Lab 4 Report

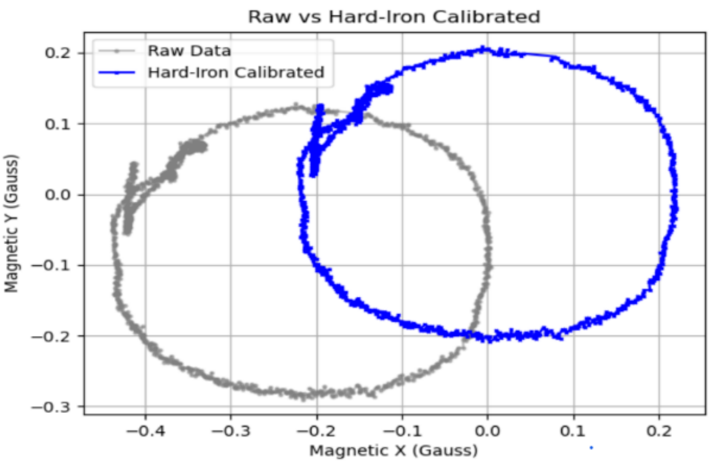
Introduction:

This report discusses an approach to navigation using a combination of GPS and IMU data for accurate position estimation. It also discusses the use of modelling techniques to streamline the process. The magnetometer is calibrated to remove soft- and hard-iron errors which improve the peddle angle. The yaw estimation is provided by employing interpolated yaw magnetometer data which is fused with data from GPS. Accelerometer data is fused to measure forward velocity and validated with the GPS. We also perform dead-reckoning by integrating the obtained velocity, which enables us to calculate the trajectory that adheres to the GPS coordinates. This method presents the intricate enhancement of modification aimed at the precision of navigation in mobile devices.

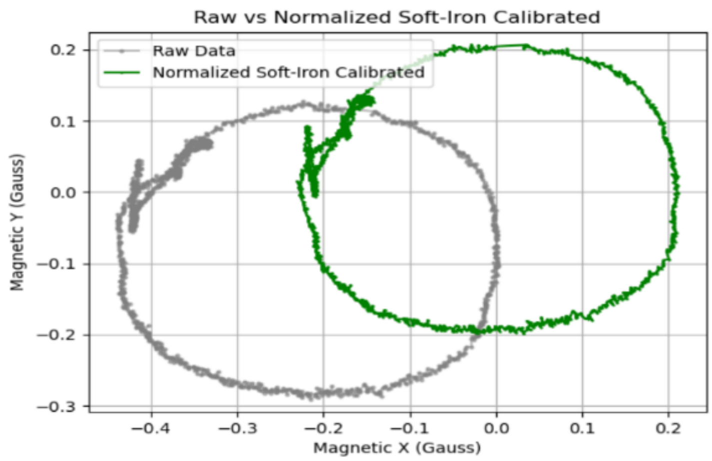
Objectives:

1. Collect the data using GPS and IMU when the vehicle is in motion.
2. Calibrate the magnetometer for hard-iron and soft-iron effects and estimate the yaw (heading).
3. Estimate the forward velocity using the forward acceleration and compare the results with GPS-derived velocity.
4. Perform dead reckoning with IMU data to obtain the vehicle's displacement and estimate its trajectory and validate it using GPS data.

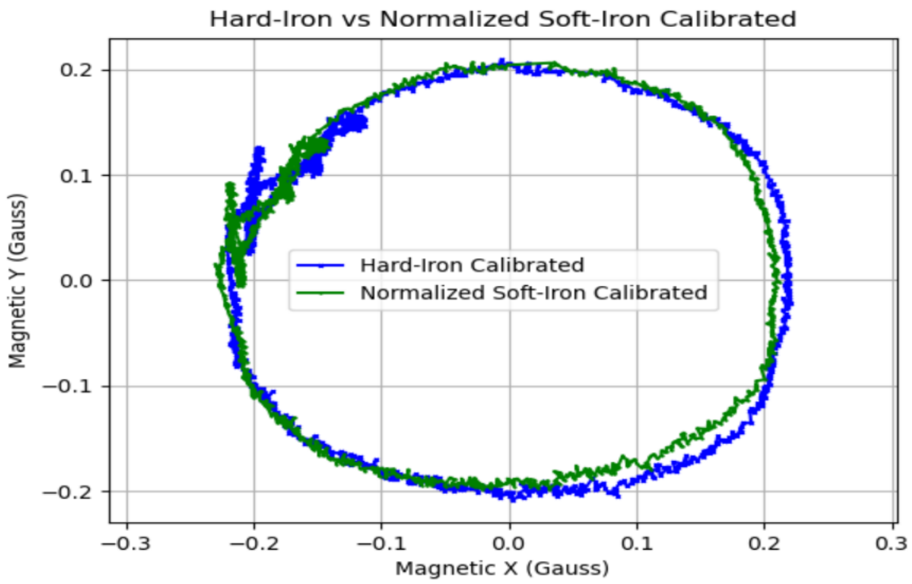
Magnetometer Calibration



The magnetometer is affected by hard-iron and soft-iron errors which distort the raw readings of the magnetic field. These errors make the data look like an ellipse which is offset from the origin. Hard-iron error causes the sphere to shift from the origin causing an offset in the plot. To calibrate the sensor for hard-iron error the offsets from the sensor for the X and Y axes are calculated based on the minimum and maximum values. This adjustment shifted the magnetic data closer to the origin, as illustrated in the "Raw vs Hard-Iron Calibrated" plot, where the offset present in the raw data is effectively removed.

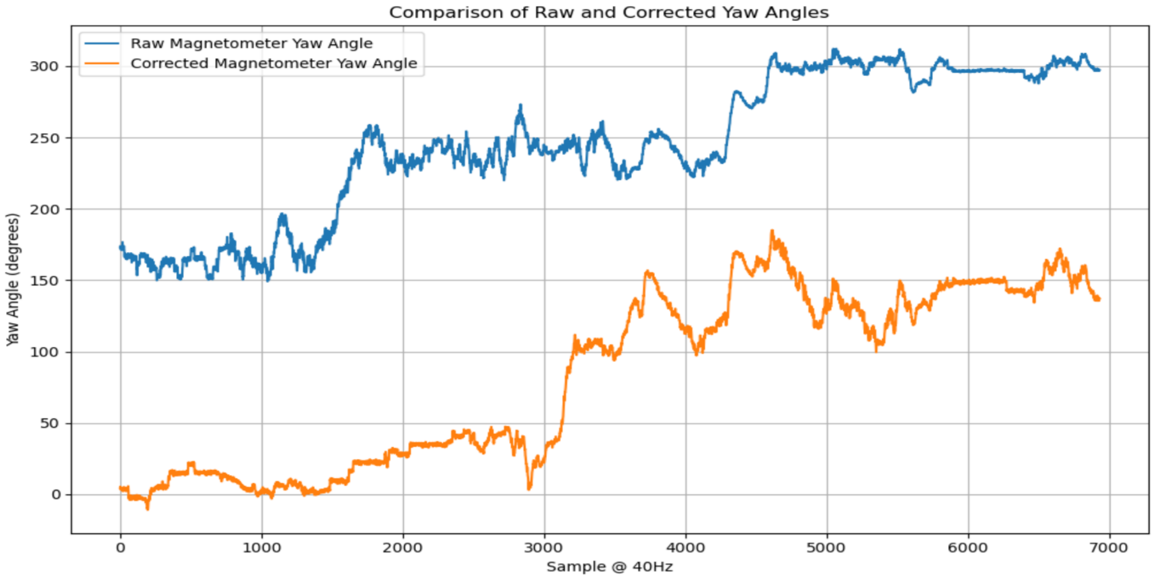


Then, soft-iron calibration was applied by fitting the data to an ellipse and rotating it to align with the principal axes. This step adjusted the scaling, making the data more circular. The corrected data was then normalized using a scaling factor to match the original radius, ensuring consistent magnitude.

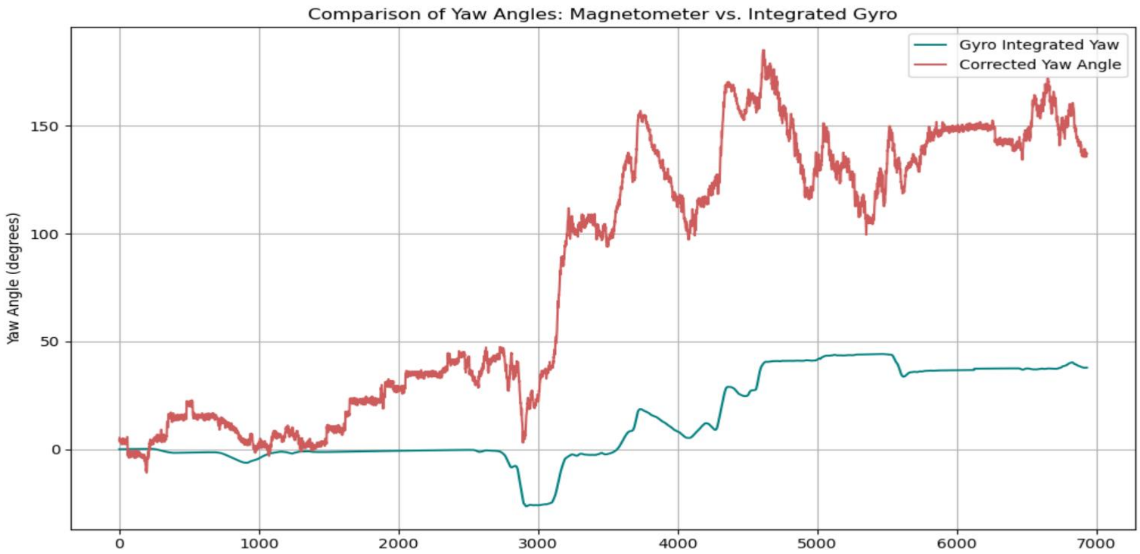


Yaw Estimation

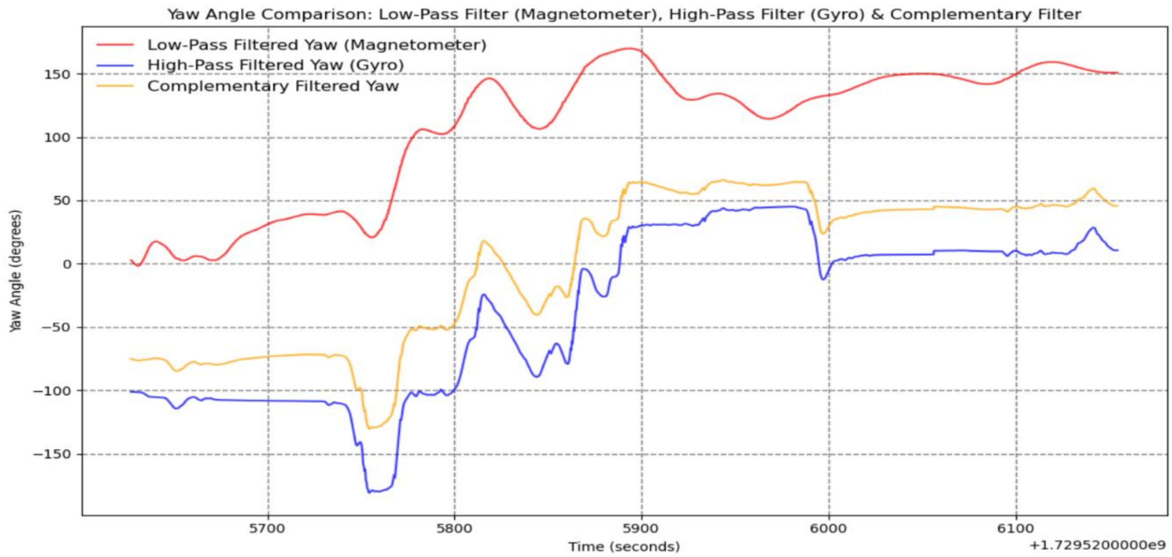
This section discusses how the Yaw angle is estimated using the calibrated magnetometer and gyroscope of the IMU sensor.



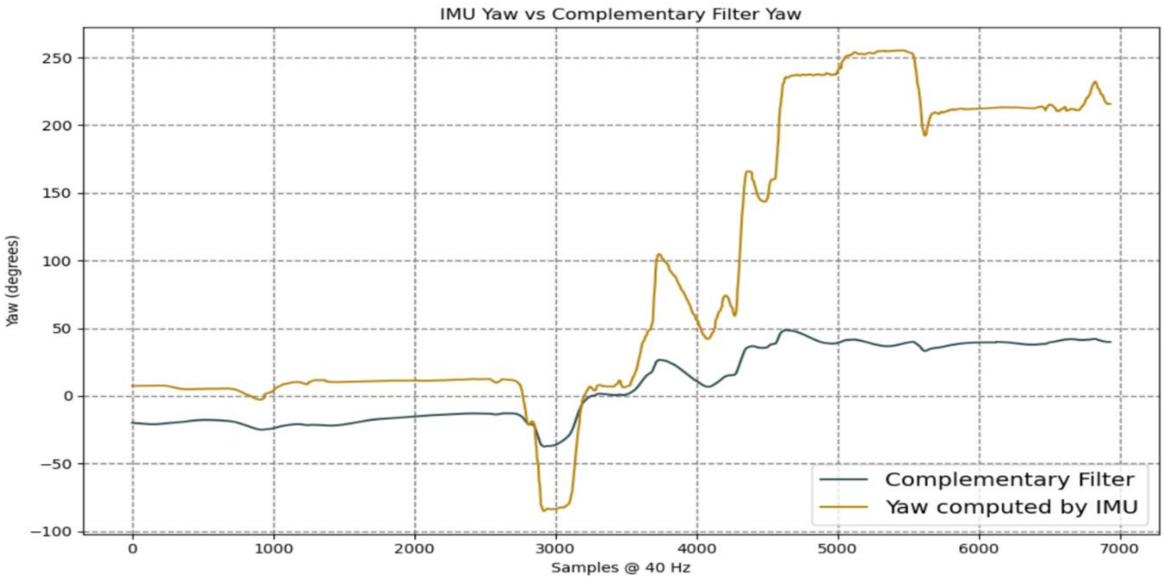
The above graph compares the yaw calculate using the raw magnetometer values and the calibrated magnetometer values. The raw yaw angle shows extensive noise and offset whereas the calibrated magnetometer yaw has reduced noise interference and the corrected offset.



The above graph compares the Yaw angle calculated using the calibrated magnetometer and the yaw angle obtained by integrating the gyroscope (gyro Z).

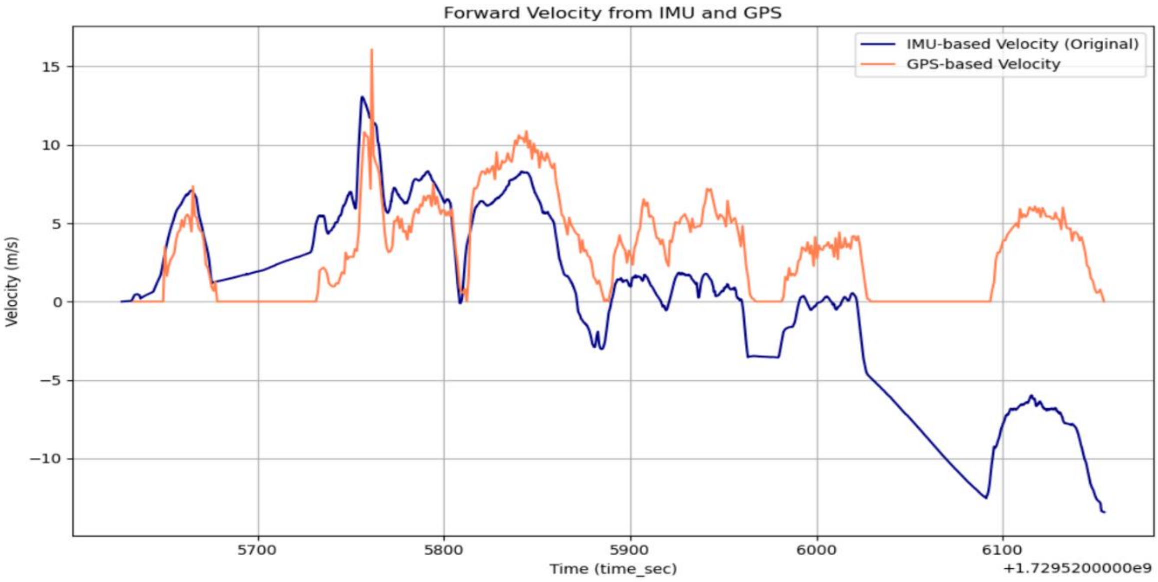


A complementary filter is used to estimate the yaw as it combines the filtered magnetometer and gyroscope data for stable and accurate heading estimation. In the complementary filter, a low-pass filter was applied to the magnetometer to reduce the high-frequency noise and the overall trend of the orientation. The high-pass filter is applied to the gyroscope data to focus small changes without the drift from the magnetometer. The LPF vs HPF plot demonstrates how each filter isolates respective aspects of the yaw data. In other words, the LPF smoothens the magnetometer signal while the HPF captures rapid gyroscope changes. The cutoff frequencies used were 0.1 for LPF and 0.0001 for HPF.

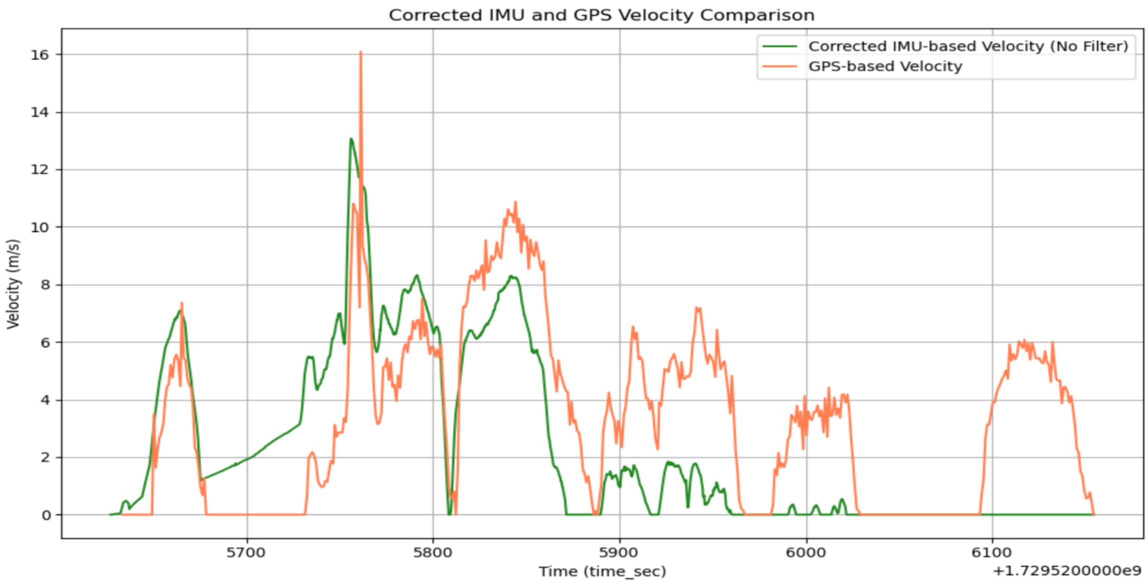


The IMU yaw vs Complementary Filter Yaw shows the stability of the complementary filter's output compared to the raw IMU yaw. Based on the plots, the complementary filter's yaw estimate is the most reliable for navigation applications as it combines both the magnetometer's long-term stability and the gyroscope's ability to monitor rapid changes which gives us both accurate and consistent heading estimates for real-time navigation.

Estimation of Forward Velocity

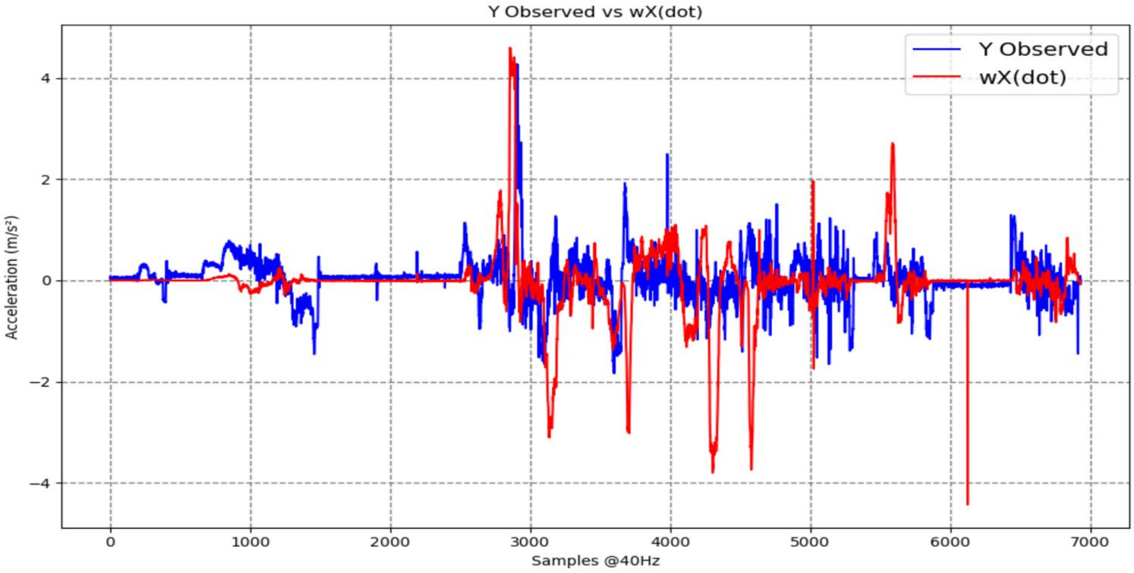


The forward velocity data obtained from the IMU was adjusted so that it shows similar trends and movement of the GPS-based velocity to improve the forward velocity estimate. The original IMU-derived velocity illustrates significant deviations and noise compared to the GPS velocity, which also has negative values. The primary reason for these discrepancies is the nature of IMU data processing. IMU-based velocity is obtained by integrating acceleration over time, which can lead to cumulative errors, especially due to sensor noise and small biases in the accelerometer. This integration process amplifies even minor inaccuracies, resulting in drift and increased noise in the IMU-based velocity.

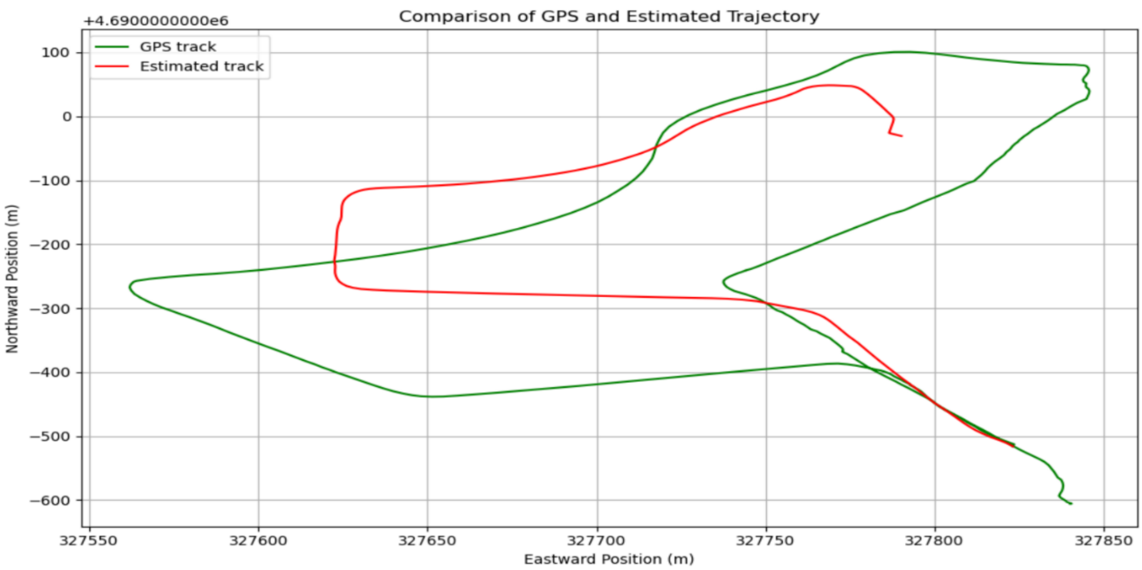


This discrepancy was corrected by adjusting the offset and zeroing any value that drops below zero. The corrected IMU velocity shows much more resemblance with the GPS-based velocity. The corrections remove the negative fluctuations provide a more accurate forward velocity estimate. The corrections are mandatory so that the IMU-based velocity accurately reflects the vehicle's actual movement. The primary reason for these discrepancies is the nature of IMU data processing. IMU-based velocity is obtained by integrating acceleration over time, which can lead to cumulative errors, especially due to sensor noise and small biases in the accelerometer. This integration process amplifies even minor inaccuracies, resulting in drift and increased noise in the IMU-based velocity

Dead Reckoning with IMU



The comparison between the Y observed and the wX (Angular velocity and linear velocity X) shows partial alignment in some areas and some regions where the discrepancies are observed. When the values align with each other it can be said that rotation captured by wX matches the actual acceleration in the Y direction. The differences seen in the plot can be due to the sensor noise, IMU misalignment, and external factors like vibrations and calibration errors. These factors cause distortion, especially in events where there is rapid acceleration.



Estimate the vehicle's trajectory (xe,xn) from inertial data and compare it with GPS by plotting them together. Adjust the heading so that the first straight line from both is oriented in the same direction.

The estimated trajectory from inertial data is compared to the actual GPS-derived trajectory.

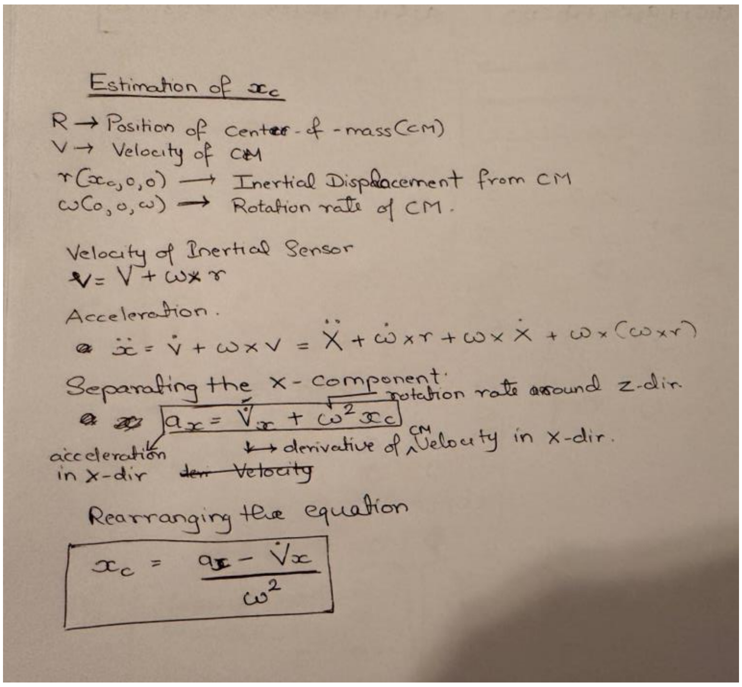
The heading is adjusted so that the initial frame of the IMU aligns with the GPS frame. The GPS track gives an exact reference to the vehicle’s actual path, while the estimated trajectory is computed from the inertial data. Theoretically, the estimated track should closely follow the GPS trajectory but there are variations in turns and rapid directional changes.

This distortion in the estimated track compared to the GPS track is due to the integration errors that accumulate over time. Despite this, the adjusted initial alignment of both paths demonstrates that the estimated trajectory captures the general direction and movement pattern of the vehicle. This comparison states the need of continuous GPS correction when using IMU data for long-term trajectory mapping to maintain accuracy.

Based on the VectorNav specifications, it is expected to navigate without a positional fix for about less than a minute. The position estimate deviation from its true value can be because of the accelerometer's and gyroscope's stability. The time when the GPS and the IMU estimates of the position closely match was less than a minute(around 55-57 seconds) most probably due to the continuous integration of the errors and environmental factors affecting the sensor's accuracy. The dead reckoning performance did not stand the theoretical expectation. This states that GPS corrections are periodically to maintain an accurate positioning in IMU.

x_c Estimation

x_c is the displacement of the IMU sensor from the center-of-mass of the vehicle along the X axis. This is the approach used to estimate the x_c value and the estimated value is ~-0.152051m



Estimation of x_c

R → Position of Center-of-mass(CM)

V → Velocity of CM

$r(x_c,0,0)$ → Inertial Displacement from CM

$\omega(0,0,\omega)$ → Rotation rate of CM.

Velocity of Inertial Sensor

$v = V + \omega \times r$

Acceleration.

$\ddot{x} = \dot{v} + \omega \times v = \dot{X} + \dot{\omega} \times r + \omega \times \dot{X} + \omega \times (\omega \times r)$

Separating the x-component.

$\boxed{a_x = \dot{V}_x + \omega^2 x_c}$ rotation rate around z-dir.

acceleration in x-dir

derivative of CM Velocity in x-dir. ~~der Velocity~~

Rearranging the equation

$$\boxed{x_c = \frac{a_x - \dot{V}_x}{\omega^2}}$$