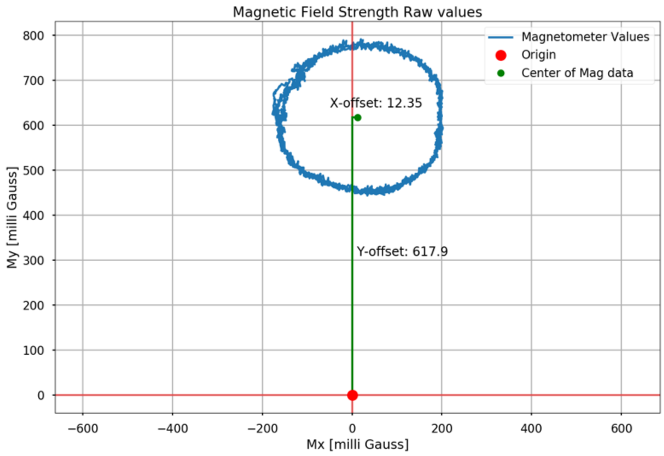
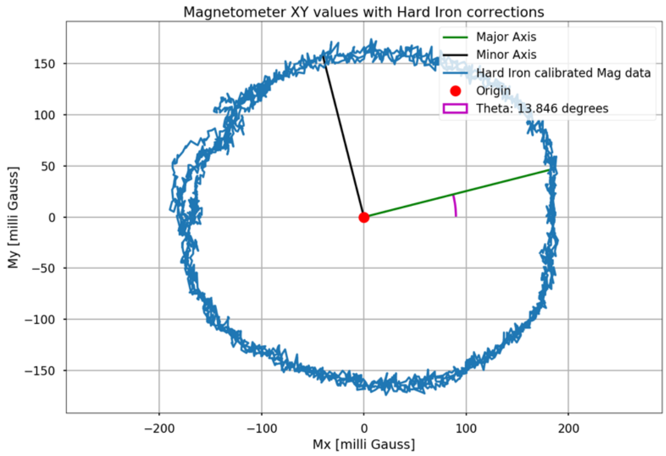
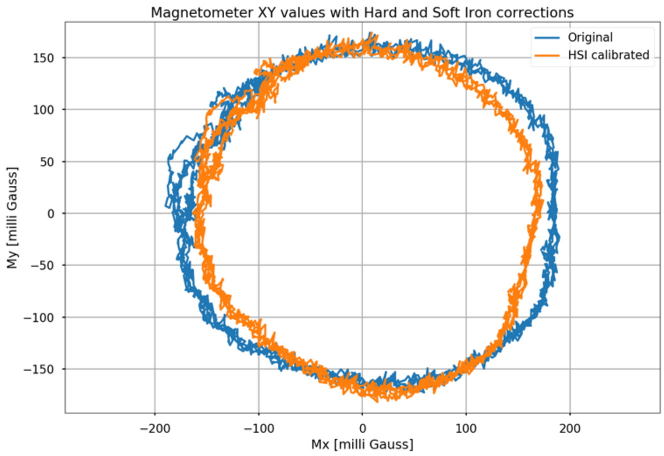
Lab 4 Report
Navigation with IMU and Magnetometer

1. Magnetometer Calibration

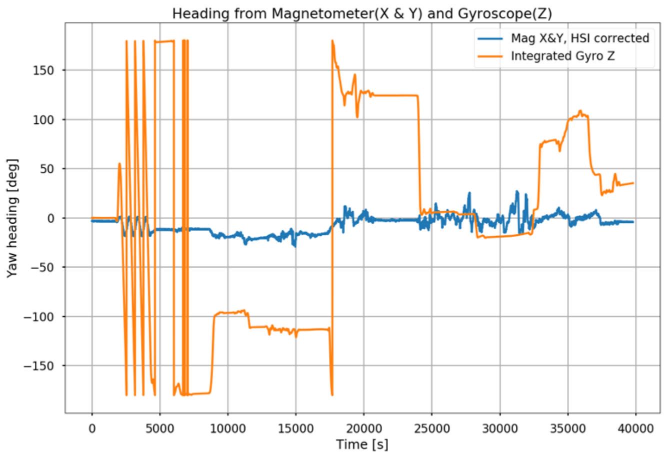


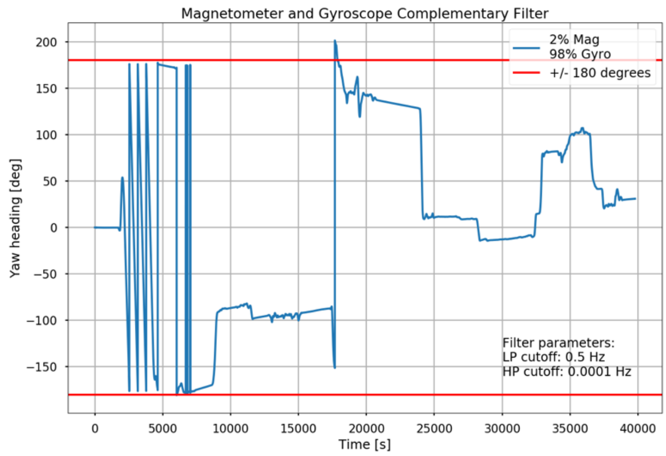


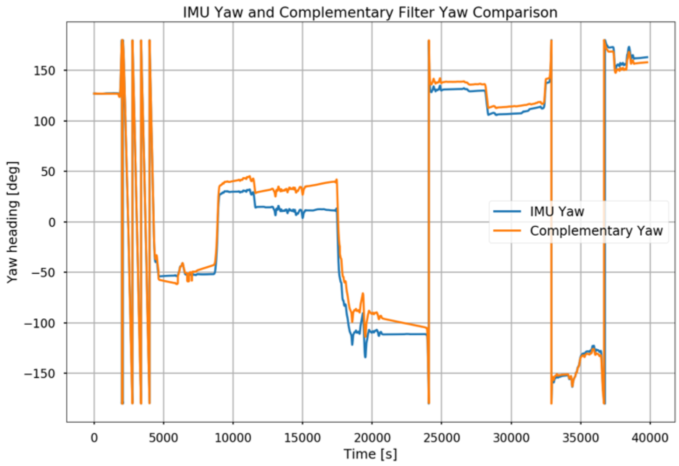


The magnetometer data will be affected by hard and soft iron effects. If there was no error in the given data, the plot obtained would be a near perfect circle, but we can see that that is not the case. Hence, we accordingly calibrate our data, adjusting the offset and hard and soft iron effects as can be seen from the plots. The scaling factor comes out to be 0.885. This corrected data is then used for further calculations.

2. Yaw Angle



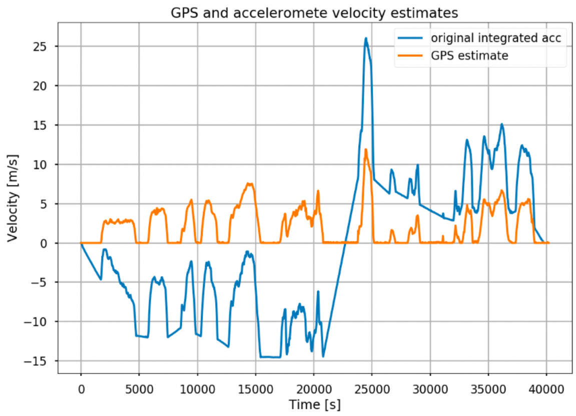




The yaw angle calculated from the corrected magnetometer readings and the yaw angle obtained by integrating the gyroscope readings, follow the same trend as can be seen from plot 1, but have drastically different values. The magnetometer data seems to have noise which can be attributed to external interference of magnetic elements such as other electronics near the sensor.
To get a better idea of the data obtained from the two sensors, we apply a complementary filter that is show in Plot 2.

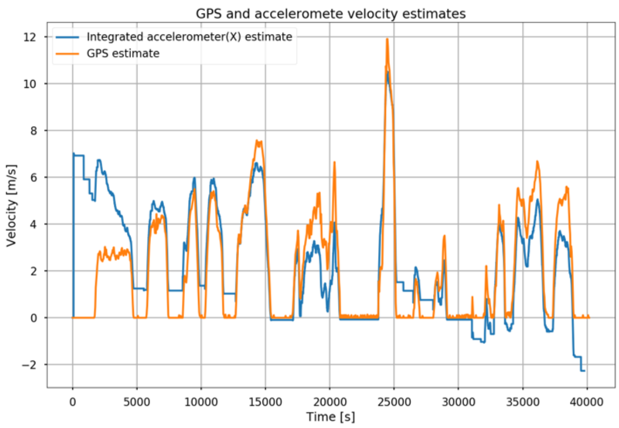
Plot 3 shows the yaw angle estimates after applying the complimentary filter. We can see that both the estimates are very similar hence validating our data and giving us an idea that the calculations being done by the sensor are same as the process we have followed above. The slight differences remaining between both the estimates can be removed by further filtering and more accurate correction of data.

3. Estimating Forward Velocity



The linear acceleration obtained from the imu in the x direction has been integrated to obtain the forward velocity. Doing so on raw acceleration data will give us erroneous estimates, as any small error in the data will accumulate and hence lead to huge deviation in the velocity estimates as can be seen from the plot. This data doesn't make sense as velocity cannot be negative based on the assumption that we're always moving forward.

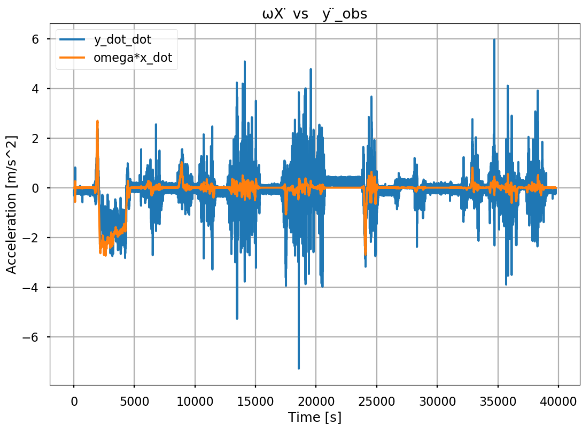
To eliminate this issue, we implemented some modifications on the acceleration data.



Firstly we scaled the acceleration data by 0.5 to make it comparable to the velocity data obtained from the GPS. Then we adjusted the data for negative values, by subtracting the mean of the acceleration values from each value. We then integrated this corrected acceleration data to obtain our velocity. This velocity was then compared to the velocity obtained from the GPS data as shown in the plot.
From the plot, we can observe that both the velocity estimates follow the same trend. There is some bias still present in the data and we could do more filtering and accurate correction of the acceleration data to obtain synchronous results, but the plot gives us a good idea about the performance of the two sensors and helps us understand the basic laws of motion.

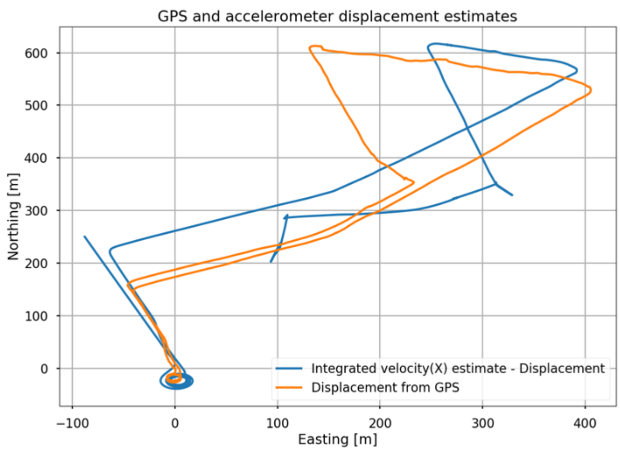
4. Dead Reckoning with IMU

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



The plot compares yaw*forward velocity and linear acceleration in y direction. We can see from the graph that both the plots follow the same trend but the linear acceleration in the y direction has a lot of noise. This can be attributed to various factors such as external interferences such as sensor movement due to car motion, the connecting wire being disturbed etc. It can also be attributed to our assumption of Xc = 0. This would work in an ideal situation, but in our case Xc is not actually 0 and will have significant weightage in the equation, as can be observed from the bias in the plot.

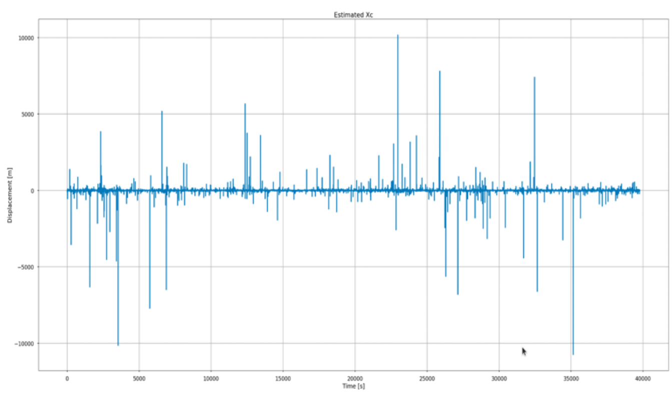
b. Estimated trajectory vs GPS track



The original displacement data obtained from integrating the acceleration and then the velocity obtained from the IMU had to be adjusted to become comparable to the GPS position. It was scaled by a factor of 0.9 and rotated by an angle of 110 degrees. We can see that they both follow the same trend for the most part. The data starts off similar but the bias increases with the integration. There is also a gap or a jump in the data which can be attributed to various factors such as our correction for the velocity measurements or external factors that led to loss or incorrect measurement of data.

This can be rectified by following a more accurate correction of data in the above steps and eliminating as much external noise as possible.

c. Estimate x_c



Xc, which represents the offset from the center of mass of the car, is estimated using the equation: $\ddot{y}_{obs} = \ddot{Y} + \omega\dot{X} + \dot{\omega}x_c$, where $\ddot{Y}$ is assumed to be 0.

We can see that there is quite a lot of variation observed in the offset values. Finding the mean of all these values gives us an offset of **-1.1m** which is in accordance with the fact that we did not keep our sensor on the dashboard but instead in the middle of the driver and passenger seat. This distance was approximately equal to 1m. As the plot trend is very similar to that observed for $\omega\dot{X}$ above, we can attribute the noise in this case to similar factors above as $\omega\dot{X}$ carries a lot of weight in the same. Differentiating and integrating corrected values can lead to enhancing any errors that may persist within the data and hence also increase the noise. Additionally external factors such as environmental interferences with the data can also be a contributing element to the noise.