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EECE5554 – Robot Sensing and Navigation

Lab#4

Analysis of the collected Data:

Two sets of dated were collected viz. 'data_going_in_circles.bag' at the Ruggles station wherein we drove the car in circles 5 times, 'data_driving.bag' – this data was collected while taking a mini tour of Boston.

1. Estimate the Heading (Yaw)

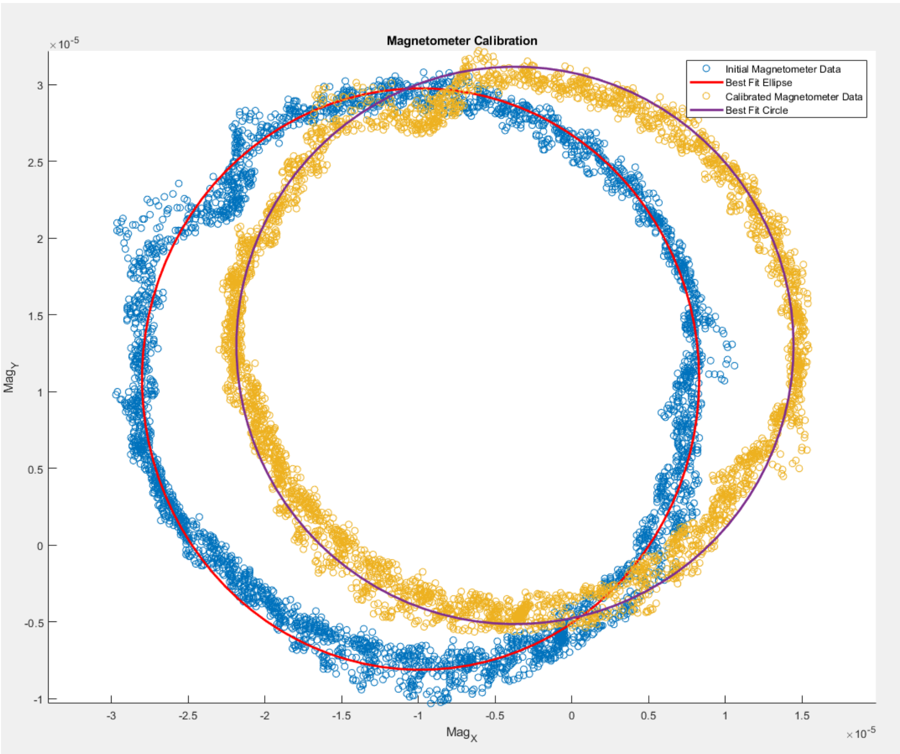

Figure 1: Magnetometer data before and after Correction from data at Ruggles

Figure 1 shows the updated best fit ellipse after correcting for Hard Iron and Soft Iron Distortions. That involves translating the ellipse from its center to the origin. This is done by then rotating the ellipse and scaling it to be a circle. The plot above consist both the original (blue points) and calibrated data (orange points).

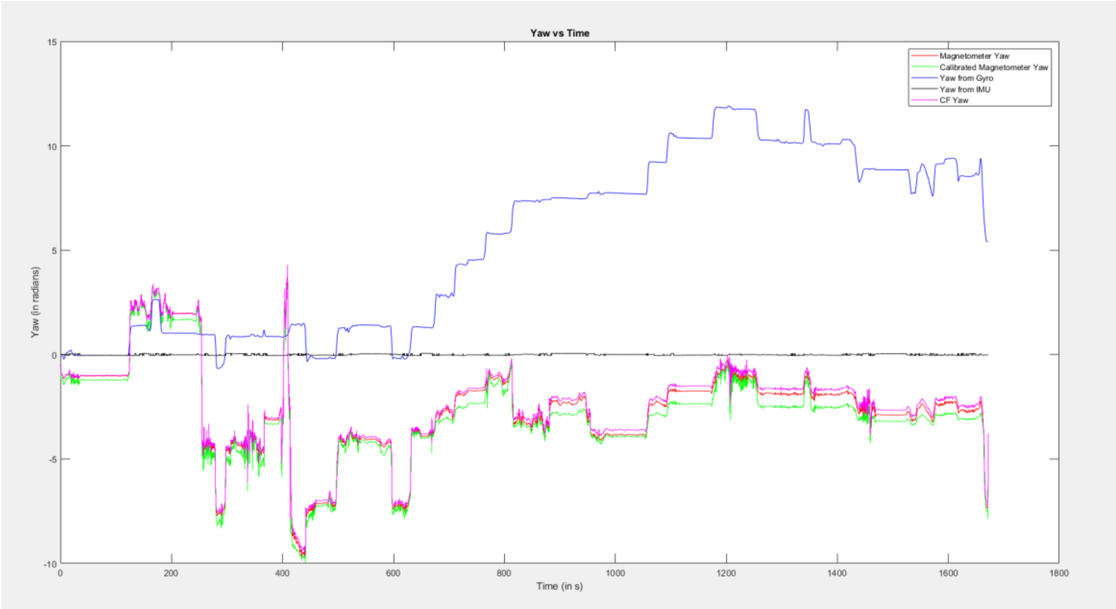

Figure 2: Time Series Magnetometer Data

Above plot has all the plots – Raw Magnetometer Yaw, Calibrated Magnetometer Yaw, Yaw from Gyro, Yaw from the IMU, and Complementary Filter estimate of the Yaw.

The Raw Magnetometer Data is corrected by removing 'Soft-iron' and 'Hard-iron' and plotted. Comparing the above with the Magnetometer yaw with the Yaw from the Gyro we can clearly observe that the Gyro is giving the values in positive half of the graph, whereas the other yaw follows similar pattern.

I would trust the yaw estimated from the gyroscope (integrating angular velocity z) as the values obtained from magnetometer are prone to getting errors from magnetic sources around the sensor. The ideal scenario would be to use both the values (magnetometer and gyro) and applying a filter on it to get the best of both worlds.

2. Estimate the Forward Velocity

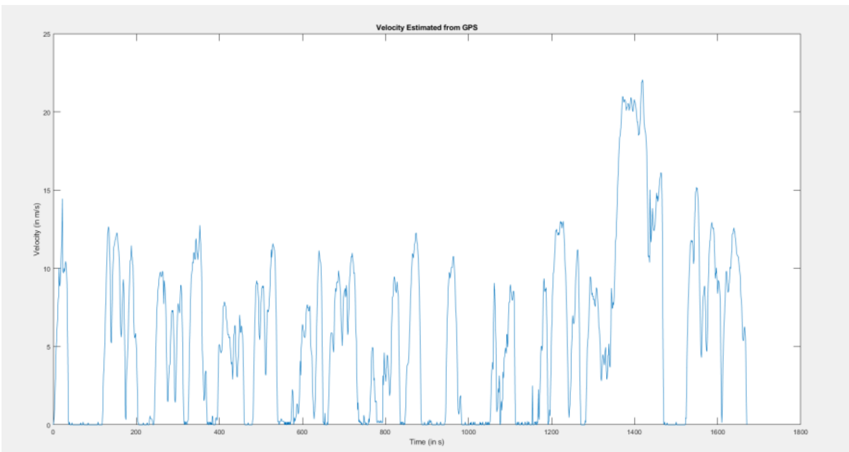

Figure 3: Velocity Estimated from the GPS

The provided data was gathered during a drive around Boston in a car. The data aligns with expectations, as the car comes to a stop at red signals, resulting in a corresponding dip in the velocity curve. Additionally, the car exhibits a tendency to decelerate during various turns. A notable increase in the curve occurs around the 1400-second mark, indicating that the driver was on Storrow Drive at that point.

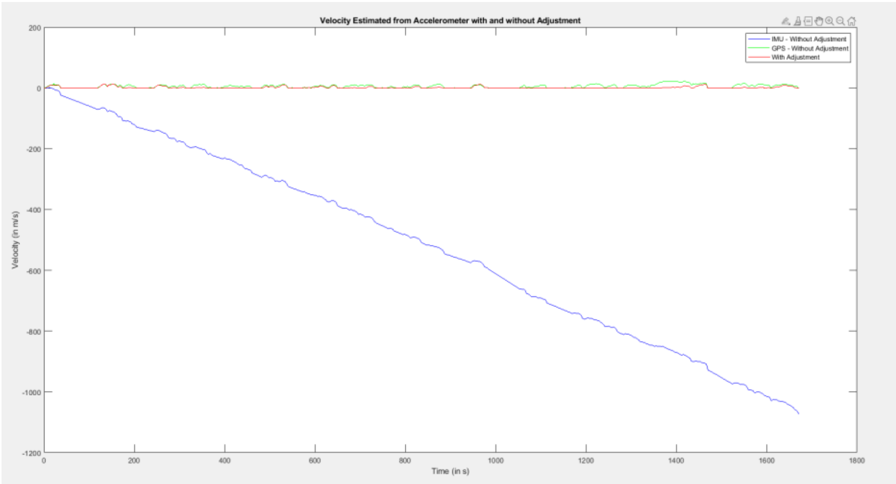

Figure 4: Velocity Estimate from Accelerometer before and after Adjustments

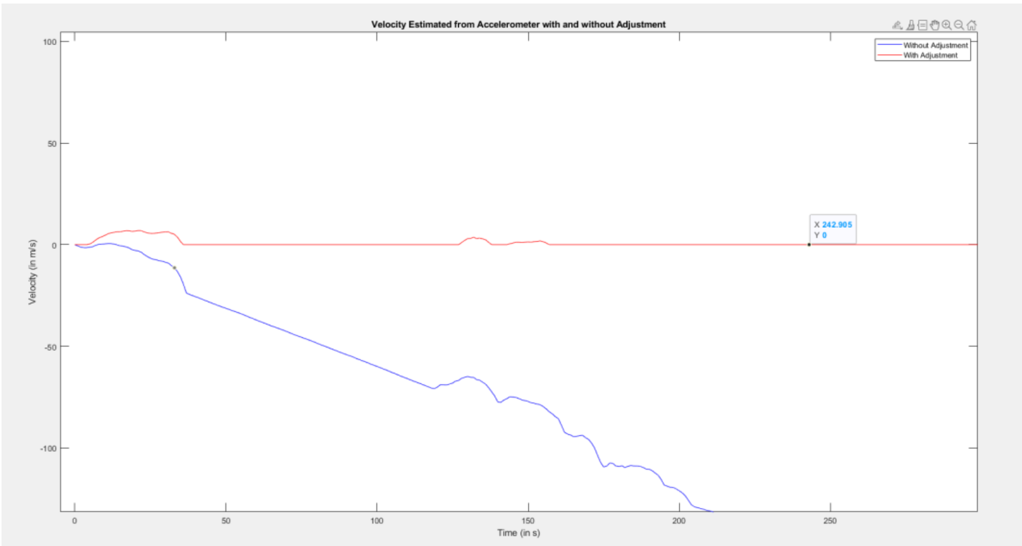

Figure 5 Zoomed in Image of figure 4

Analysing the Velocity from the accelerometer, we see that a huge correction was made.

The IMU Velocity estimated by integrating the X component of Linear Acceleration. The linear acceleration data is prone to biases. As shown in Figure , when the vehicle is stationary, there is still a value of acceleration associated. When integrated over time, this would be a function of time (integrating a constant over time gives a linear graph). This is seen in Figure 6.

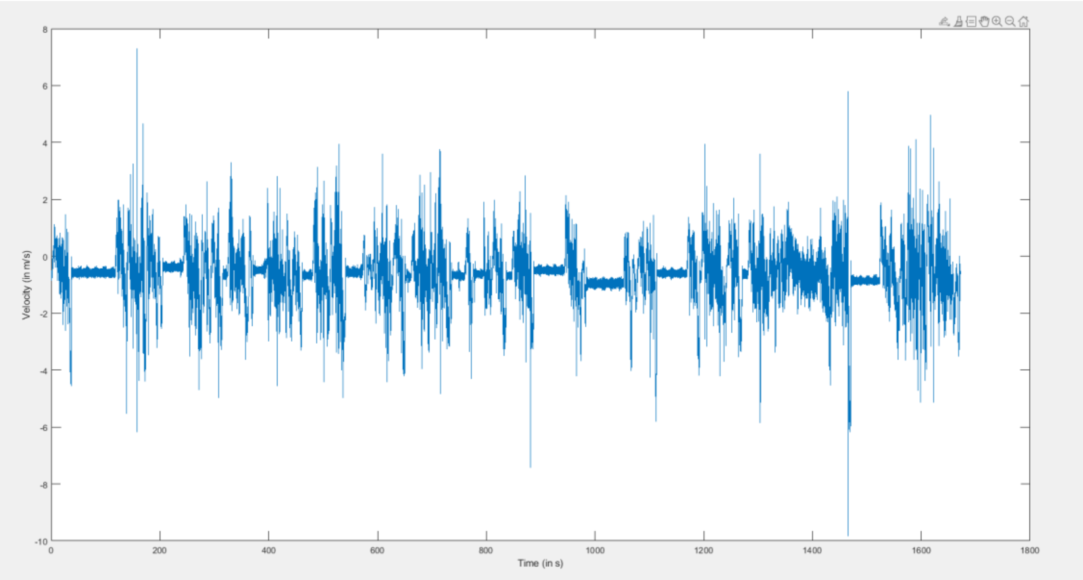

Figure 6: Linear acceleration in X vs Tim

There are regions where the vehicle is stationary and despite the vehicle being stationary, there is a value of acceleration associated. So we correct for it by subtracting the bias from that region. The regions where the moving standard deviation is less than a threshold can be considered for the regions with bias. Once the biases are subtracted (positive bias) or added (negative bias), we can go ahead and integrate. The discrepancies between the GPS and IMU velocity can majorly be attributed to the biases and random sensor noi.

3. Dead Reckoning

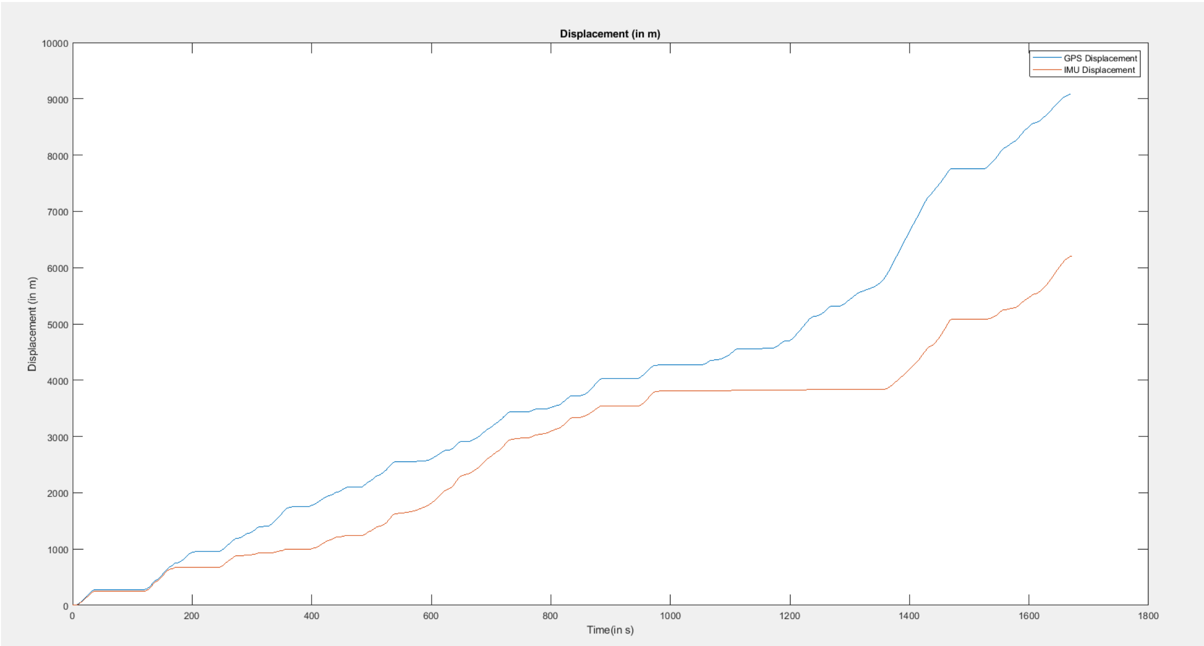

Figure 7: GPS and IMU Displacement

Figure 7 shows the displacement vs time graph from both GPS and IMU. This shows the absolute displacement of the vehicle is calculated by integrating the GPS and IMU velocities obtained in the previous step. There is a deviation after a certain point in Figure 7. It can be attributed to random noise and bias from the sensor readings obtained from linear acceleration being integrated twice to get the linear displacement.

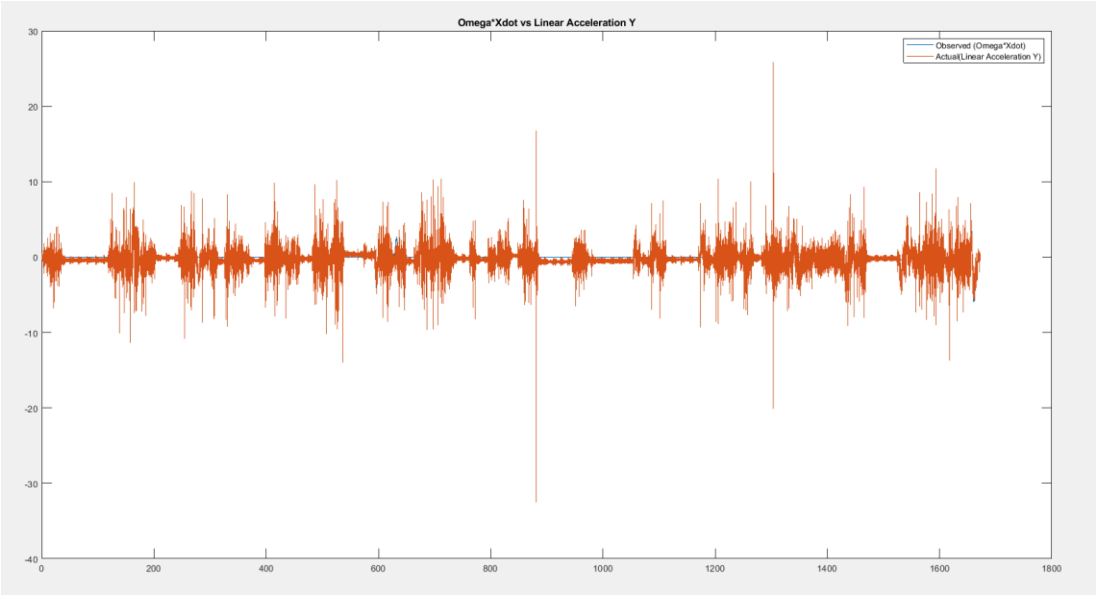

*Figure 8: Omega*Xdot vs Linear Acceleration in Y*

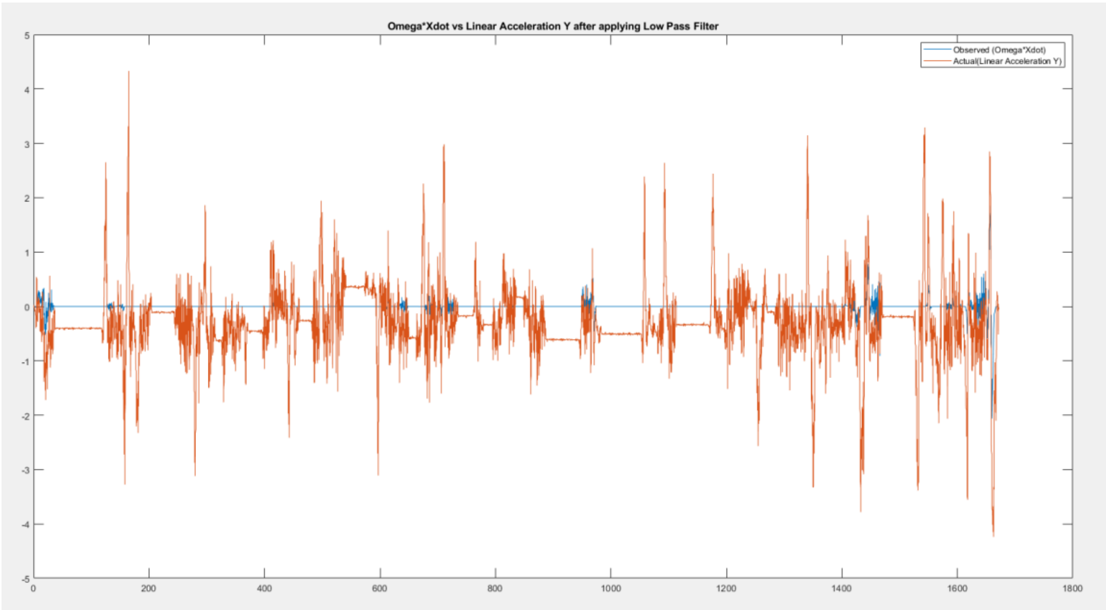

*Figure 9: Omega*Xdot vs Linear Acceleration in Y after applying Low Pass filter*

As can be seen from Figure 7, the linear acceleration Y values are pretty noisy. It can be taken care of by applying a filter, lowpass filter in this case. Upon applying it, we obtain Figure 9. The values are much closer to each other in Figure 9.

The difference in the values can be attributed to the fact that we are assuming the sensor to be placed at the center of mass of the vehicle, while it need not necessarily be the case.

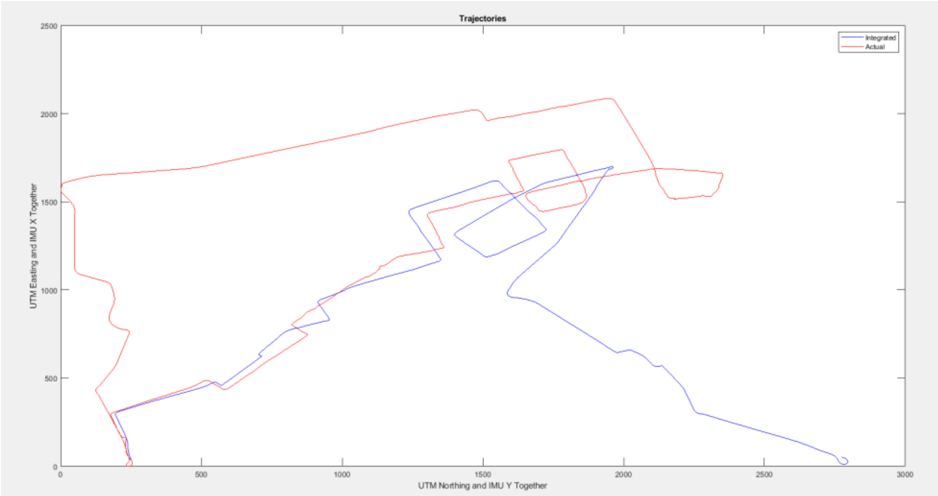

Figure 10: Trajectories

The easting and northing from GPS and the trajectory obtained by integrating the IMU Velocities and their components is shown in Figure 10. As it can be seen from the Figure, the heading angles don't initially coincide. They are made to coincide by applying a transformation to the IMU Values to match the GPS values. After a point the yaw angle does not follow the trajectory and gives us random path. The scaling was roughly equal to 1 (I used a value of 0.95).

Questions and Answers:

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

   Magnetometer calibration comprises the process of fitting an ellipse to the raw data and implementing transformations to rectify both hard and soft iron distortions. Hard iron distortions, induced by magnetic materials in proximity, are addressed through translation corrections. Meanwhile, soft iron distortions, arising from non-uniform magnetic field interactions, are rectified through scaling adjustments. Upon inspecting Figure 1, it becomes evident that the raw data is notably affected by hard iron distortion.

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?

   A complementary filter combines yaw estimates from the magnetometer and gyroscope. The filter uses an alpha parameter (set to 0.98) to blend magnetometer and gyroscope data. A lowpass filter with a cutoff frequency of 0.001 is applied to the magnetometer yaw data for noise reduction.

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

For navigation, the complementary filter yaw estimate is preferred as it combines gyroscope and magnetometer data, providing a responsive and stable orientation estimate while mitigating gyroscopic drift. The gyroscopic estimate is suitable for short-term dynamics, and the magnetometer estimate offers an absolute reference but requires careful calibration and noise filtering.

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

   The discrepancies between the velocity estimates obtained from the accelerometer and GPS data are due to several factors, including noise, gravity, multipath effects, and satellite availability. GPS measurements are generally more accurate, but accelerometers can provide valuable short-term velocity information.

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

   Disparity was observed in the output. Upon thorough investigation into the factors influencing the accuracy of the dead reckoning system. Potential sources of discrepancy, including sensor noise, integration errors, modeling assumptions, calibration issues, and external forces, were scrutinized. To address these discrepancies, considerations such as implementing advanced filtering techniques for sensor noise reduction, refining integration algorithms, reassessing and adjusting modeling assumptions, ensuring precise sensor calibration, and accounting for external influences were explored. This comprehensive analysis serves as a foundation for refining the dead reckoning algorithm, with the aim of aligning its predictions more closely with the actual dynamics of the vehicle.

Q6 & Q7 answered above.

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?

   Looking at the Figure 10, we can observe that the GPS and IMU position don't match that closely and after a point that completely lost the track of the path. The GPS did perform well as we took, I observe it did make the Trajectory that we followed but the IMU till a point did follow but after certain lost it. The stated performance for dead reckoning did not match the actual measurement.

9. Estimate xc and explain your calculations

Estimating x_c:

Inertial Sensor displayed by $r = (x_c, 0, 0) \rightarrow$ const^n

$\omega = (0, 0, \omega)$

$v = V + \omega \times r$

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

$\omega = \omega\hat{k} \longrightarrow$ along z

$r = x_c\hat{i} \longrightarrow$ along x

$\ddot{X} = \ddot{X}\hat{i}$

$\dot{\omega} = \dot{\omega}\hat{k}$

$\dot{X} = \dot{X}\hat{i}$

$\ddot{x}\hat{i} = \ddot{X}\hat{i} + (\dot{\omega}\hat{k}) \times (x_c\hat{i}) + (\omega\hat{k}) \times (\dot{X}\hat{i}) + \omega\hat{k} \times ((\omega\hat{k}) \times (x_c\hat{i}))$

$\therefore \ddot{x}\hat{i} = \ddot{X}\hat{i} + \dot{\omega}x_c(\hat{j}) + \omega\dot{X}\hat{j} + \omega\hat{k} \times (\omega x_c(-\hat{j}))$

$\therefore \ddot{x}\hat{i} = \ddot{X}\hat{i} + \dot{\omega}x_c\hat{j} + \omega\dot{X}\hat{j} - \omega^2 x_c\hat{i}$

~~Thus~~, there is no $\hat{j}$ component in $\ddot{x}$

$\dot{\omega}x_c + \omega\dot{X} = 0$.

$x_c = \dfrac{-\omega\dot{X}}{\dot{\omega}} = \dfrac{-\omega\dot{X}}{a_x/r'} = \dfrac{-\omega r'\dot{X}}{a_x}$

$\boxed{\therefore x_c = \dfrac{-\omega r'\dot{X}}{a_x}}$ $\longrightarrow$

$\omega \rightarrow$ angular vel^n z

Close

$\dot{X} \rightarrow$ linear vel^n x

$a_x \rightarrow$ linear accl^n x

$r' \rightarrow$ Instantaneous center of curvature

We can estimate r' from the circles data and find x_c.

$x_c = \dfrac{-\omega r'\dot{X}}{\ddot{X}}$