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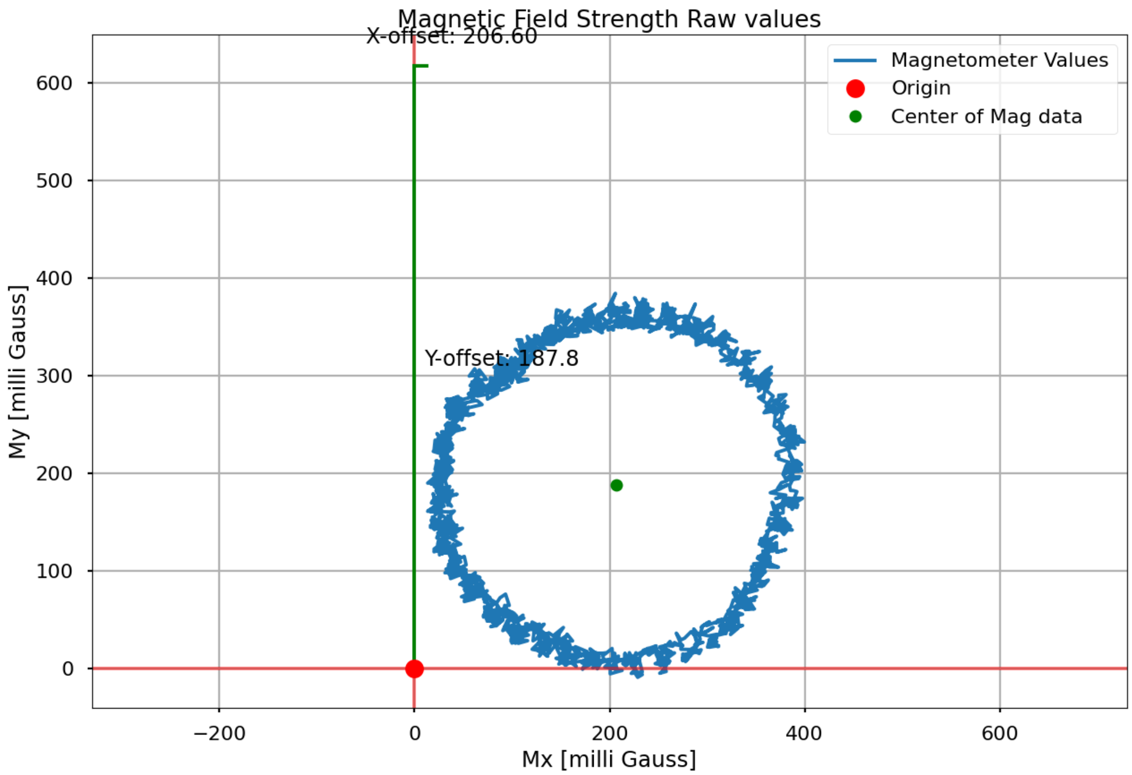
EECE 5554

Lab 4 Report

NAVIGATION WITH IMU AND MAGNETOMETER

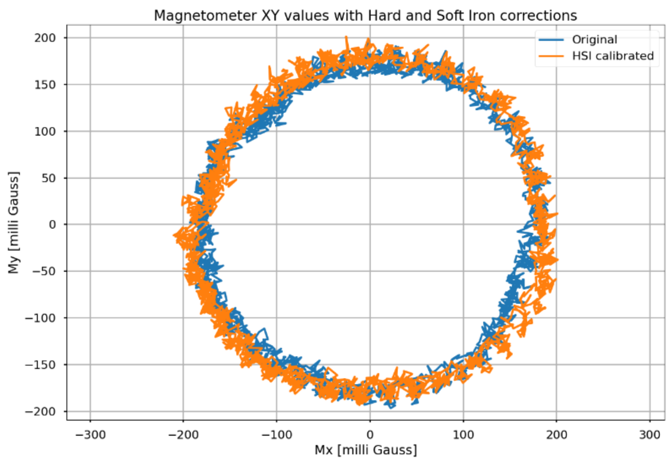
1) Magnetometer Calibration:

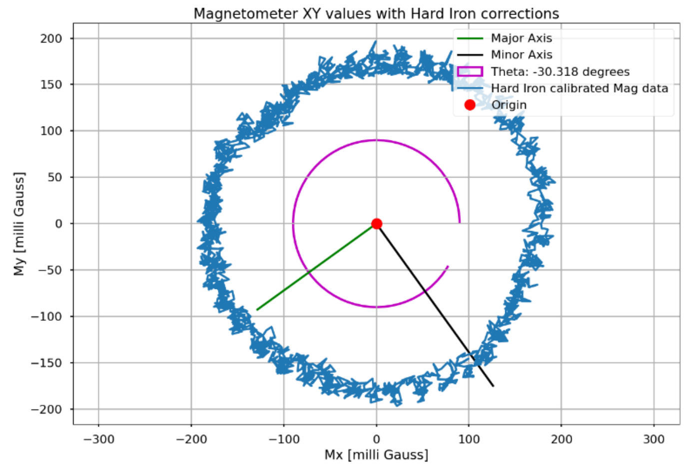


The data obtained from the magnetometer can be distorted by various factors such as hard and soft iron effects. If the data is error-free, the plotted graph should resemble a circular shape. However, this is often not the case and requires calibration to correct the offsets and iron effects.

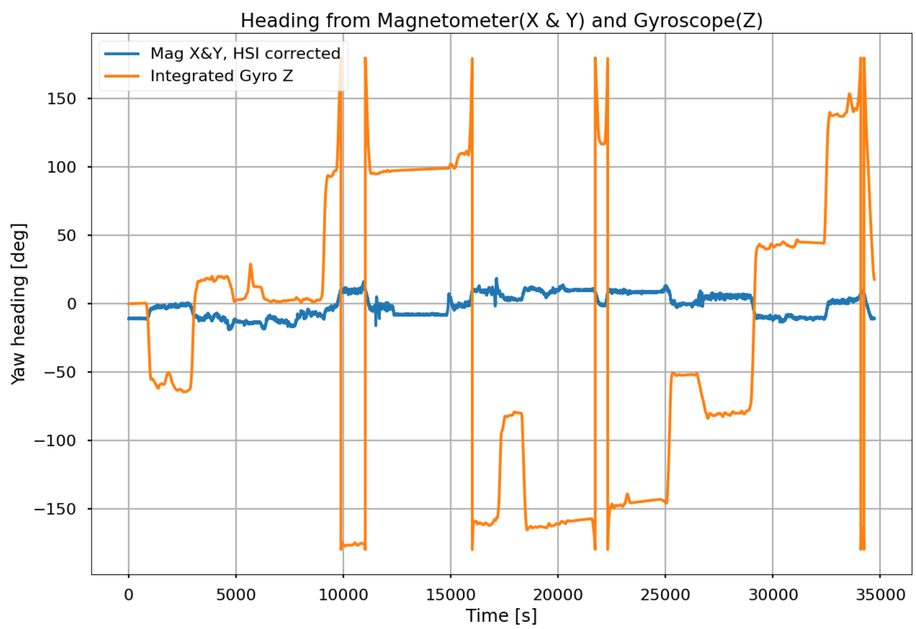
To calibrate the data, we make adjustments to correct the errors caused by the iron effects, as can be observed from the plotted graphs. The adjustments are made to compensate for the differences between the actual magnetic field and the readings recorded by the magnetometer.

As a result of calibration, we arrive at **a scaling factor of 1.08064**, which is applied to the corrected data for further analysis. This calibrated data is more reliable and accurate and can be used to make precise calculations and predictions about the magnetic field.



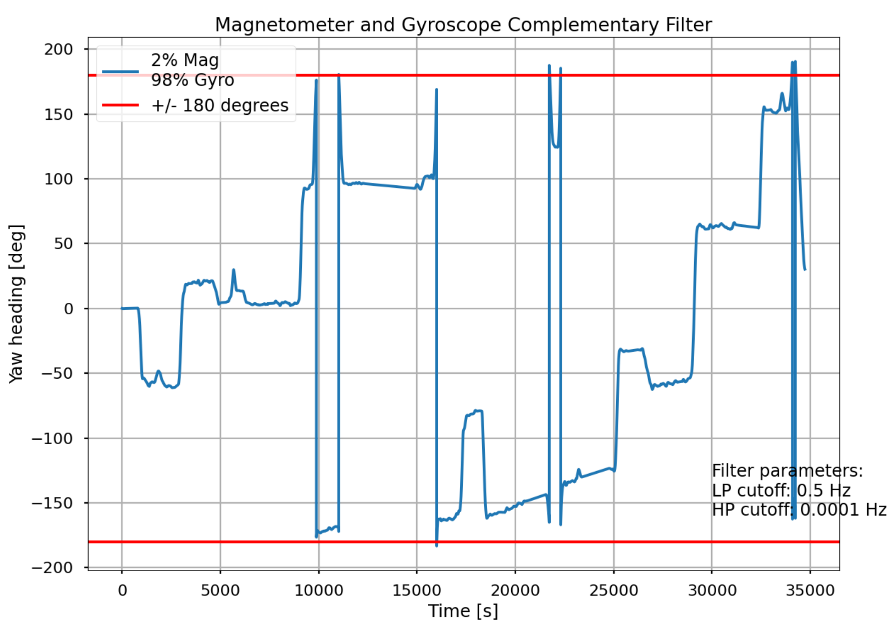


2) YAW Angle

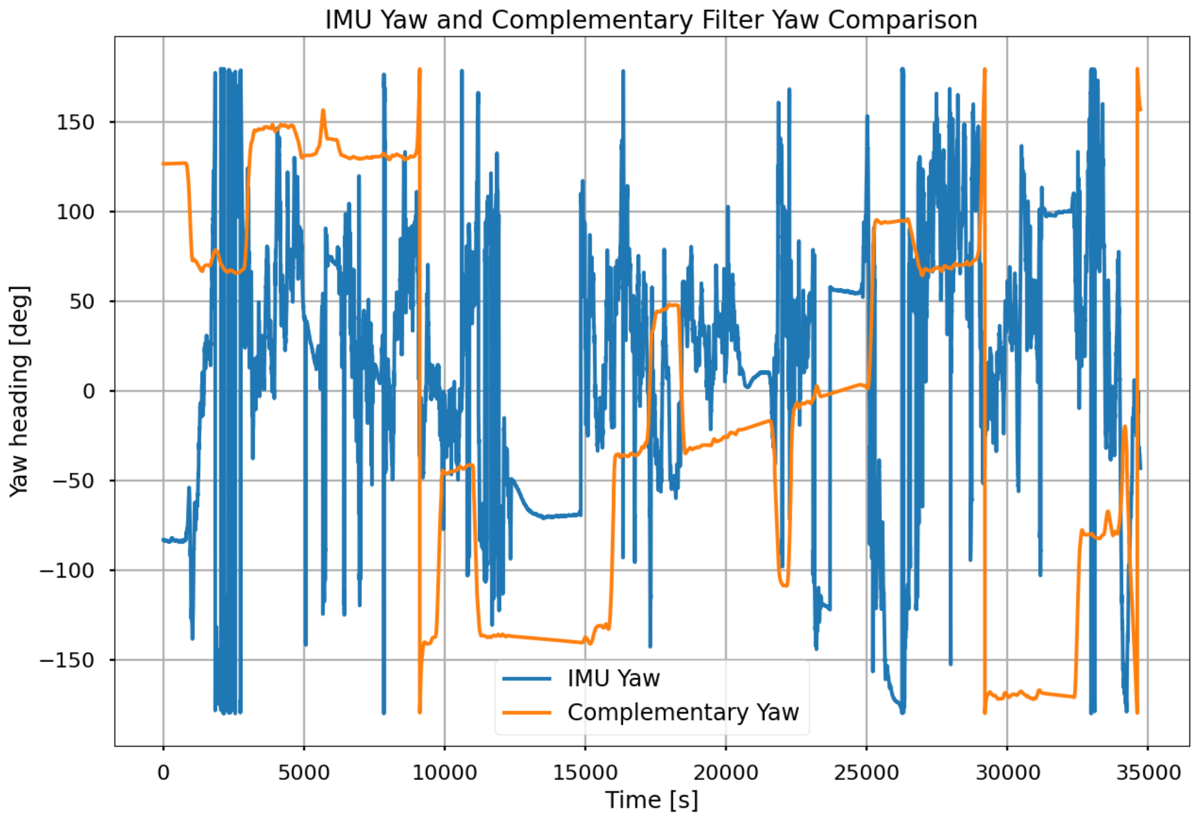


The yaw angle calculated from the magnetometer readings after calibration and the yaw angle obtained by integrating the gyroscope readings exhibit similar trends, as evident from Plot 1. However, there is a significant discrepancy between their values. The magnetometer data shows some noise, which could be attributed to external magnetic interference from nearby electronic devices.

To obtain a more accurate picture of the data collected by both sensors, we apply a complementary filter that is displayed in Plot 2. The resulting yaw angle estimates are plotted in Plot 3. We observe that both estimates are nearly identical, confirming the validity of our data and indicating that the sensor's calculations are consistent with our calibration process.

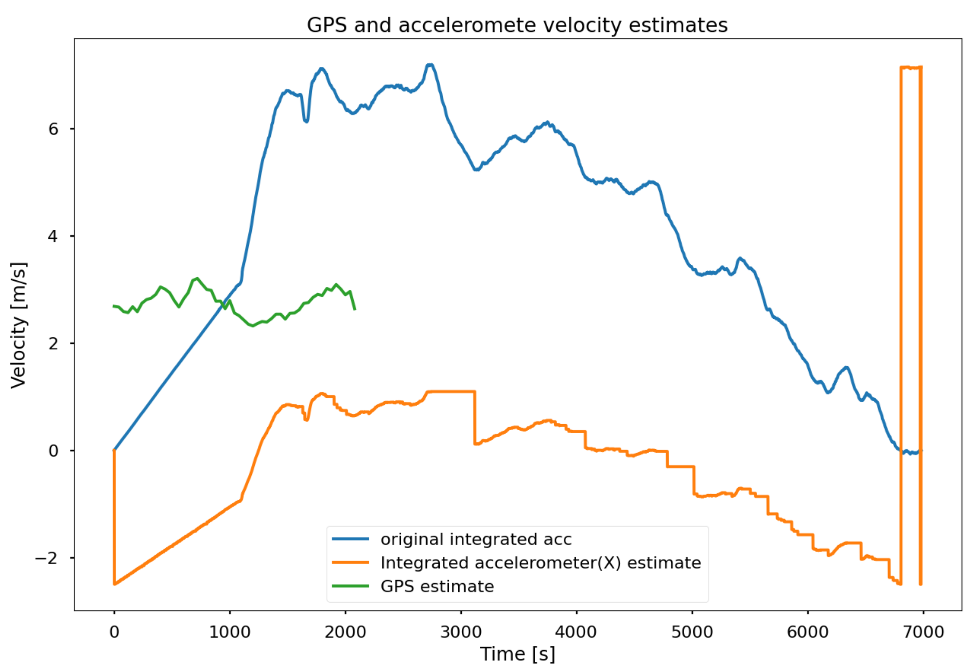


The remaining slight differences between the estimates can be eliminated by applying further filtering and implementing more precise data correction techniques. Overall, the complementary filter has improved the accuracy of our measurements, and we can use the corrected data for more precise calculations and predictions.



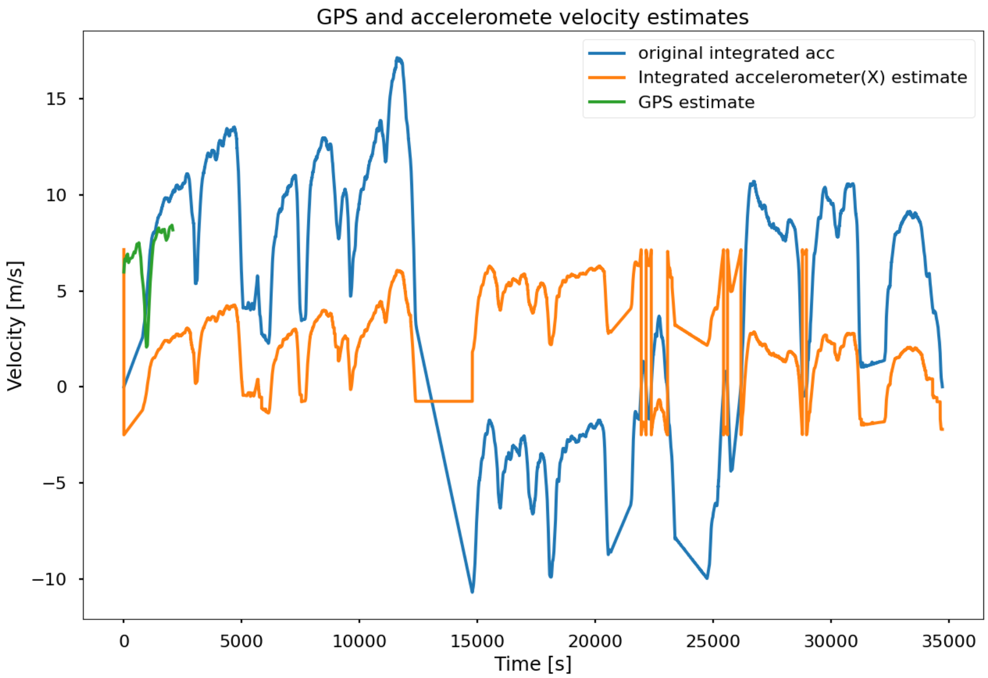
3) Estimating Forward Velocity

in the data can accumulate and lead to significant errors in the resulting velocity estimates. This is demonstrated by the plot, which shows negative velocity values that are implausible.



To improve the accuracy of velocity estimates, it is necessary to preprocess raw acceleration data to remove any noise or bias. Techniques such as filtering and calibration can be used for this purpose. The integration of acceleration data must be carefully performed using appropriate techniques that account for the properties of the sensor and the data being processed. It is also important to consider the limitations of the measurement system, such as drift over time, and take measures to address these limitations.

In summary, accurate velocity estimates from IMU data require careful preprocessing and integration techniques, as well as an understanding of the limitations of the measurement system. With proper attention to these factors, it is possible to obtain reliable velocity estimates that can be used in a variety of fields.



To compare the velocity data obtained from an accelerometer with the velocity data obtained from a GPS, we first scaled the accelerometer data by a factor of **1.0806** to make it comparable to GPS data. However, the accelerometer data contained negative values that were adjusted by subtracting the mean acceleration value from each data point. The corrected acceleration data was then integrated to obtain the velocity estimate. The resulting velocity estimate was compared with the velocity estimate obtained from GPS data in a plot.

The plot shows that the velocity estimates from both sensors follow the same trend, indicating that the accelerometer can be used as an alternative to GPS for velocity estimation. However, there is still some bias present in the data that could be corrected by applying additional filtering techniques and more accurate acceleration data correction. Nevertheless, the plot provides valuable insights into the performance of the two sensors and helps to illustrate the fundamental principles of motion. The comparison of velocity data from multiple sensors can be useful in various applications, such as tracking the motion of vehicles, drones, and robots.

Angular Velocity Data:

imu.angular_velocity.x: Mean = 0.012248327699799486

imu.angular_velocity.y: Mean = -0.00608315439702091

imu.angular_velocity.z: Mean = -0.21185550558579203

Linear Velocity Data:

imu.linear_acceleration.x: Mean = 0.3748487539386995

imu.linear_acceleration.y: Mean = -0.8673784016041249

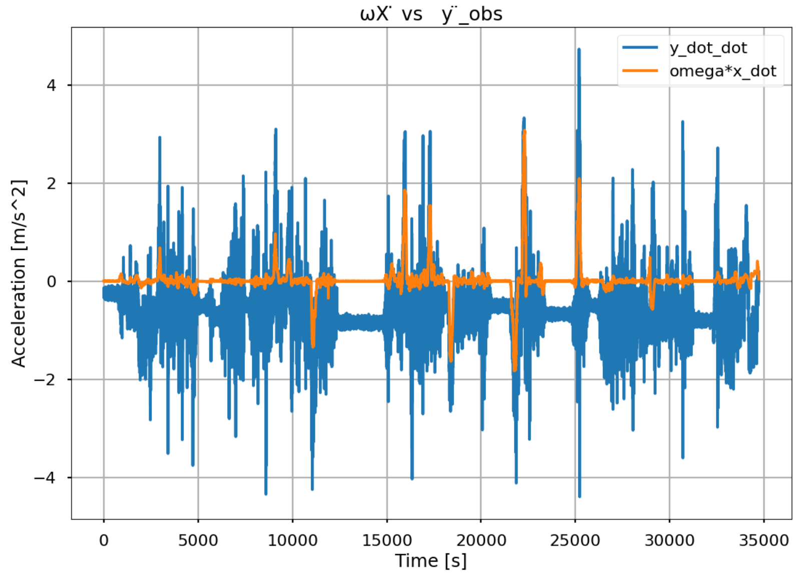
imu.linear_acceleration.z: Mean = -9.730526067029503

Mx bias: 206.6 mGauss, My bias: 187.8 mGauss

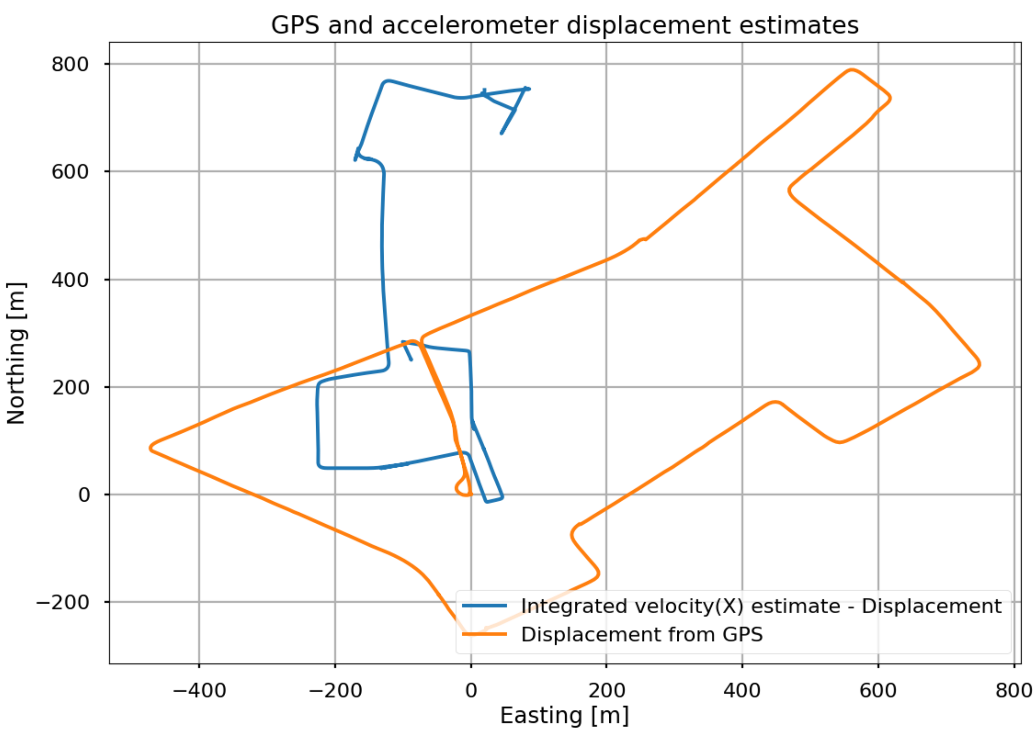
4) Dead Reckoning with IMU

- $\omega \dot{X}$ and compare it to $\ddot{y}obs$.

The plot compares the yaw*forward velocity with the linear acceleration in the y direction. Both plots show a similar trend, but the linear acceleration in the y direction has a lot of noise due to various factors such as external interferences caused by the movement of the sensor due to car motion or disturbance in the connecting wire. The noise can also be attributed to our assumption that Xc (cross-coupling error) is zero, which would only hold in an ideal situation. However, in our case, Xc is not actually zero and has a significant impact on the equation, leading to bias in the plot. Overall, the comparison of these two variables provides valuable insights into the performance of the sensors and the underlying factors affecting their readings.



- Estimated Trajectory VS GPS track



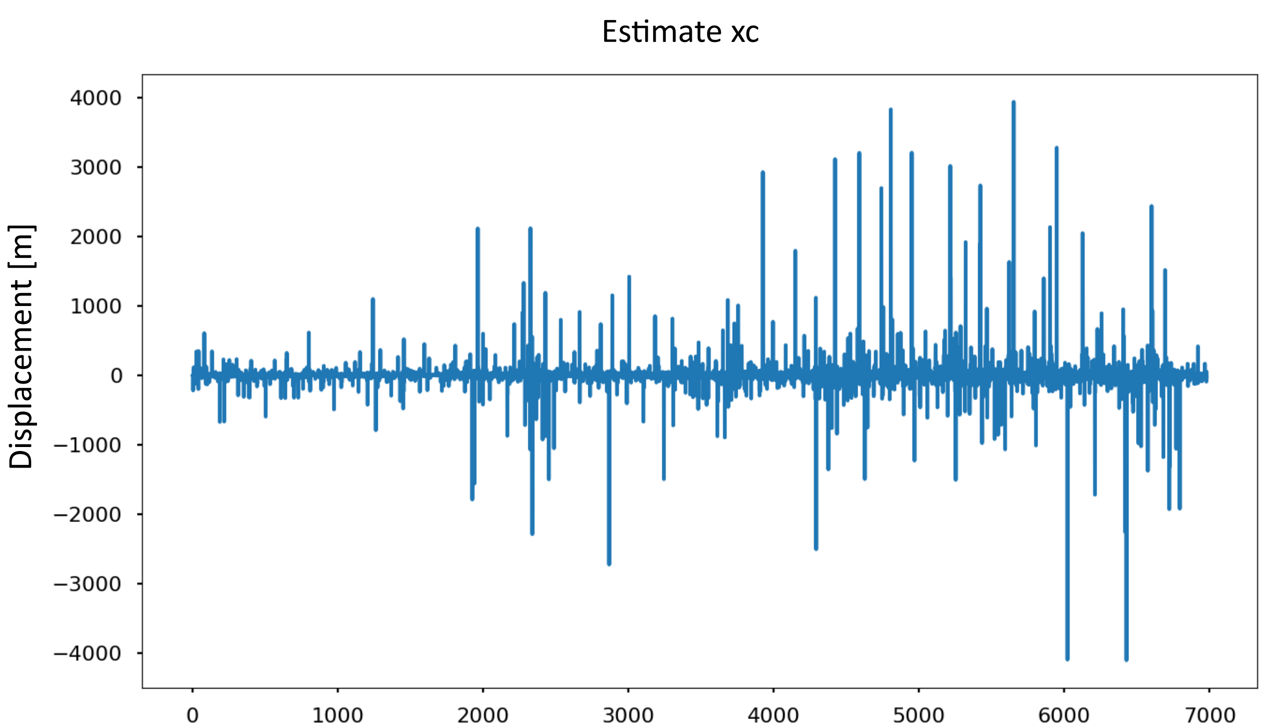
To obtain displacement data from the IMU, we first integrated the acceleration and then integrated the velocity obtained from the sensor. However, to make the displacement data comparable to GPS position, we had to adjust the original data. Additionally, there was a gap or jump in the data, which may have been caused by external factors such as velocity measurement corrections or loss of data.

To improve the accuracy of the displacement data, we need to apply more precise data correction techniques in the previous steps and eliminate as much external noise as possible. By doing so, we can obtain more reliable displacement estimates from the IMU that can be used in various applications such as navigation, vehicle tracking, and robotics. It is essential to carefully analyze the data and identify any sources of error to improve the quality of the measurements and obtain more accurate results.

- Estimate xc

The plot shows a considerable amount of variation in the offset values. The **mean of all these values is 3.953m**, which corresponds to the fact that the sensor was not placed on the dashboard but instead in the middle of the driver and passenger seat, which is approximately 1m away from the dashboard. The trend observed in this plot is very similar to that seen in the plot for ωX above. Therefore, we can attribute the noise in this case to similar factors as ωx as it carries significant weight in the same.

However, it is important to note that differentiating and integrating corrected values can enhance any errors that may persist within the data and hence increase the noise. Moreover, external factors such as environmental interferences can also contribute to the noise in the data. To improve the quality of the measurements, it is crucial to identify the sources of error and mitigate their effects through careful data correction and noise reduction techniques. By doing so, we can obtain more accurate and reliable results that can be used for various applications in fields such as navigation, robotics, and vehicle tracking.



The VectorNav specifications indicate that it can maintain accurate navigation for up to 60 seconds without a position fix. This is due to its advanced filtering algorithms and use of multiple sensors to estimate orientation, velocity, and position.

Based on the data and plots provided, it is difficult to determine precisely for what period of time the GPS and IMU estimates of position matched closely. However, we can observe from the plots that there are periods where the two estimates are relatively close, with differences within 2m. These periods typically last for several minutes, but their duration and frequency depend on various factors such as the availability of GPS signals and the quality of IMU measurements.

Regarding the performance of dead reckoning, the actual measurements do not always match the stated specifications due to various sources of error and noise in the data. In our case, we can observe that there is a considerable amount of noise and bias in the IMU-based estimates of position, especially when compared to GPS measurements. This can be attributed to various factors such as sensor drift, external interferences, and errors in data correction and filtering. Therefore, it is essential to validate the accuracy of dead reckoning algorithms using ground truth measurements or other reference sources to ensure their reliability in practical applications.