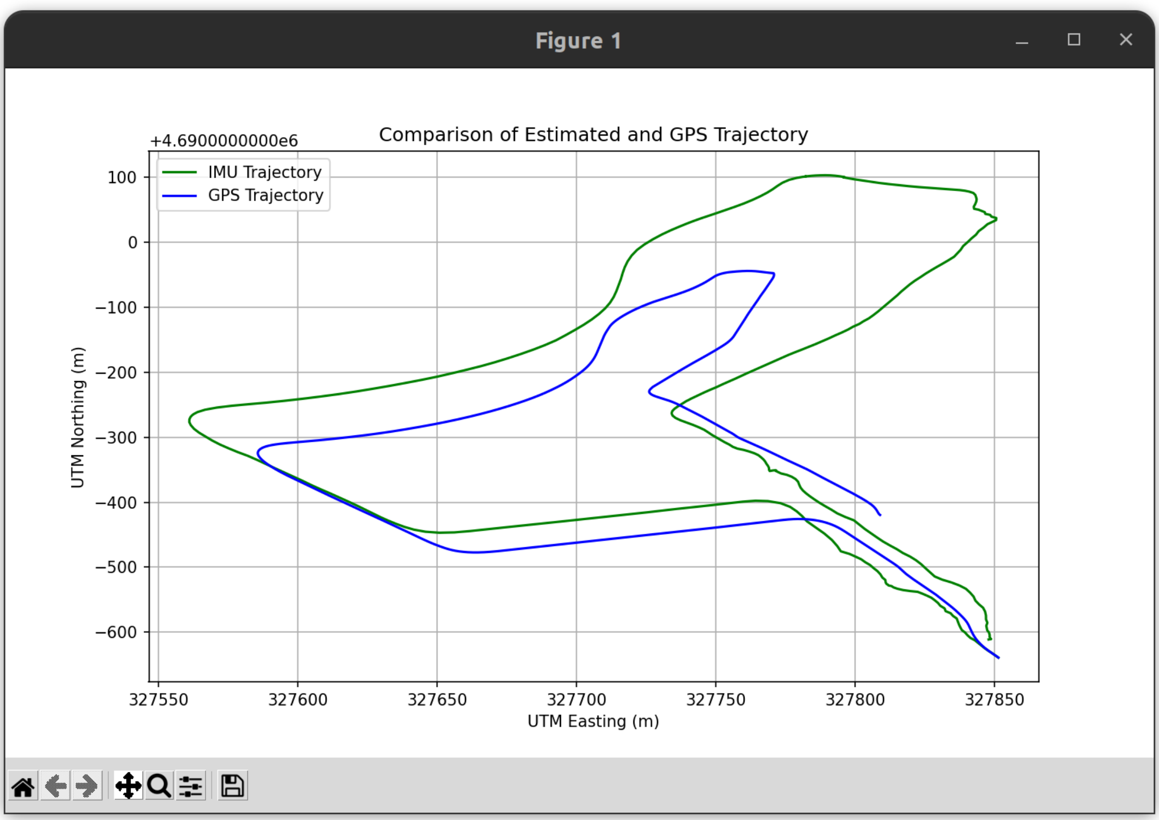
Velocity estimate from the GPS with Velocity estimate from accelerometer before adjustment



Velocity estimate from the GPS with Velocity estimate from accelerometer after adjustment

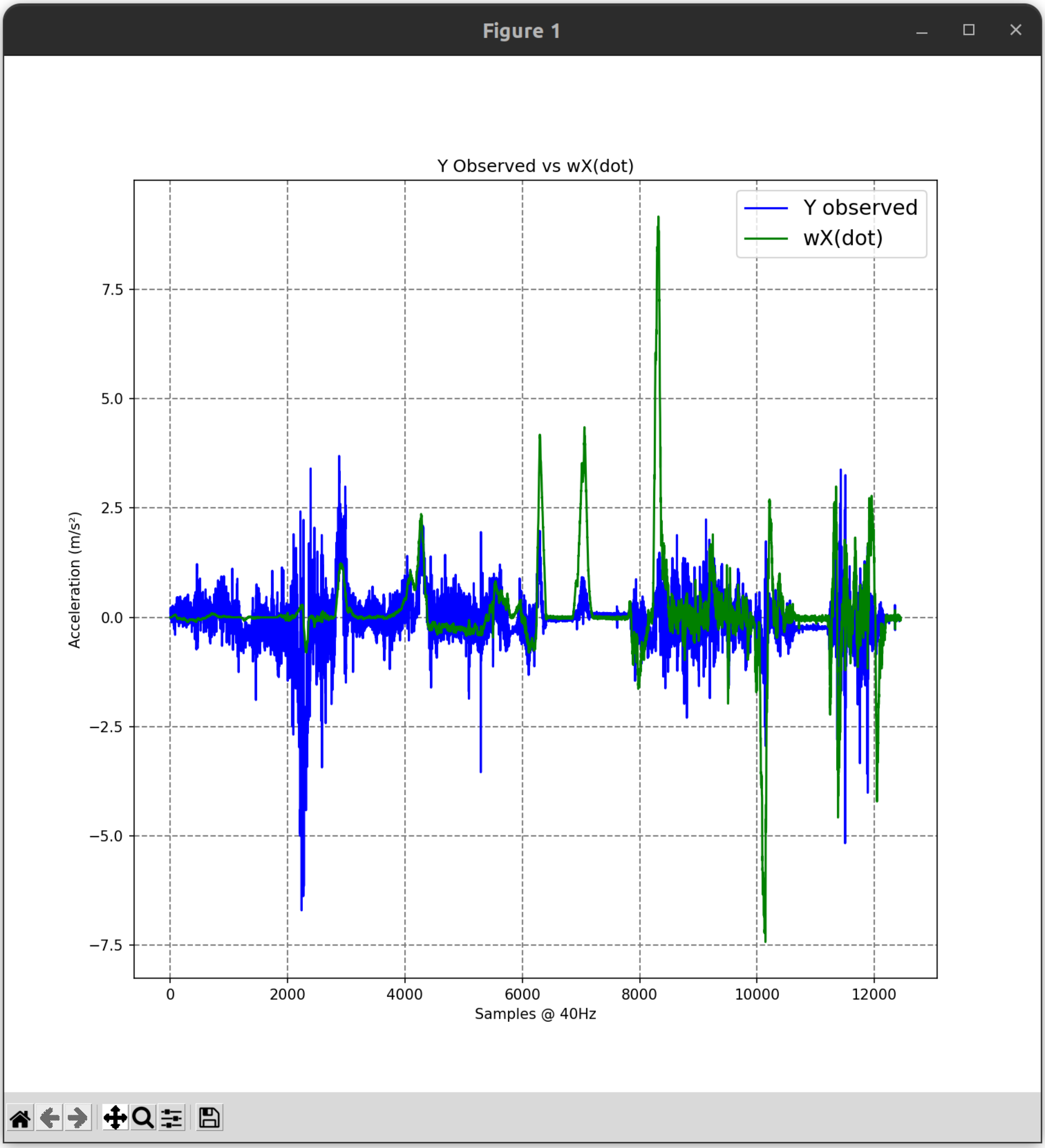


Comparison of Estimated Trajectory from IMU and GPS Trajectory



In this plot, the estimated trajectory is obtained from the IMU which can be useful to predict the trajectory in the case when GPS is unavailable. Although GPS trajectory is more accurate, but the IMU trajectory generally follows the turns, and we can get a rough idea of the trajectory.

Plot of ωX and $\ddot{y}_{obs}$ Together



X, the forward velocity, is derived from integrating the forward acceleration x_{obs} (from the IMU's accelerometer) over time. This calculation provides the velocity along the vehicle's forward axis.

ω represents the yaw rate (angular velocity around the z-axis), which is directly measured by the IMU. By multiplying ω with X, we obtain ωX, representing the lateral (sideways) acceleration component due to rotational motion.

$\ddot{y}_{\mathrm{obs}}$ is the lateral acceleration directly measured by the IMU. By plotting ωX and $\ddot{y}_{\mathrm{obs}}$ together, we can evaluate how well they align.

The difference might arise due to IMU sensor noise, inaccuracies in yaw rate or accelerometer readings, or assumptions in vehicle dynamics. External factors like road conditions or skidding can also introduce deviations.

The VectorNav VN-100 IMU is known for its high-precision orientation, acceleration, and angular rate measurements. However, without a GPS position fix, the IMU relies solely on dead reckoning, integrating acceleration and rotation data to estimate position over time. This process accumulates errors due to sensor noise, biases, and integration drift, which typically worsens the longer the IMU operates without a GPS correction. It can provide reliable dead reckoning for a short period, typically under a minute, depending on the dynamics of the motion. Under ideal conditions, a well-calibrated VN-100 might maintain position accuracy within 1–2 meters for up to 30 seconds to a minute without a position fix. After that, drift and accumulated errors make the position estimate unreliable.

Our GPS and IMU estimates of position were match closely for the first 20 seconds till the first turn, the position of IMU was within 2m of the GPS position.

While the IMU dead reckoning performed adequately for short durations, it did not fully meet the expected long-term accuracy due to drift, heading inaccuracies, and environmental factors. These limitations highlight the importance of using sensor fusion (combining IMU with GPS data) for long-term navigation accuracy, as dead reckoning alone cannot sustain precise positioning over extended periods in real-world conditions.

Conclusion:

Both IMU and GPS devices are invaluable technologies for positioning, each with distinct advantages and limitations depending on the application. This study demonstrates that GPS is superior for long-distance and extended-duration positioning due to its stability and accuracy over time. Conversely, IMUs excel in detecting rapid, small-scale changes in vehicle orientation, even over prolonged periods. Understanding the strengths of each system, as well as the impact of factors like noise, gravitational effects, and external interference on raw data, is essential for effective positioning. When combined correctly, IMU and GPS data provide a robust solution for accurately determining position and orientation in a wide range of robotic applications.