LAB - 4

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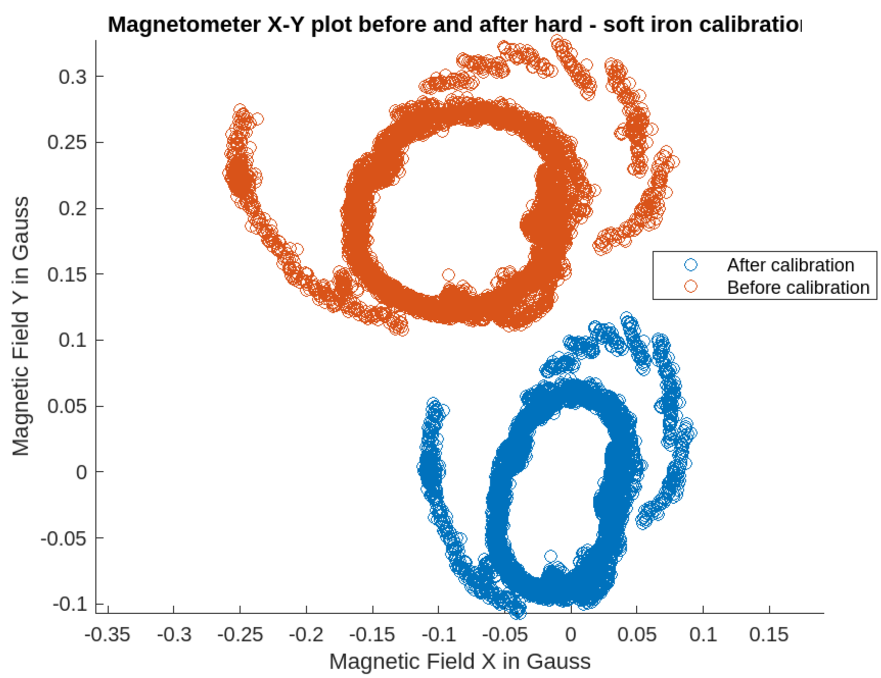
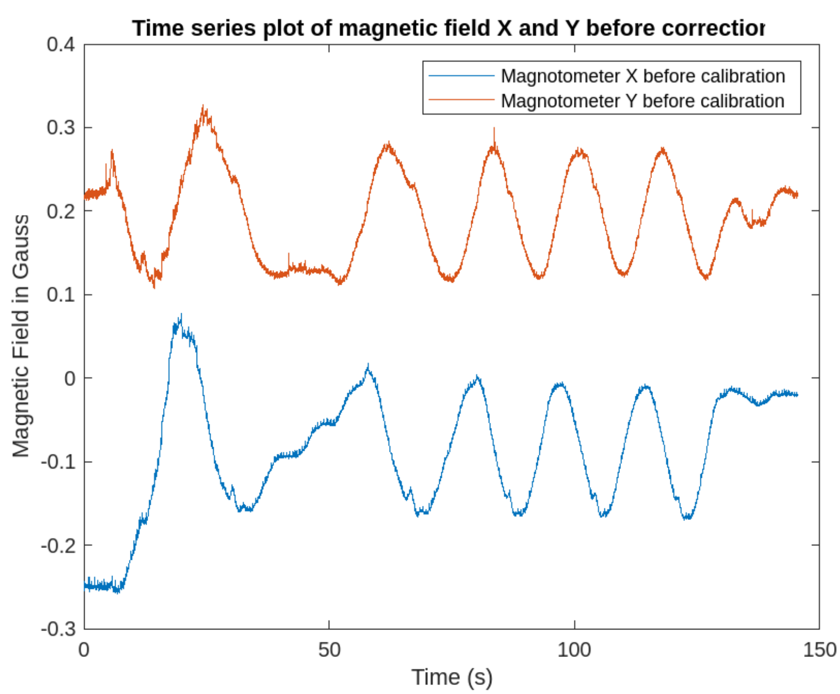
Analysis Plots:

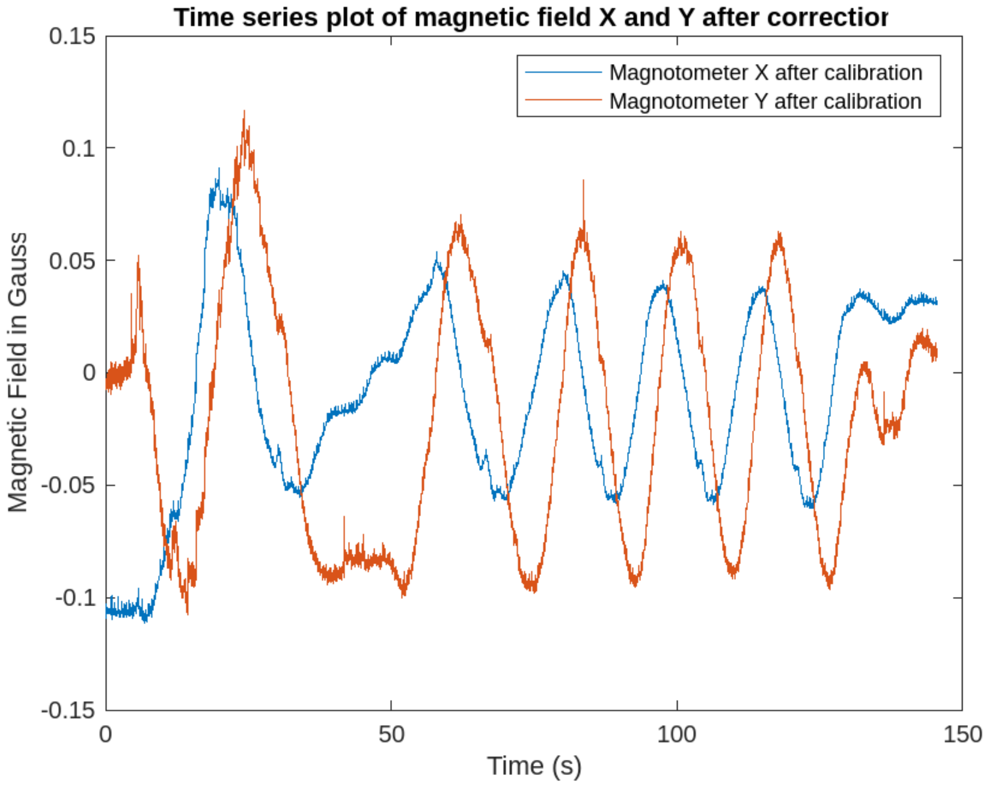
1. Estimating the Yaw:
    a. *Fig 1 - Magnetometer before and after calibration:*



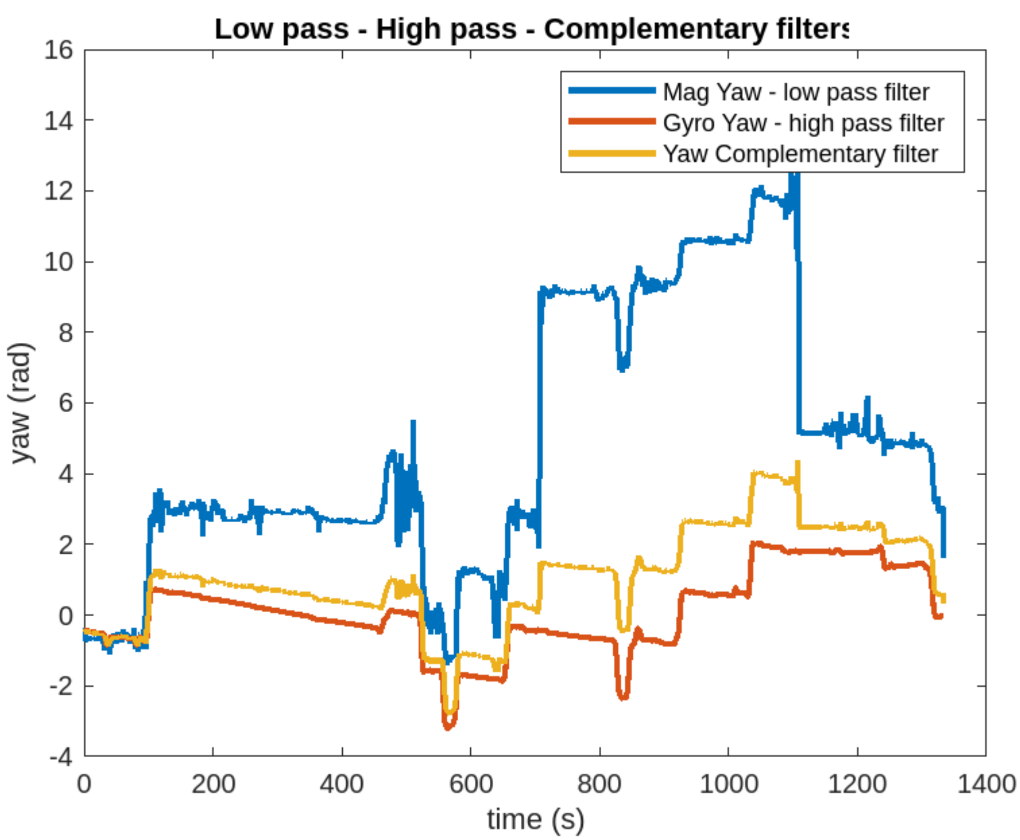
    b. *Fig 2 - Time series of Magnetometer data before correction:*



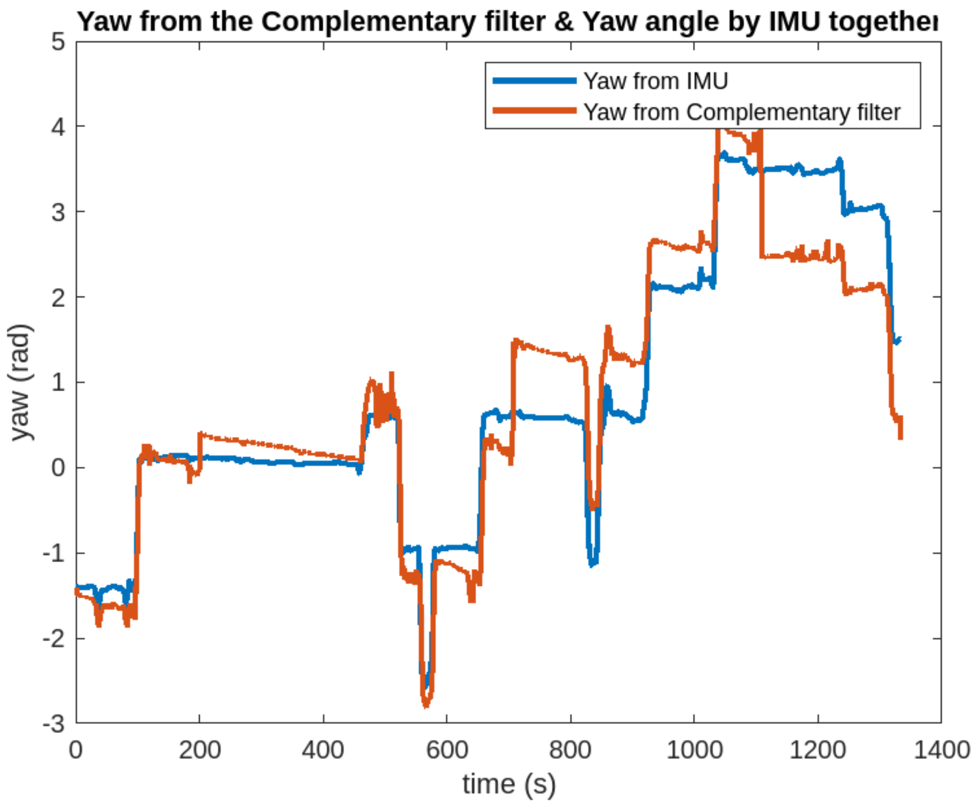
c. Fig 3 - Time series of magnetometer data after correction:



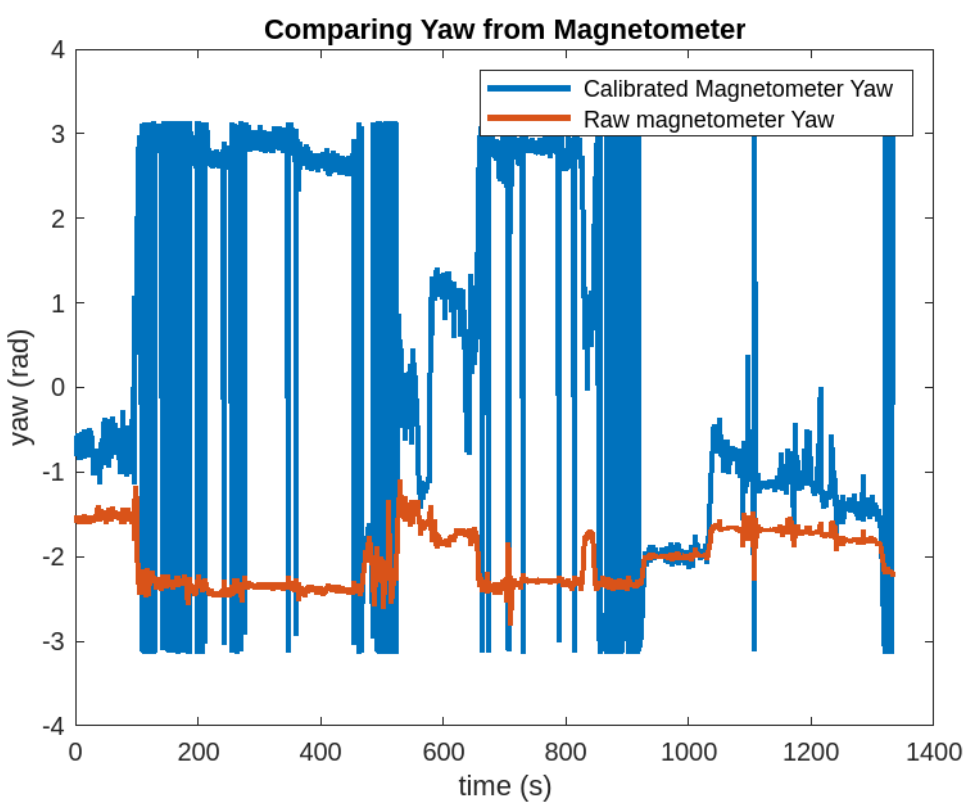
d. Fig 4 - Low pass filter, high pass filter and complementary filter together:



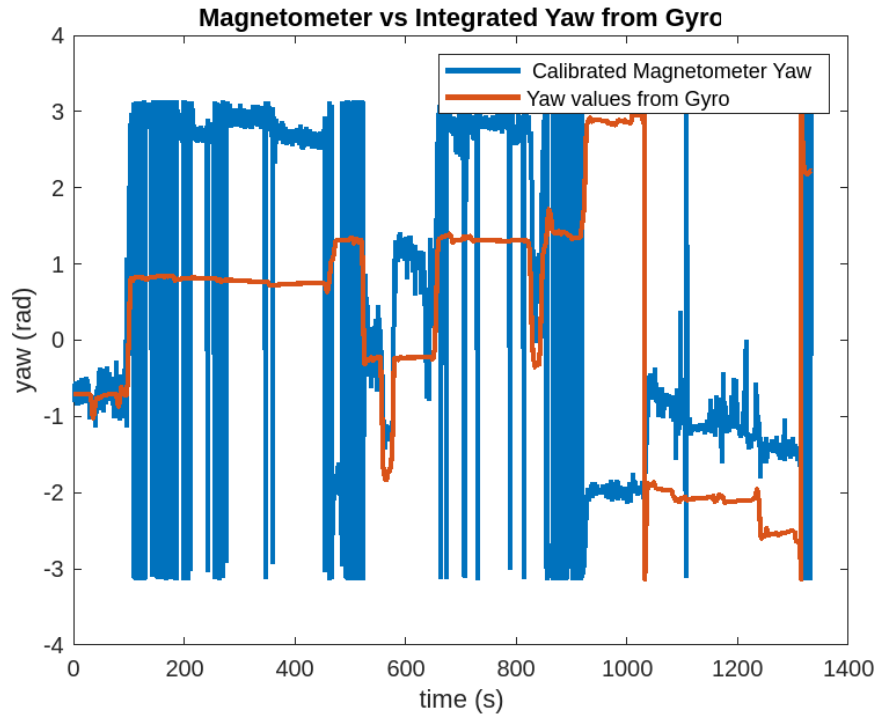
e. *Fig 5 - Yaw from complementary filter vs Yaw angle by IMU together:*



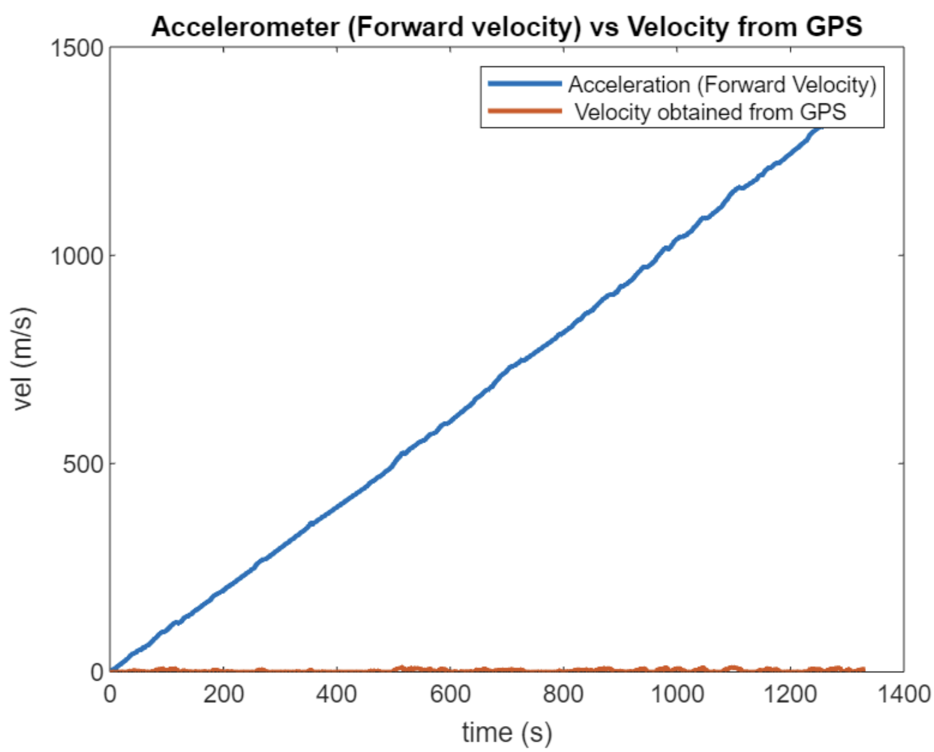
f. *Fig 6 - Raw Yaw vs Corrected Yaw from the magnetometer:*



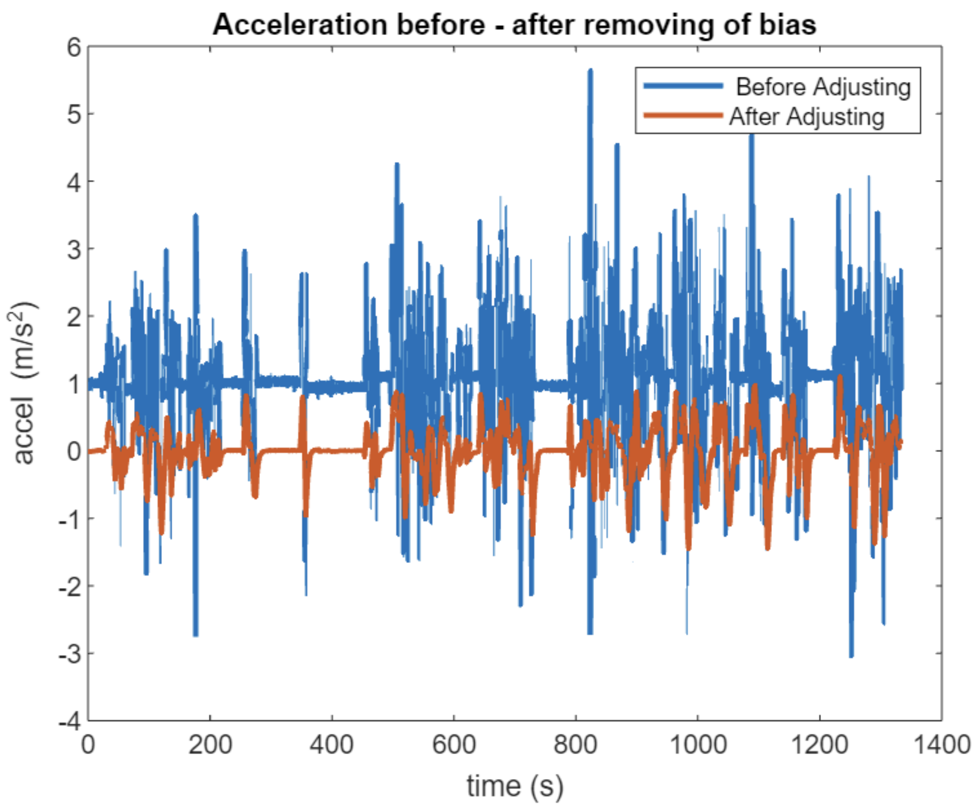
g. *Fig 7 - Magnetometer vs Integrated Yaw from Gyro:*



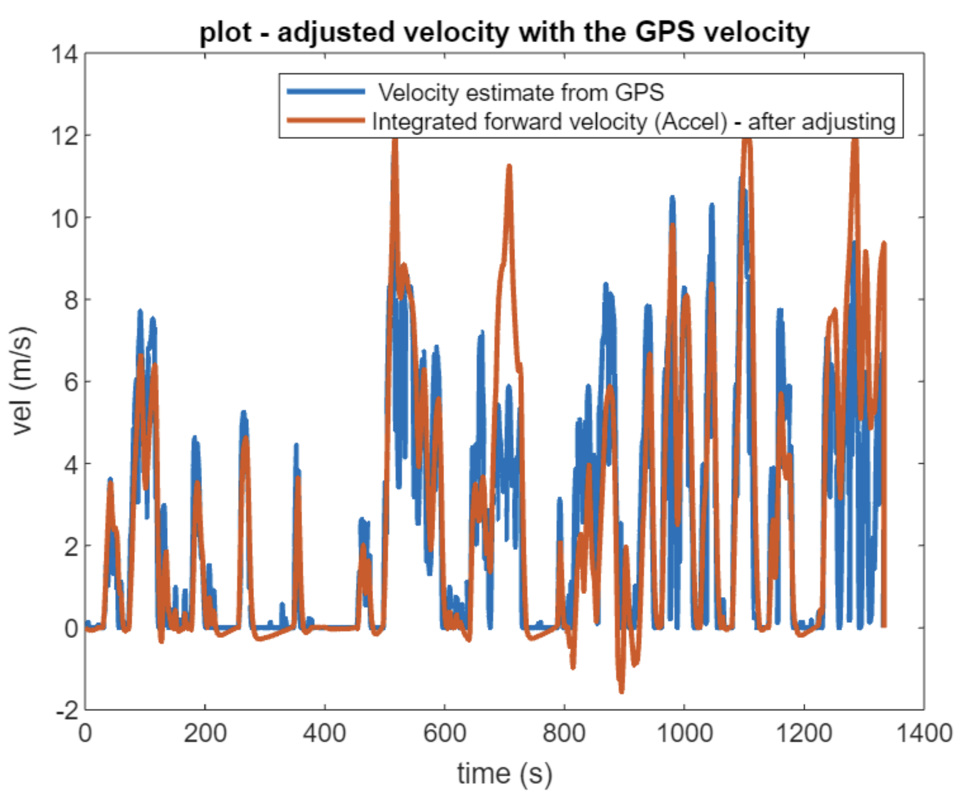
2. Estimate the forward velocity:
   a. *Fig 8 - Integrated forward velocity vs Velocity from GPS*



b. Fig 9 - Corrected vs Uncorrected Acceleration

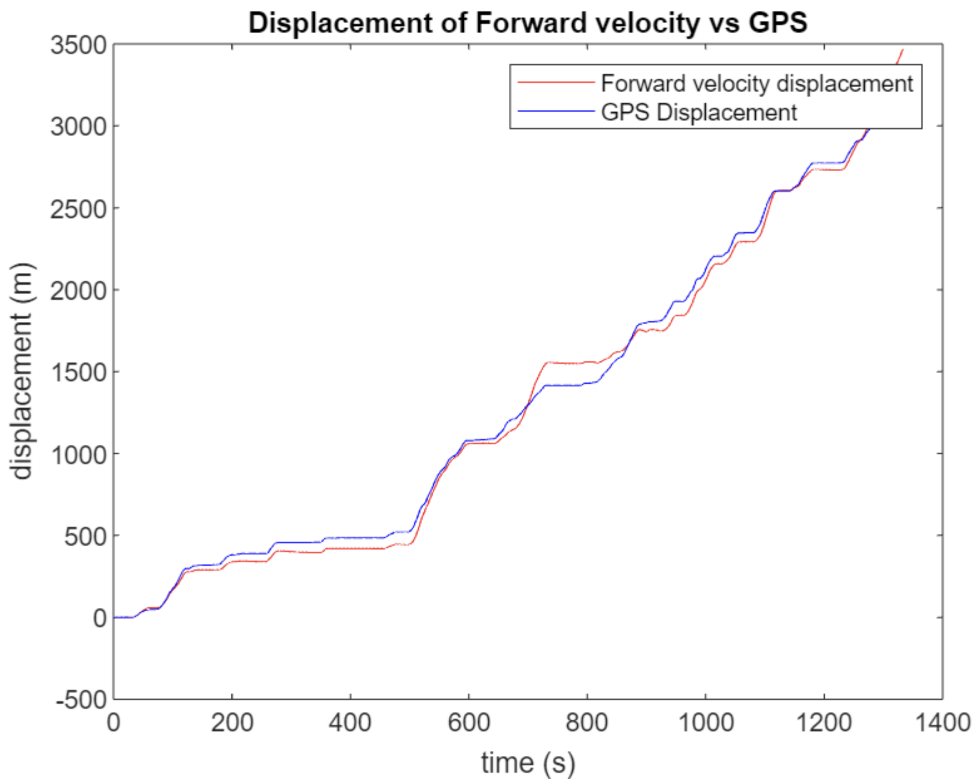


c. Fig 10 - Integrated linear velocity vs Velocity estimates from the GPU

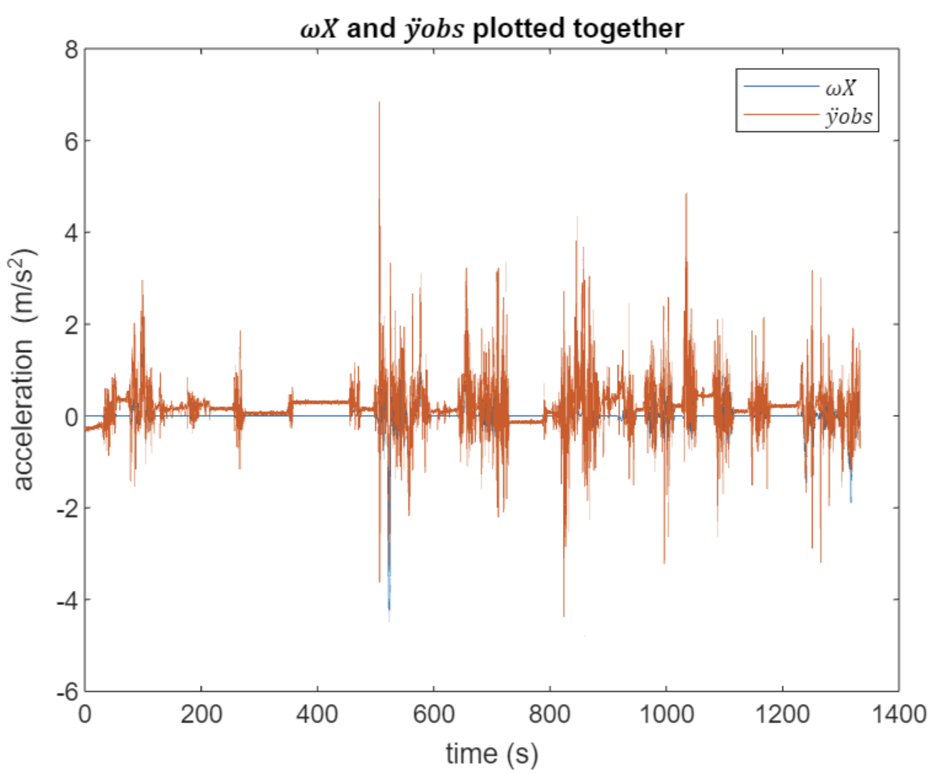


3. Dead Reckoning with IMU:

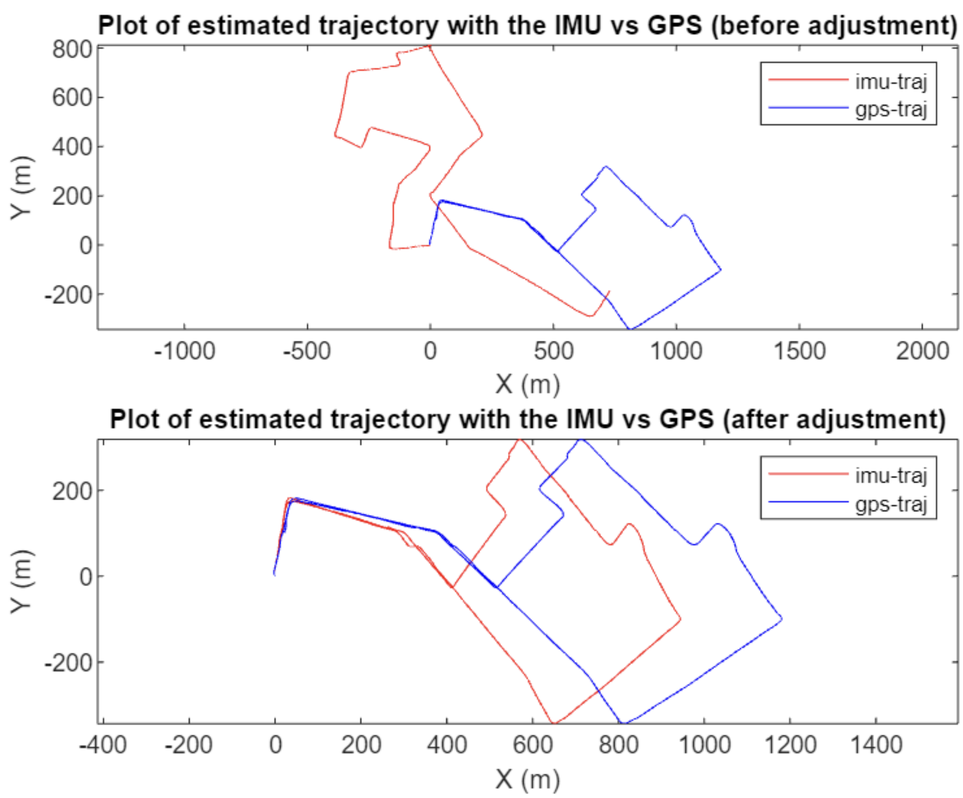
a) *Fig 11 - Total traveled distance calculated from GPS and forward velocity*



b) *Fig 12 - ωX˙ and y¨obs plots*



c) *Fig 13 - Trajectories of IMU and GPS before and after corrections*



Questions:

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

Magnetometers can suffer from two types of distortion: hard iron and soft iron. Hard iron distortion is caused by nearby ferromagnetic materials or equipment, which add a constant interference to the earth's magnetic field. This interference shifts the sensor readings by a particular offset from the origin of our reference frame. To correct for hard iron distortion, we fit an ellipse to the magnetic field data plotted between its values in the X and Y axes, and subtract the center of the fit ellipse from all the values.

Soft iron distortion, on the other hand, is caused by materials that influence a magnetic field. This distortion shows up as the perturbation of the ideal circle into an ellipse. To correct for soft iron distortion, we fit an ellipse onto the magnetic field data plotted between its values in the X and Y axes, and rotate the major axis of the ellipse so that it aligns with the reference frame X. We then use a scaling factor to create the desired circle, and rotate the data back to its original position to account for soft iron distortion. The rotation matrix is calculated from the angle formed by the major axis with the reference frame X, and the scale factor is the ratio of the minor axis length to the major axis length. Finally, we perform one last rotation using the negative of the angle used for the first rotation matrix.

By correcting for both hard and soft iron distortion, we can calibrate the magnetometer data and obtain accurate readings. This is important in many applications, such as navigation, where accurate magnetic heading information is crucial.

2) 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?

To estimate the yaw of a device, we used a complementary filter that combined data from both the magnetometer and gyroscope. In static conditions, the magnetometer provided accurate orientation data, while in dynamic conditions, the gyroscope provided better tilt data.

We used a low pass filter for the magnetometer to remove high frequency noise caused by vibrations, and a high pass filter for the gyroscope to remove low frequency drift. The cutoff frequency for the magnetometer was set to 0.0002 Hz, and for the gyroscope, it was set to 0.0002 Hz. The sampling frequency was set to 40 Hz.

The complementary filter combined the filtered magnetometer and gyroscope readings to obtain a more accurate estimate of the yaw. We used a weightage (alpha) of 0.2 for the complementary filter, which allowed for a smooth and gradual transition between the magnetometer and gyroscope data. The filter gave more weight to the magnetometer data in static conditions, and more weight to the gyroscope data in dynamic conditions.

Overall, the use of a complementary filter allowed us to obtain a more accurate estimate of the yaw by combining the strengths of both the magnetometer and gyroscope. The filtering of the data helped to remove noise and drift, and the weightage used in the filter helped to smooth out the transition between the two data sources.

3) Which estimate or estimates for yaw would you trust for navigation? Why?

For navigation purposes, we need a reliable estimate of yaw that takes into account both static and dynamic conditions. The magnetometer provides accurate orientation data in static conditions, while the gyroscope provides better tilt data in dynamic conditions. We used a complementary filter to combine these two sources of data, which involved applying a low pass filter to the magnetometer and a high pass filter to the gyroscope data to remove noise and drift.

The resulting estimate of the orientation was more accurate and reliable for navigation due to the complementary filter's ability to take advantage of the strengths of both the magnetometer and gyroscope readings. This approach allowed us to obtain an estimate of yaw that we could trust for navigation purposes.

4) What adjustments did you make to the forward velocity estimate, and why?

During the data collection process, we encountered zero velocity regions in the GPS velocity plots due to traffic stops. These regions resulted in constant easting and northing values, but noisy acceleration readings. This noise caused uncontrollable velocity increase as the acceleration was being integrated. To address this issue, we implemented dynamic bias correction by calculating the time intervals where the bias correction was needed.

To reduce the impact of vibrations, we first applied a moving average filter to the accelerometer readings. Next, we identified the intervals where the GPS velocity showed zero velocity. Within these intervals, we computed the bias by taking the mean of the corresponding acceleration values. We then subtracted the bias from all acceleration values within the interval. With the corrected acceleration values, we computed the forward velocity.

By dynamically calculating the bias and correcting for noisy acceleration values, we were able to obtain a more accurate and reliable estimate of the forward velocity. This approach helped to improve the overall performance of the navigation system, especially in situations where the vehicle came to a stop or experienced vibrations.

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

The velocity estimate derived from the GPS data shows sudden spikes in acceleration and deceleration, which are not observed in the velocity estimate derived from the accelerometer. This discrepancy can be attributed to the fact that the GPS data was recorded at a much lower frequency (1Hz) than the IMU data (40Hz), resulting in abrupt changes in the northing and easting coordinates that may be falsely interpreted as rapid acceleration or deceleration.

Additionally, the accelerometer data was corrected for bias and smoothed using a moving average filter to mitigate the impact of vibrations, while the GPS data was not subject to any post-processing.

6) Compute $\omega\dot{X}$ and compare it to $\ddot{y}$obs. How well do they agree? If there is a difference, what is it due to?

We noticed a consistent offset between the observed angular acceleration $\ddot{y}$obs and the product of the estimated angular velocity and the rate of change of the roll angle $\omega\dot{X}$. However, the observed angular acceleration $\ddot{y}$obs is highly noisy, making it difficult to obtain an accurate estimate. To address this issue, we applied a low pass filter to $\ddot{y}$obs to remove any high frequency components caused by error accumulation. This filtering technique was previously used to remove high frequency components from the acceleration data along the X axis, which also suffered from error accumulation. By filtering the noisy signal, we obtained a smoother and more reliable estimate of the observed angular acceleration, which allowed us to make more accurate predictions of the system's behavior. Plotted the graph at the figure 12.

7) Estimate the trajectory of the vehicle (xe,xn) from inertial data and compare with GPS. (adjust heading so that the first straight line from both are oriented in the same direction). Report any scaling factor used for comparing the tracks

The trajectory estimation from GPS, as well as the corrected IMU trajectory before and after correction, are illustrated in Figure 13.

It is observed that the IMU trajectory had the same as that of the GPU for the first few mins, but after a certain time, the trajectory estimated from the IMU tends to vary considerably. This occurs because of errors in compensating the gravity component in the heading direction. This, in turn, causes a rise in the estimation errors for velocity. These errors are further compounded during integration and multiplication with yaw calculated from the complementary filter, which leads to a significant increase in errors. As a result, the trajectory traced by the IMU becomes increasingly unreliable over longer periods of time.

8) Given the specifications of the VectorNav, how long would you expect that it is able to navigate without a position fix? For what period of time 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 VectorNav specifications state that it can navigate without a position fix for up to 30 seconds. Based on this, we can expect that the VectorNav can provide reliable estimates of orientation and velocity for up to 30 seconds without a GPS fix.

For the first 4 mins, my IMU and GPS data were correlated. But as the time passes, the error too has increased between them. This is because the dead reckoning method relies on the initial position estimate and integrating accelerometer and gyroscope readings over time to estimate the position and velocity. As time passes, errors in the initial position estimate and in the integration accumulate, leading to distortion in the position estimates. Additionally, external factors such as variations in the environment, magnetic interference, and sensor noise can further contribute to errors in the estimates, making it difficult for the dead reckoning method to provide accurate estimates over longer periods of time. By this, I can say that the actual measurements did not match the stated performance for dead reckoning.