# Lab 4

Shankara Narayanan Vaidyanathan

# 1 Estimate the heading (yaw)

## 1.1 Magnetometer Calibration

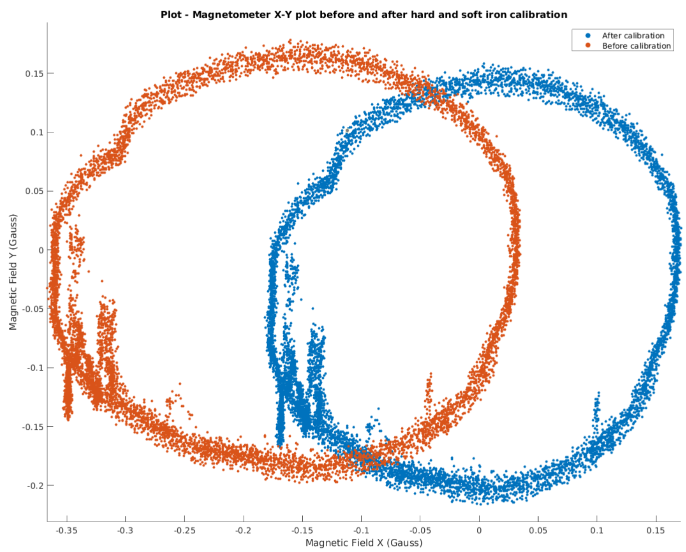


Figure 1: The magnetometer X-Y plot before and after hard and soft iron calibration

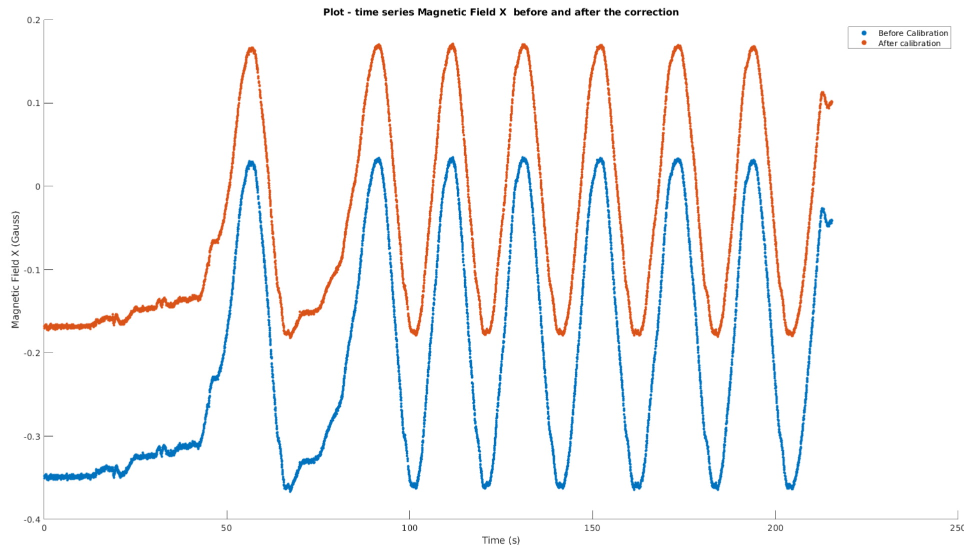


Figure 2: The time series magnetometer data (along X axis) before and after the correction

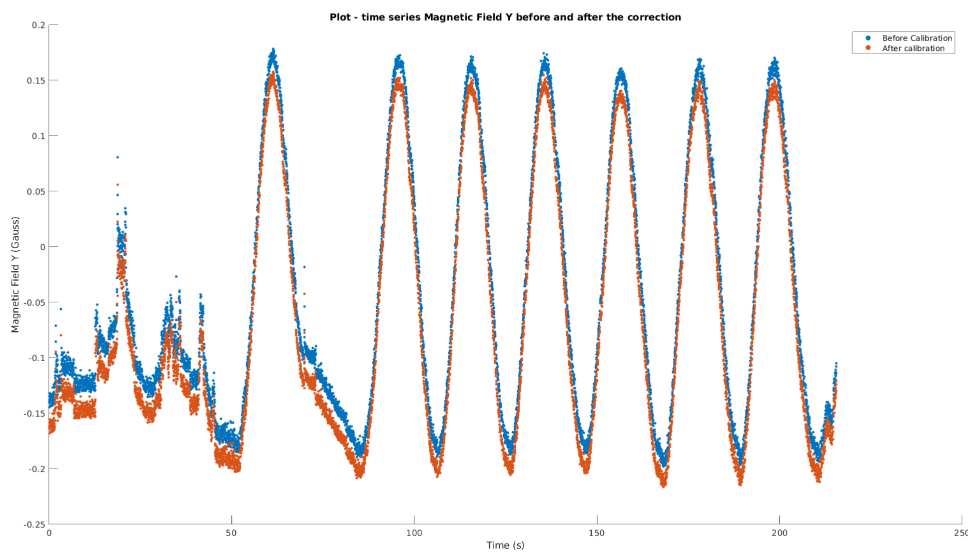


Figure 3: The time series magnetometer data (along Y axis) before and after the correction

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

- **Hard Iron Calibration**: This is additive to the earth's magnetic field. This is due to the constant interference caused by ferromagnetic materials or equipment in the vicinity of the magnetometers. This shifts the sensor readings by a particular offset from the origin of our reference frames. It is simply corrected by removing the offset. An ellipse is fit [1] onto the magnetic field data plotted between its values in the X and Y axes. The center of the fit ellipse is the offset, so this offset is subtracted from all the values.

- **Soft Iron Calibration**: This distortion is caused by materials that influence a magnetic field but do not necessarily produce one. This shows up as the perturbation of the ideal circle into an ellipse. The ellipse fit onto the magnetic field data plotted between its values in the X and Y axes is rotated so that the major axis of the ellipse is aligned with the reference frame X. A scaling factor is used to create the desired circle. After scaling, the data is rotated back to its original position to account for soft-iron distortion.[2]

- The rotation matrix is calculated using the angle formed by the major axis with the reference frame X. The scale factor is the ratio of minor axis length and major axis length. The last rotation is done using the negative of angle used for the first rotation matrix. [3]

## 1.2 Filtering

### 1.2.1 Raw magnetometer yaw with the corrected yaw for comparison

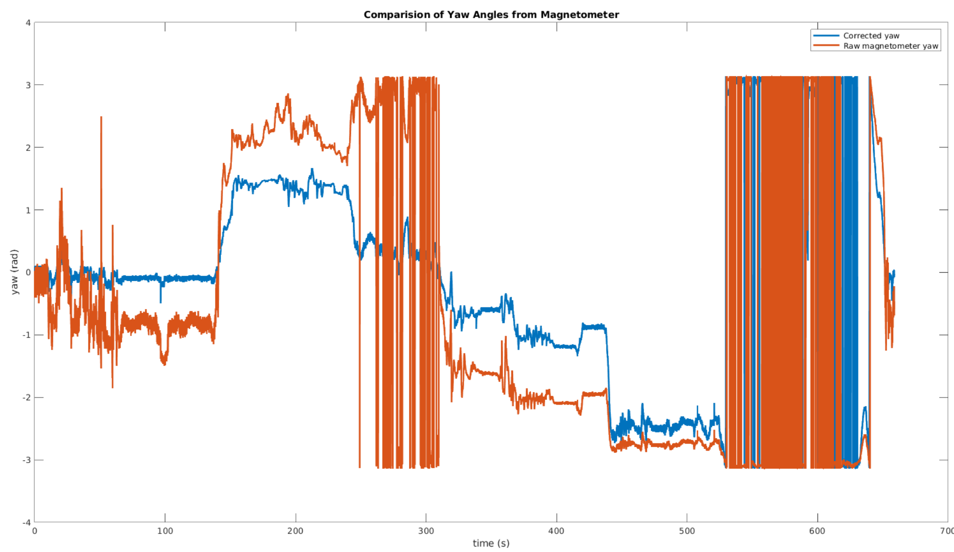


Figure 4: Comparison of raw magnetometer yaw with the corrected yaw

### 1.2.2 Magnetometer Yaw vs. Yaw Integrated from Gyro

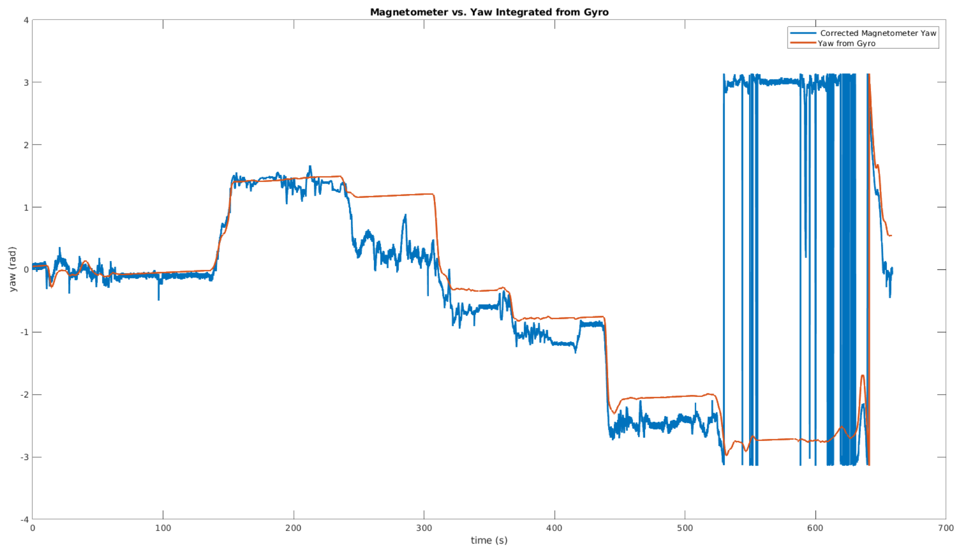


Figure 5: Comparison of yaw angles from magnetometer and yaw Integrated from Gyro

#### 1.2.3 Low Pass, High Pass and Complementary Filter

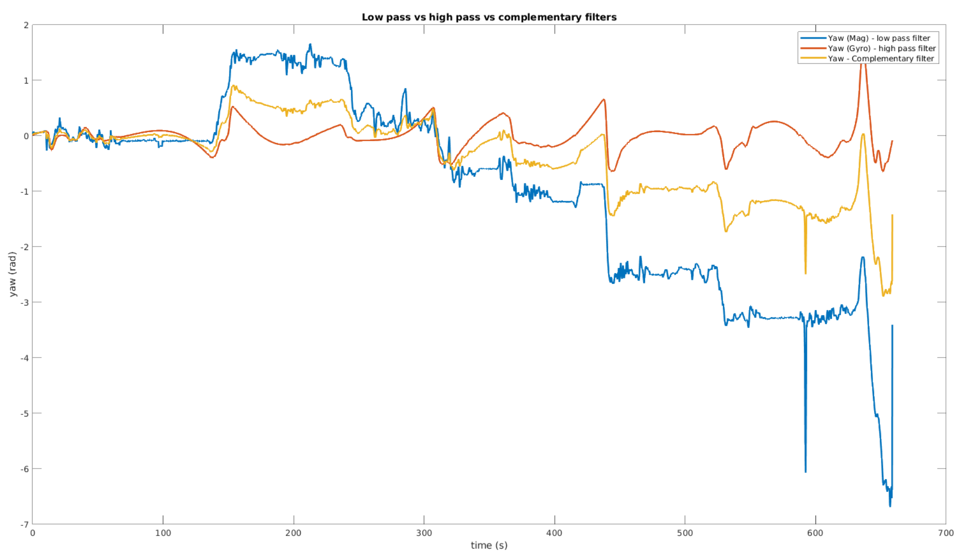


Figure 6: Low Pass filter on magnetometer data, high pass filter on gyro data and complementary filter results

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

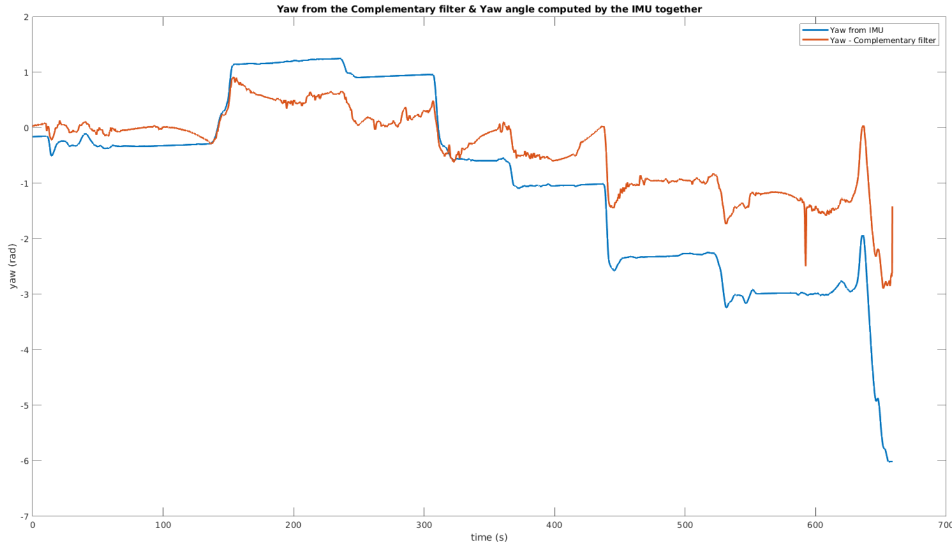


Figure 7: Sensor fusion yaw result with the yaw angle computed by the IMU

**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?**

- In static conditions, the magnetometer provides a good indication of orientation, while gyroscope readings provide a good indication of tilt in dynamic conditions. So we take the magnetometer and gyroscope readings and combine them with a complementary filter.
- The low pass filter filters high frequency signals caused by noisy vibrations in the magnetometer, while the high pass filter filters low frequency signals caused by gyroscope drift. In the complementary filter, we combine these two. [4]
- Thus for the magnetometer, when implementing the low pass filter, *lowpass(x,fpass,fs)*, fs = 40 and fpass = 0.001 gave the best results. [5]
- For the Gyroscope, when implementing the high pass filter, *highpass(x,fpass,fs)*, fs = 40 and fpass = 0.01 gave the best results.
- A weightage (alpha) of 0.992 has been used for the complementary filter.

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

- Like discussed above, the yaw from the magnetometer gives a good indication of orientation in static conditions, while gyroscope readings provide a good indication of tilt in dynamic conditions. So, to get the best estimate of both, we can use the yaw after passing a low pass filter on the magnetometer and a high pass filter on the gyroscope readings. The orientation from the complementary filter can be trusted for navigation since it incorporates the best of both.

# 2 Forward Velocity Estimation

## 2.1 Velocity estimate from the GPS vs integrated forward velocity

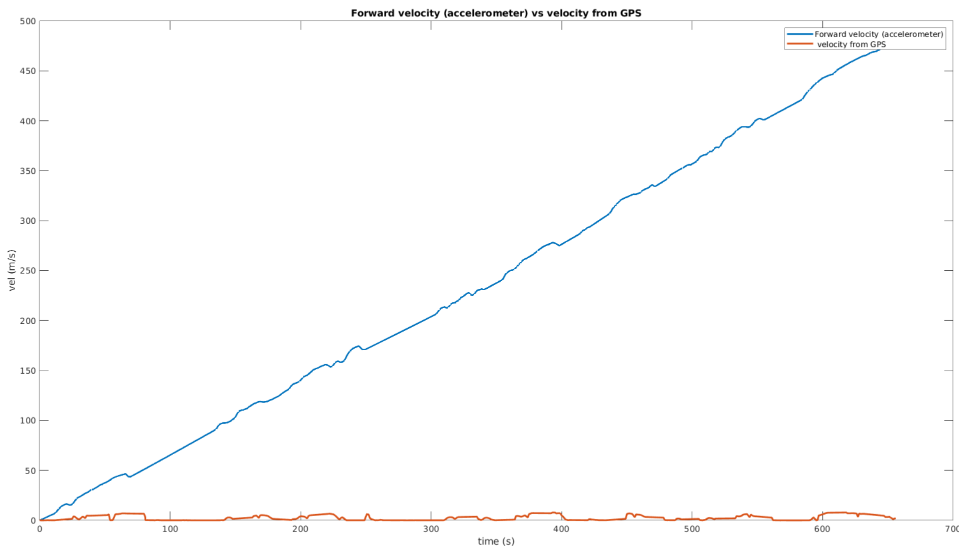


Figure 8: Velocity estimate from the GPS with Velocity estimate from accelerometer before adjustment

## 2.2 Corrections to the forward acceleration measurements

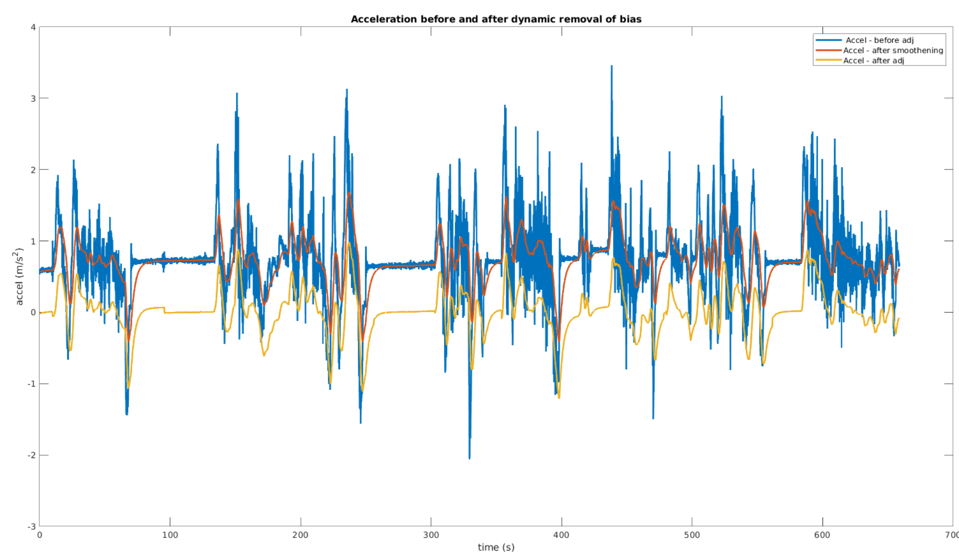


Figure 9: Acceleration before adjustment, Acceleration after performing smoothing and Acceleration after bias removal

## 2.3 Velocity estimate from the GPS vs integrated forward velocity(after acceleration adjustment)

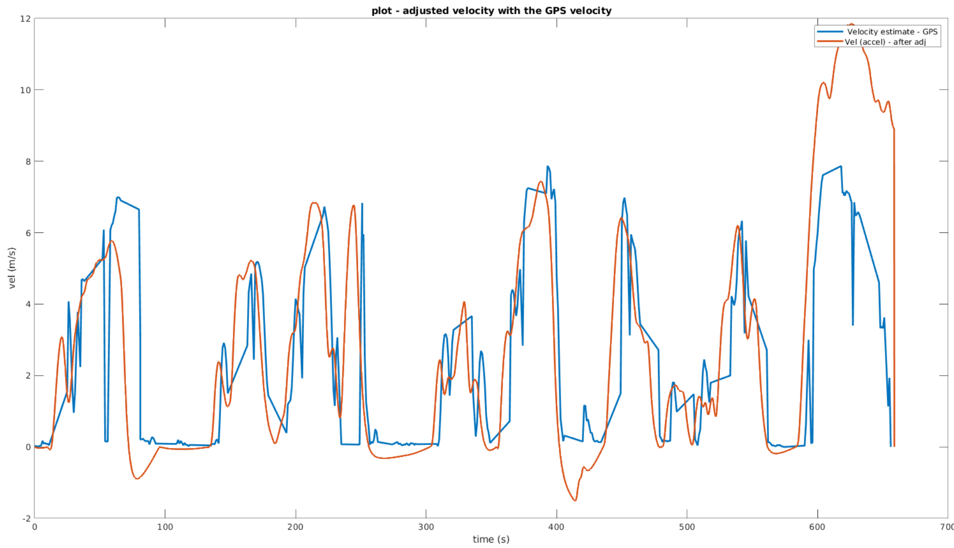


Figure 10: Velocity estimate from the GPS vs integrated forward velocity(after acceleration adjustment)

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

- While collecting data, we stopped at certain locations due to traffic. These appeared as zero velocity regions on the GPS velocity plots because we hadn't moved at those locations and thus the easting and northing values remained constant along those regions. However, the acceleration reading revealed noisy data along those time intervals. Since the acceleration was being integrated, the velocity began to increase uncontrollably, as shown in Fig. 8. This was solved by dynamically calculating the time intervals where the bias needed to be corrected.

- The accelerometer readings were first smoothened using a moving average filter. This was done to correct readings caused by vibrations.
  The time intervals where the GPS velocity showed zero velocity were then calculated.
  For these values, the corresponding range of acceleration values was calculated, and bias was calculated by taking the mean of the values in the interval. All acceleration values within that interval had their bias subtracted. The forward velocity was calculated using the corrected acceleration values.

- The velocity due to the adjusted acceleration values can be seen in Fig. 10

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

- The GPS velocity plot shows sharp rise (accelerations and deceleration) when compared to the velocity estimate based on acceleration. This could be because we collected GPS data at 1Hz rather than 40Hz for IMU data. Thus, the abrupt change in northing and easting could be indicating this sharp acceleration and deceleration.

- In certain regions (75s - 100s and $>$ 600 seconds), we can see that the correction of acceleration values has not corrected the velocity for this region to a good extent. Instead of taking the mean of the values in the region, we may need to find bias using another method that best approximates it in order to correct these anomalies.

# 3 Dead Reckoning with IMU

## 3.1 Comparison of displacement by integrating forward velocity with GPS displacement

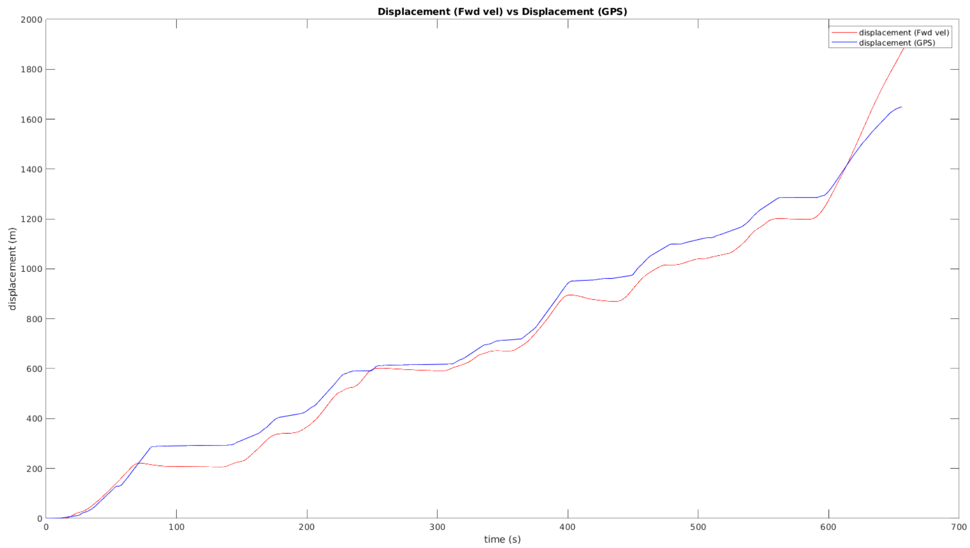


Figure 11: Comparison of displacement by integrating forward velocity vs GPS displacement

## 3.2 $\omega \dot{X}$ and $\ddot{y}_{obs}$ plotted together

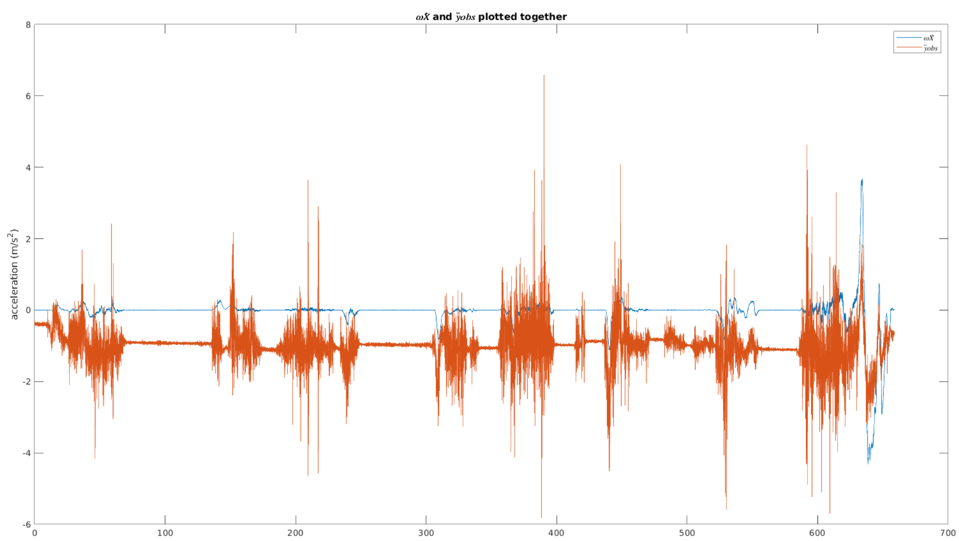


Figure 12: $\omega \dot{X}$ and $\ddot{y}_{obs}$ plotted together

## 3.3 GPS and IMU trajectories

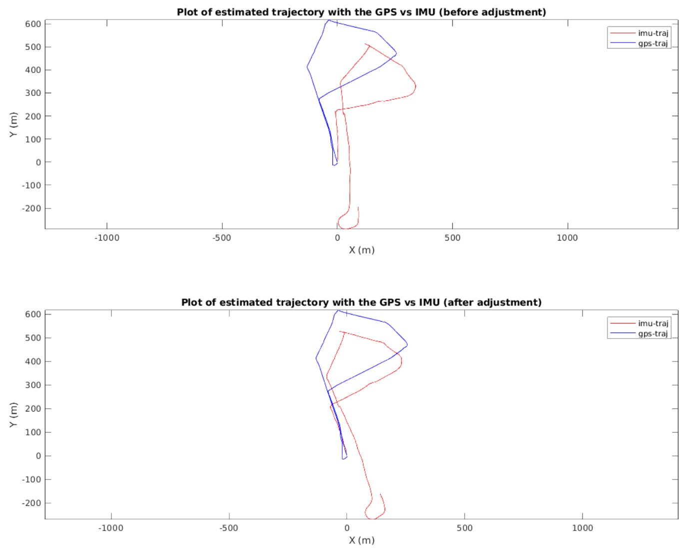


Figure 13: Estimation of the trajectory of the vehicle from inertial data and GPS

**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 can observe a consistent offset between $\ddot{y}_{obs}$ and $\omega\dot{X}$. $\ddot{y}_{obs}$ values can be observed to be very noisy and there are a lot of intermediate high frequency terms. These high frequency components can be removed using a low pass filter like we did before with acceleration along X axis to remove the high frequency components that are occurring due to accumulation of errors.

**7. Estimate the trajectory of the vehicle (xe,xn) from inertial data and compare with GPS by plotting them together. (adjust heading so that the first straight line from both are oriented in the same direction)**

- Fig 13 represents the trajectory estimation from GPS, and before and after correction of IMU trajectory.

- It can be observed in Fig 13 that despite correction of the start location and the heading of the first straight line, the final locations are not matching for the IMU trajectory.

**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?**

- In Fig 13 we can observe that there is an offset between the imu trajectory and gps trajectory plots. It matches along the first straight line but after that despite the turns looking the same, but the straight line distance travelled between those turns looks scaled down.

- The straight distance calculated using the IMU can be observed to be not reliable. This error in distance estimation shows up between all the turns resulting in the final location not matching the GPS trajectory. Thus without a position fix, we cant expect it to be able to navigate reliably.

# References


[1] R. Brown. (2016) fitellipse.m. [Online]. Available: https://www.mathworks.com/matlabcentral/fileexchange/15125-fitellipse-m

[2] C. Konvalin. (2009) Compensating for tilt, hard-iron, and soft-iron effects. [Online]. Available: https://www.fierceelectronics.com/components/compensating-for-tilt-hard-iron-and-soft-iron-effects

[3] M. Tuupola. (2010) How to calibrate a magnetometer? [Online]. Available: https://www.appelsiini.net/2018/calibrate-magnetometer/

[4] H. Vathsangam. (2010) Complementary filter. [Online]. Available: https://www.mathworks.com/matlabcentral/fileexchange/15125-fitellipse-m

[5] (2022) lowpass. [Online]. Available: https://www.mathworks.com/help/signal/ref/lowpass.html