LAB4 Report

Introduction

In this lab, the focus is on sensor fusion, which is the process of combining data from multiple sensors to create a more accurate and complete representation of a physical system or environment. The lab aims to teach the importance and benefits of sensor fusion, as well as how it can be utilized in navigation systems.

One specific area of interest is the comparison of GPS and IMU sensors. GPS is a global navigation satellite system that provides location and timing information, while IMU (inertial measurement unit) is a device that measures the motion, orientation, and acceleration of an object. Both sensors have their advantages and disadvantages, and it's important to analyze them in detail to determine the best way to utilize them in a navigation system.

Questions to answer in your report.

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

The nuance car collected data while traversing Ruggles circle at Northeastern University. Despite following a circular path, the data points captured in Figure 1 are scattered across the circle because of the presence of hard and soft iron effects. The accuracy of a magnetometer reading can be affected by the presence of both hard and soft iron, even if the magnetometer has no noise.

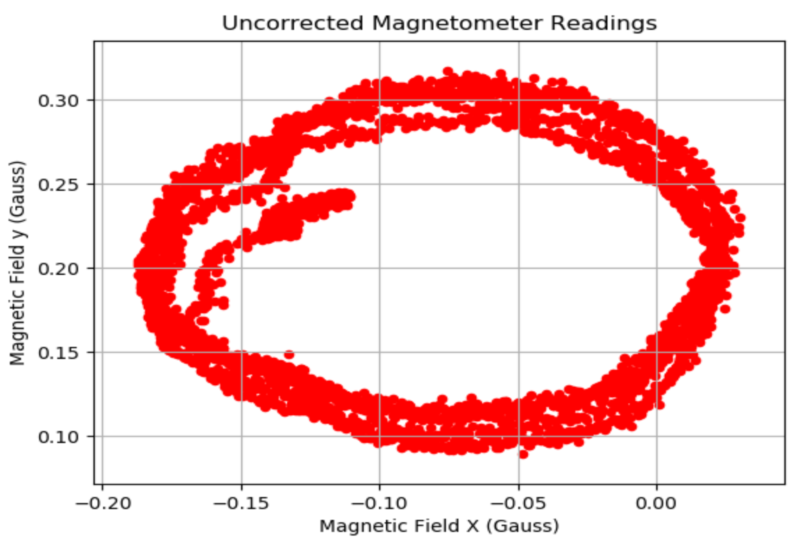
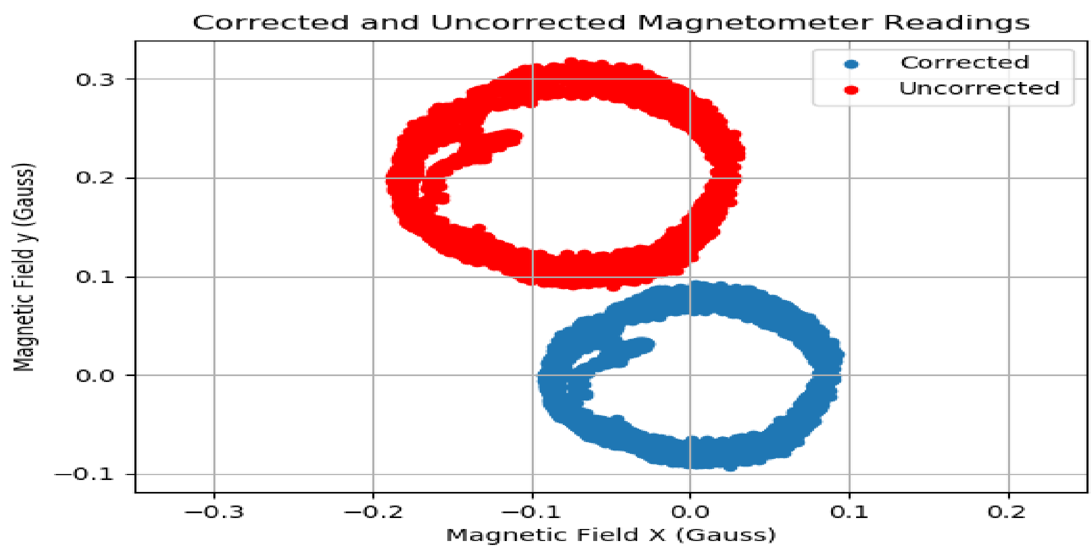


Fig 1 Magnetometer data before correction

Correction or Calibration of Hard iron and soft iron Effects

The data plotted on a graph would form a perfect circle centered at the origin if there were no magnetic interference from external sources such as the Earth's magnetic field or other magnetic forces. However, such interference always exists, leading to hard and soft iron effects. While the updated data shows a reduced hard iron effect, the soft iron effect cannot be eliminated by merely removing the offset. Unlike hard iron distortion, soft iron distortion is not cumulative and results from substances that influence a magnetic field instead of producing one. Its magnitude varies based on the orientation of the material with respect to the magnetic field and the sensor. Therefore, a complex method is necessary to differentiate between strong and weak soft iron distortion.



Distortions in magnetic field readings can be caused by both hard iron and soft iron sources.

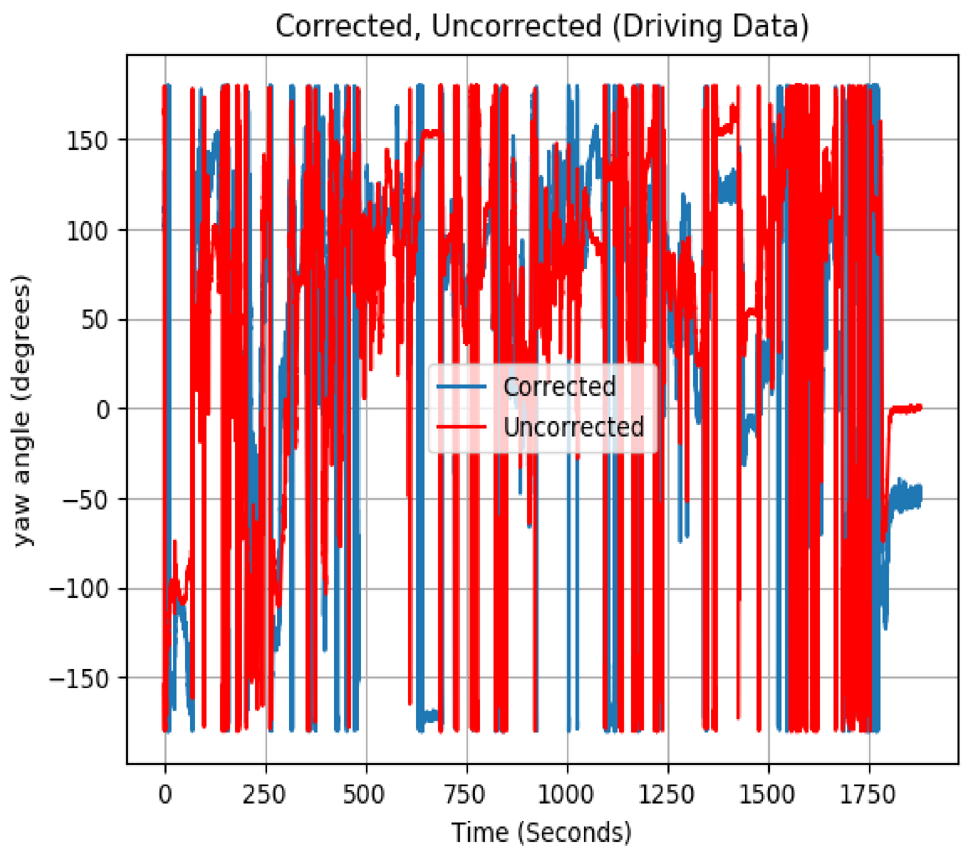
Hard iron distortions result from magnetic components such as speakers or magnetic iron that produce a persistent bias in the sensor output if they are physically coupled to the same reference frame as the sensor.

Soft iron distortions are caused by metals like nickel and iron that stretch or distort the magnetic field in relation to the sensor. Other factors such as the banking and elevation angles can also affect data collection accuracy, and these variables must be taken into account before estimating the incidence of errors.

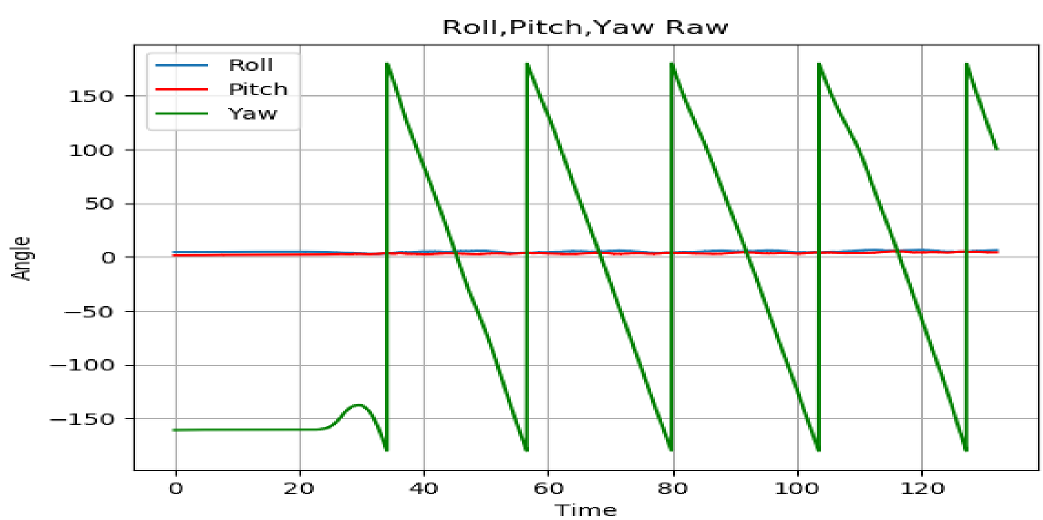
The banking angle is the angle at which the vehicle is inclined around its longitudinal axis with respect to the horizontal, and it can be calculated by taking the tan inverse of the mean of the linear acceleration in the x and z directions. The elevation angle refers to the angle made by the x-axis and the ground, and it can be calculated using the tan inverse of the linear acceleration in the x and z directions.

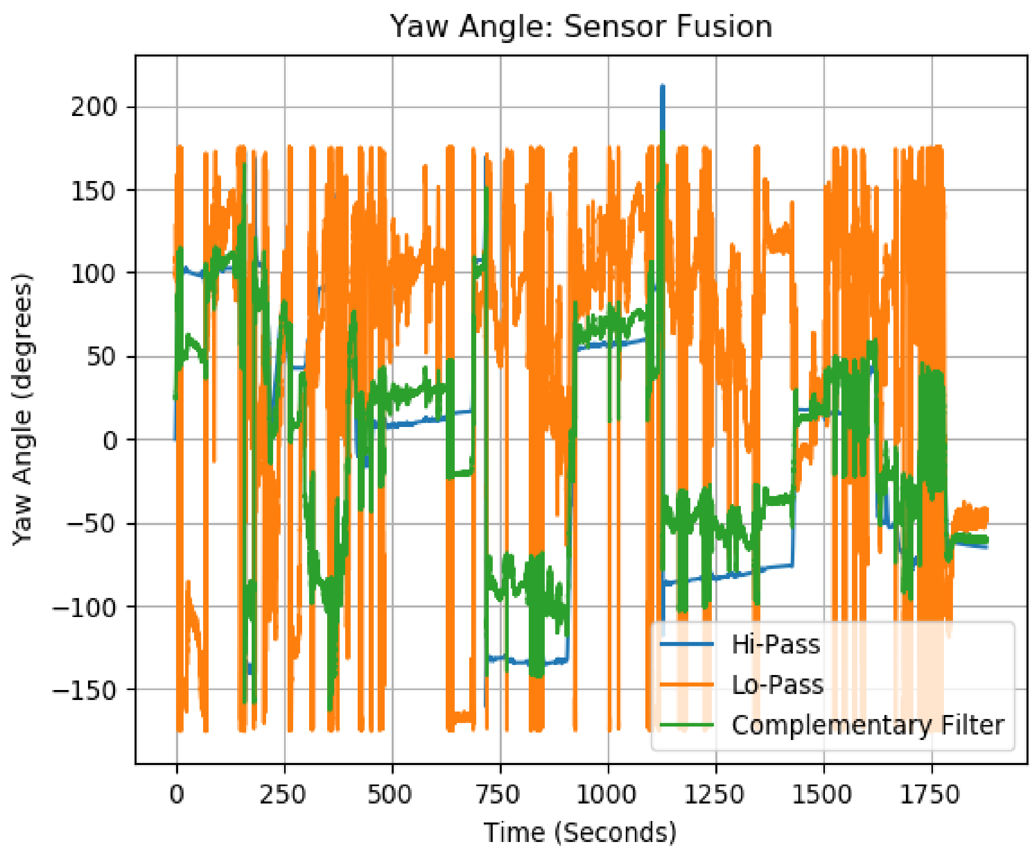
Qs. How did you use a complementary filter to develop a combined estimate of yaw? What components of the filter were present, and what cutoff frequency(ies) did you use? Which estimate or estimates for yaw would you trust for navigation? Why?

In order to obtain a more accurate estimation of a system's orientation, a complementary filter is used to combine the outputs of two sensors: an accelerometer and a gyroscope. The accelerometer is reliable in providing an orientation indicator under static conditions, while the gyroscope is useful in dynamic situations. In our specific case, we used a complementary filter to obtain a more precise measurement of the quadcopter's yaw angle. The filter consists of a high-pass filter applied to the gyroscope readings and a low-pass filter applied to the accelerometer readings. The cutoff frequencies of the filters were selected to balance between noise filtering and responsiveness. Generally, the cutoff frequency of the low-pass filter is set lower than that of the high-pass filter. We utilized a low-pass filter with a 0.75 Hz cutoff frequency and a high-pass filter with a 0.001 Hz cutoff frequency.

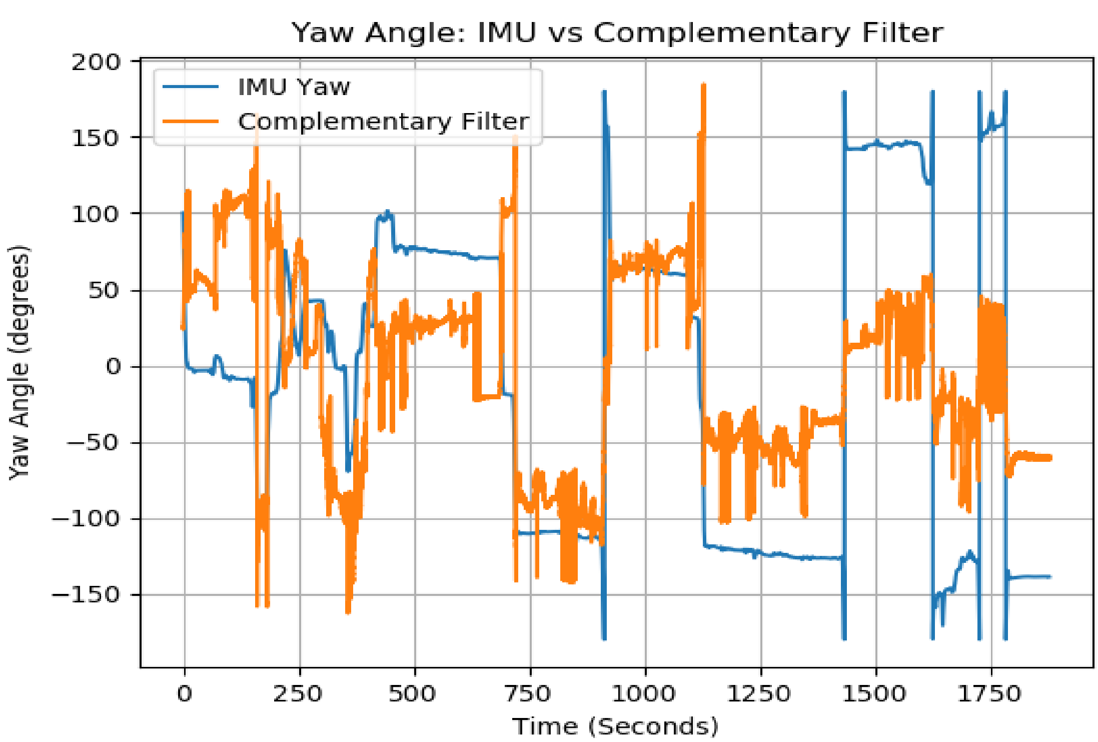


In order to calculate the final yaw angle, the signals from the magnetometer and gyroscope need to go through respective low-pass and high-pass filters. We notice that the high pass filter is applied on the gyroscope data with a cut-off frequency of 0.001 Hz and the low-pass filter is applied on the magnetometer data with a cut-off frequency of 0.75 Hz to eliminate some noise. Furthermore, the high pass filtered data is given a weightage of 80% and the lowpass filtered data is given a 20% weightage in the complimentary filter which smooths some noise as well as corrects some outlying data. Figure 3 illustrates the calibrated magnetometer yaw (represented by the blue line) and the uncorrected data from the imu (represented by the red line).





Yaw Angle: Sensor Fusion
Yaw Angle (degrees)
Time (Seconds)
Hi-Pass
Lo-Pass
Complementary Filter
200
150
100
50
0
−50
−100
−150
0
250
500
750
1000
1250
1500
1750

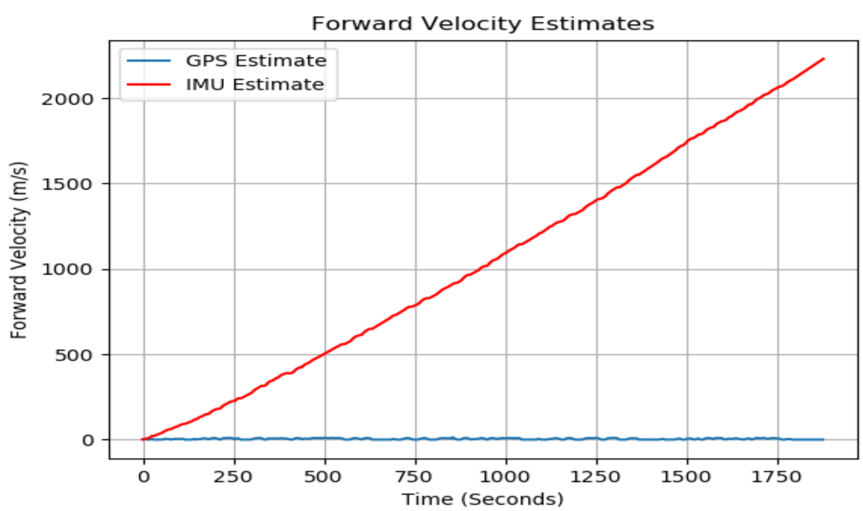


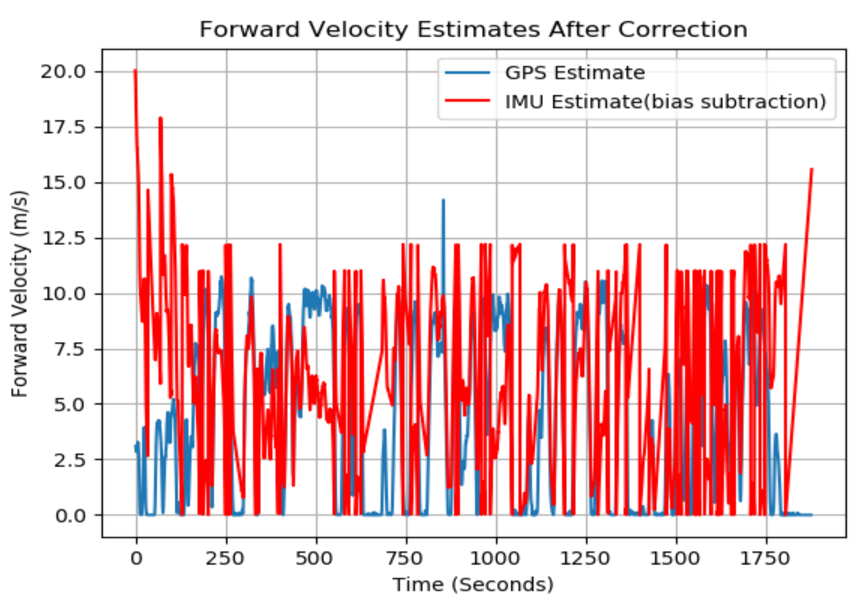
Yaw Angle: IMU vs Complementary Filter
Yaw Angle (degrees)
Time (Seconds)
IMU Yaw
Complementary Filter
200
150
100
50
0
−50
−100
−150
0
250
500
750
1000
1250
1500
1750

When comparing the filtered yaw angle and the raw data from the IMU, it can be seen that the magnetometer is trustworthy and that it is also reasonably aligned with the raw data. We saw calibrated data when driving around in the previous data. Here, we calibrated the identical data while operating a motor vehicle, which yields the intended outcome and is less noise-prone. The angle in the plot above is in radians because the data was initially gathered in radian quaternion and then converted to Euler form in the driver. The filtered yaw is obtained through the complementary filter, to which I added the data of the low pass filter and high pass filter with the fine-tuning, and we get 2 variables in their weights.

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

Calculating the forward velocity estimate requires taking into account any bias in the accelerometer measurement. This is true because the accelerometer captures both the acceleration of the moving vehicle and the acceleration brought on by gravity. The gravitational acceleration must be subtracted from the measured acceleration to get the vehicle's true forward acceleration. After that, the predicted forward speed can be determined by integrating the adjusted acceleration through time.



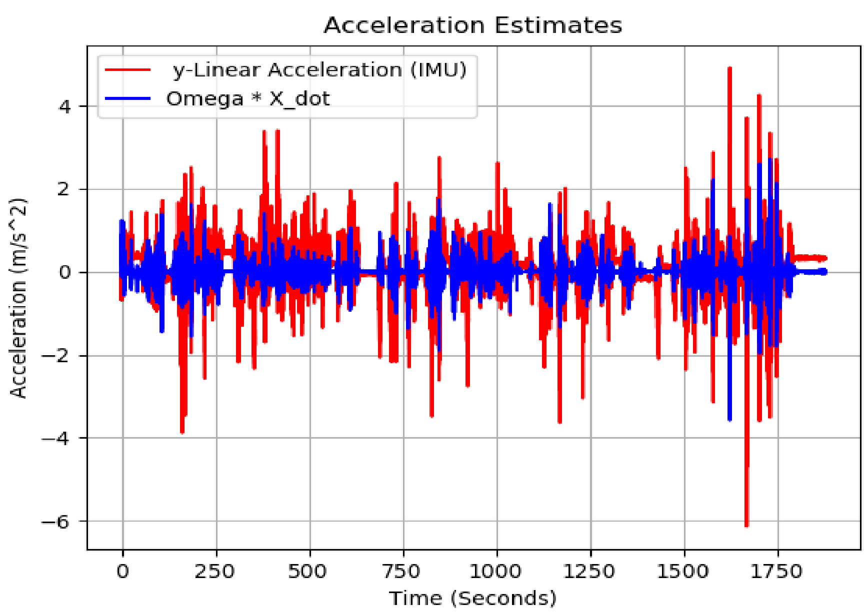


The difference between the true and computed velocities is significantly affected by drift and noise, requiring further adjustments to the accelerometer. The sampling rates of GPS and IMU sensors are dissimilar, with GPS having a rate of 1 and IMU having a rate of 40. This causes a difference in scale for the readings, as shown in Figure 5. To compensate for this, Figure 6 shows the representation after scaling both readings to the same level and compensating for velocity scale. The acceleration data was divided into intervals by placing stops at various locations and times. A new bias was calculated and subtracted from each subsequent acceleration value for every interval. The integrated velocity array was created by adding all the intervals back together after integration.

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

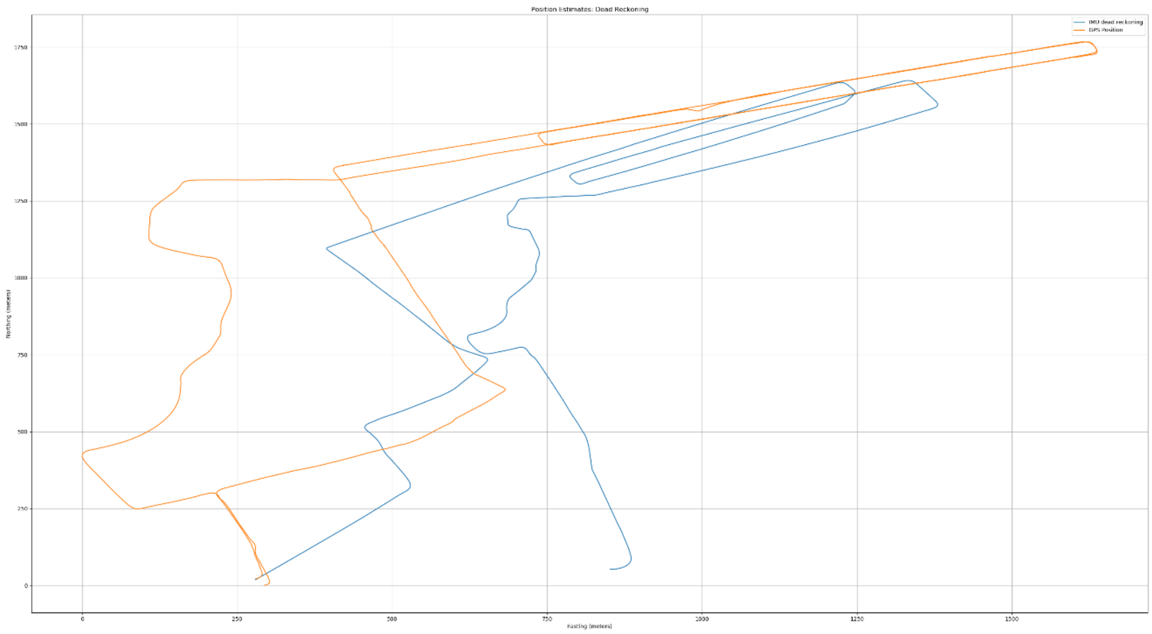
The estimates of velocity derived from GPS and accelerometer data may not always match due to various factors. Accelerometer-based velocity estimates can be inaccurate due to vehicle vibrations, shocks, and noise, which affect their ability to measure the vehicle's acceleration. Furthermore, the velocity estimates obtained from accelerometers can drift over time, leading to discrepancies in their measurements. On the other hand, GPS-based velocity estimates are less susceptible to noise and vibration because they are based on the movement of the GPS receiver. However, they may still have errors due to factors such as atmospheric conditions, satellite geometry, signal interference or loss, which can cause inaccuracies in the GPS-based measurements. Therefore, differences in the velocity estimates obtained from GPS and accelerometer data can arise due to inaccuracies and noise in both sources of data

Qs. Compute ωX and compare it to y. How well do they agree? If there is a difference, what is it due to?



Qs. Given the specifications of the VectorNav, how long would you expect it to be able to navigate without a position fix? For what period did your GPS and IMU estimates of position match closely? (Within 2 m) Did the stated performance for dead reckoning match actual measurements? Why or why not?

The VN-300 device can utilize IMU data for a maximum of 5 minutes without needing a position fix and has a position update rate of up to 400 Hz. However, the precision of the dead reckoning estimate deteriorates over time because of flaws in the IMU data. In the conducted experiment, the GPS and IMU position estimates matched closely initially, but after a minute, they began to deviate. The accuracy of the estimates was highest during this 60-second period. However, the actual performance of the dead reckoning estimate did not match the anticipated level of accuracy despite the IMU-based initial position estimates being in line with the GPS position. As the flight progressed, the location estimates became more inaccurate due to the rapid expansion of errors in the dead reckoning estimate caused by a variety of factors, including imprecise IMU measurements, environmental conditions such as wind and air currents, and incorrect sensor calibration.



In navigation, a reckoning refers to the process of determining the current position of a moving object using a known starting position. Inertial sensors are often used to determine the position and orientation of a device. By combining the values from the gyroscope, the sensor's orientation can be determined. The accelerometer measurements can be double-integrated after subtracting the earth's gravity to reveal the sensor's location. Understanding the sensor's orientation is necessary to calculate the effects of the earth's gravity accurately. Therefore, the assessment of the sensor's position and orientation is closely related to inertial sensors.