EECE5554 – ROBOTIC SENSING AND NAVIGATION

LAB -4 REPORT

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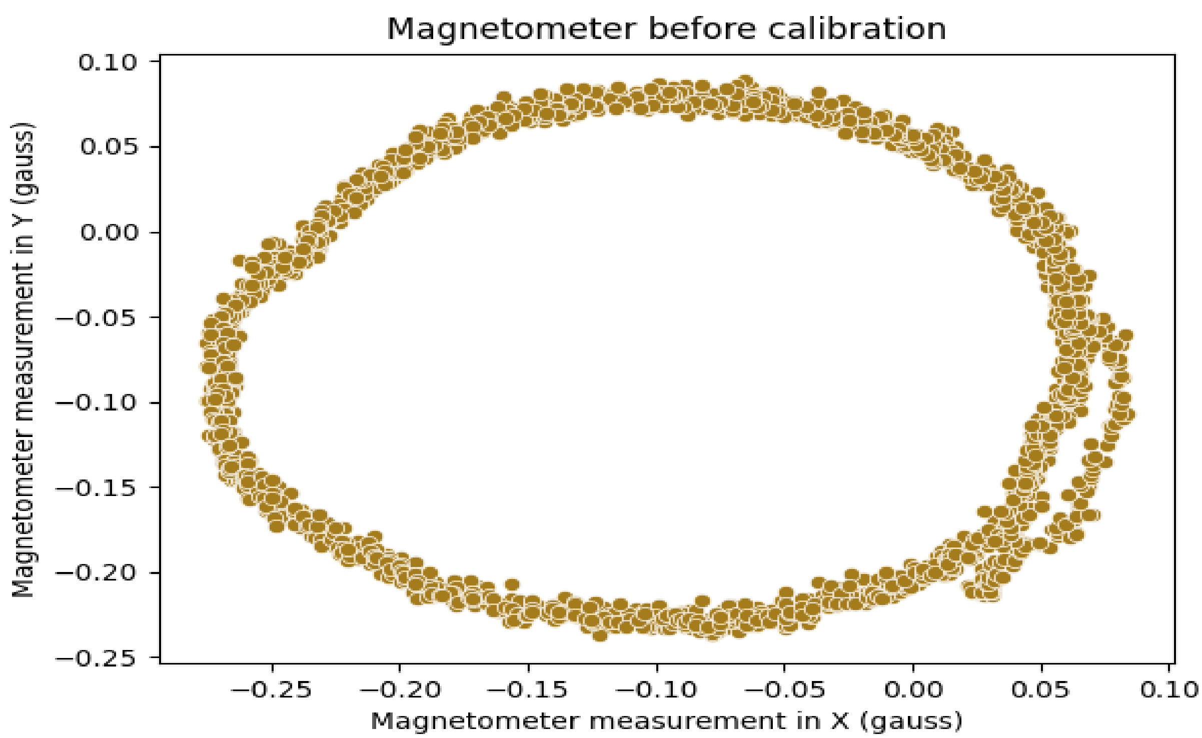
Lab Background

For the Lab4 experiment data was collected using a car. The route taken followed the path described in class starting and ending at the sentinel circle. Two sets of data were taken one by driving around in circles in the sentinel circle while the other around the university. The driver code and data was taken by tower.w.

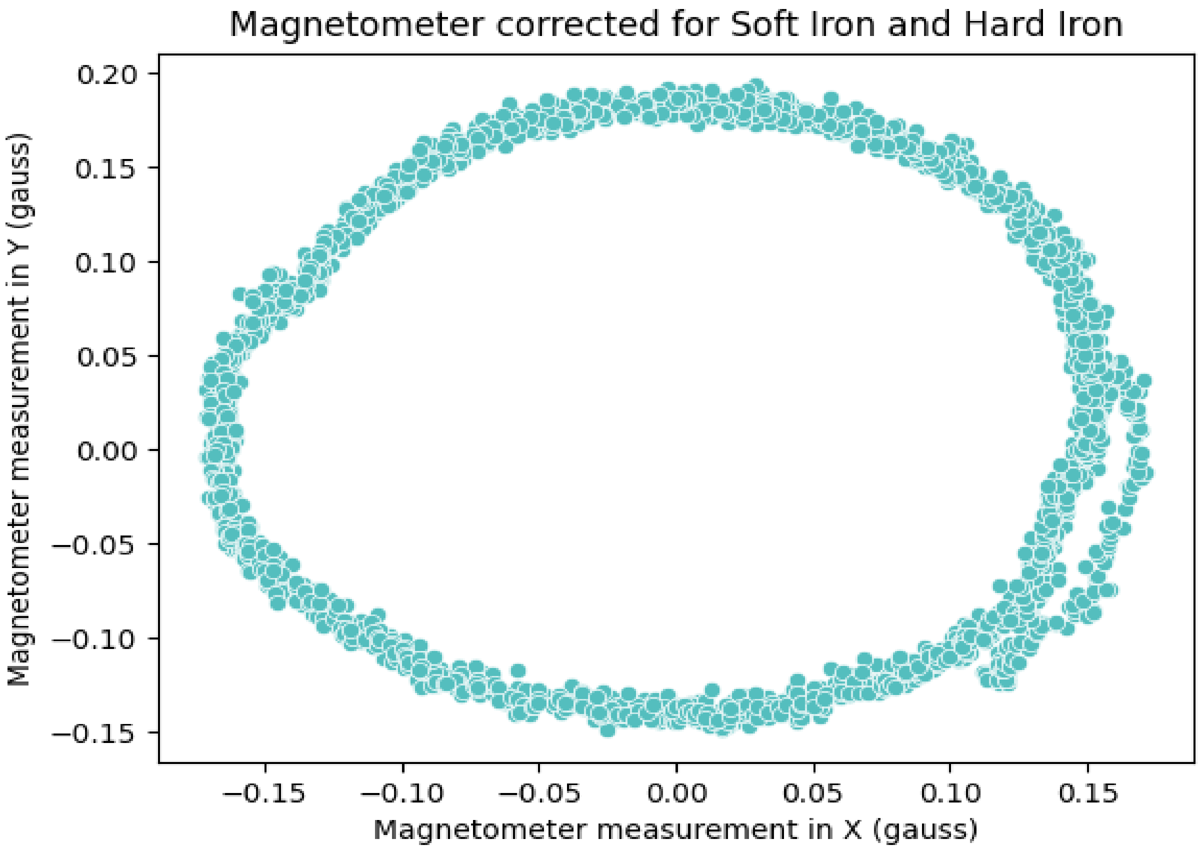
Estimate The Heading (yaw)

The data gathered while driving in a circle around the sentinel circle will be used to calibrate the magnetometer data by considering the hard and soft iron effects. The two major sources of errors where the soft-iron and hard-iron effects. The soft-iron effect is described as the distortion of the ellipsoid from a sphere and the tilt of the ellipsoid, and the hard-iron effect is described as the offset of the ellipsoid center from the origin. The hard-iron effects caused the circle data to be offset at every point from the origin.

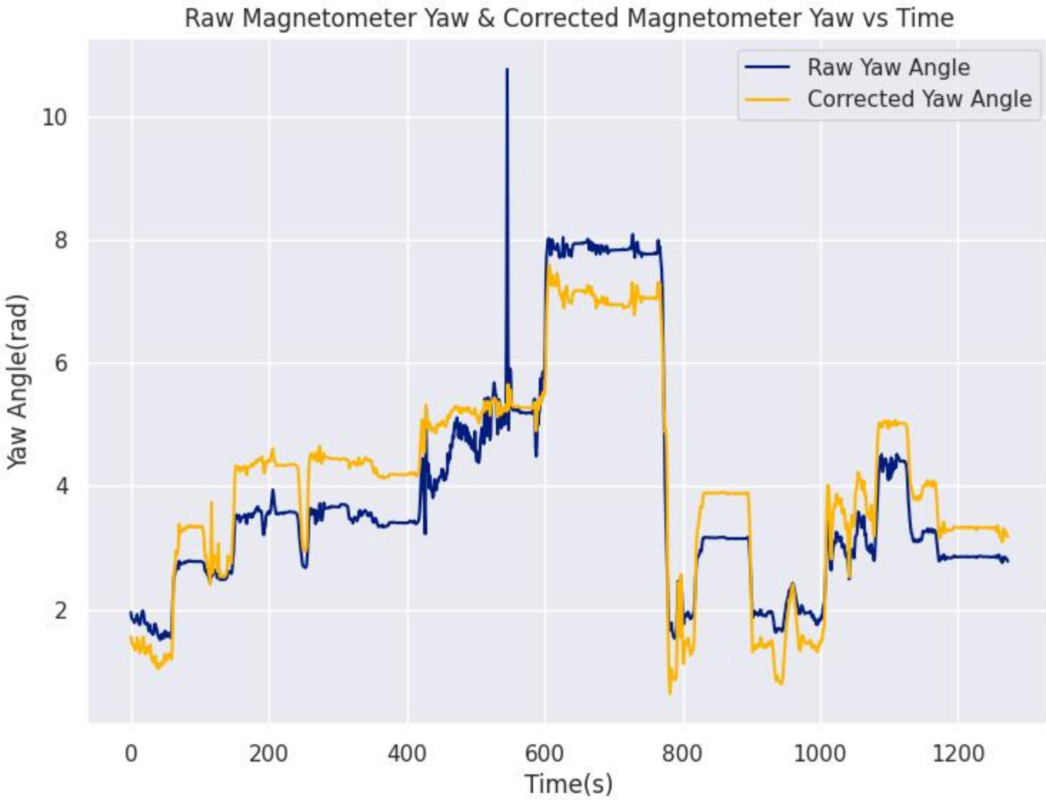


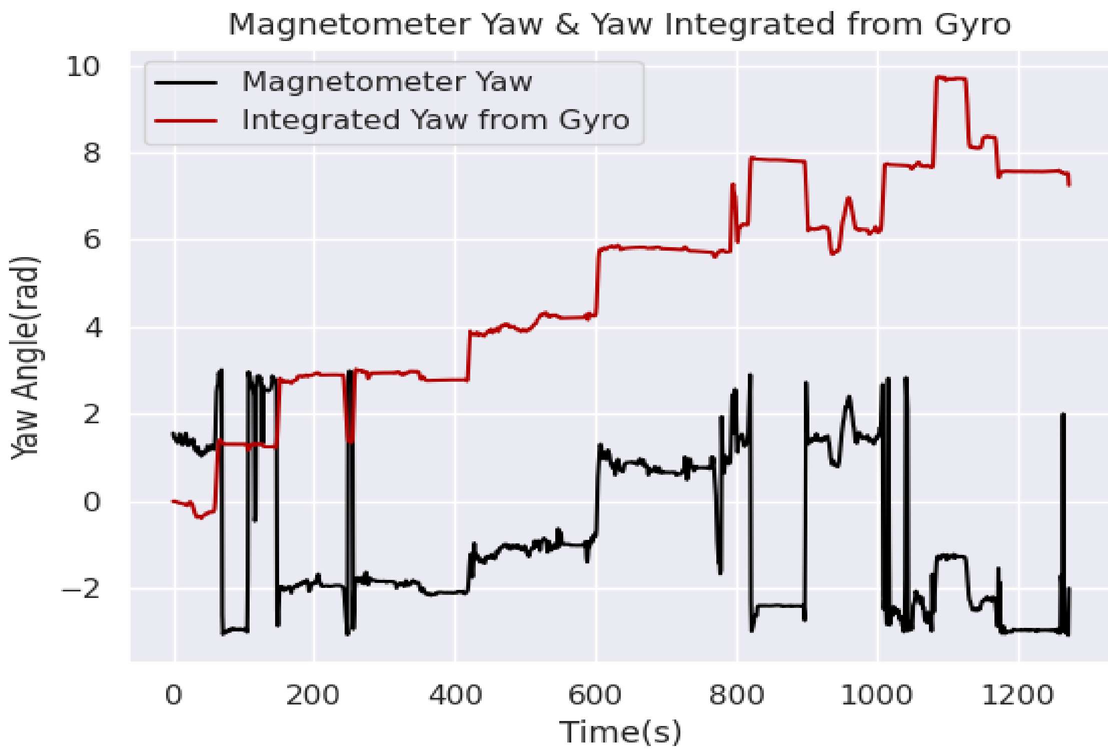
The magnetometer is calibrated by removing the hard iron error coefficient which is derived from the max and min value of magnetometer and then dividing it by 2, for soft Iron correction a scaling factor is derived and multiplied with the magnetometer readings.

The figure below shows the calibrated magnetometer data after removing the errors. We can see here that the below figure has its center at the origin so there is no error.



Now the yaw angle can be calculated using the corrected magnetometer readings. Now onwards for all analysis the corrected magnetometer readings are used. The new data can be used to estimate the yaw angle by taking the arctangent of the ratio of the Y and X components representing the angle the vehicle is turning at every instantaneous point in time. The figure given below shows the corrected yaw angle and the raw yaw angle. The time series magnetometer data before and after the correction.



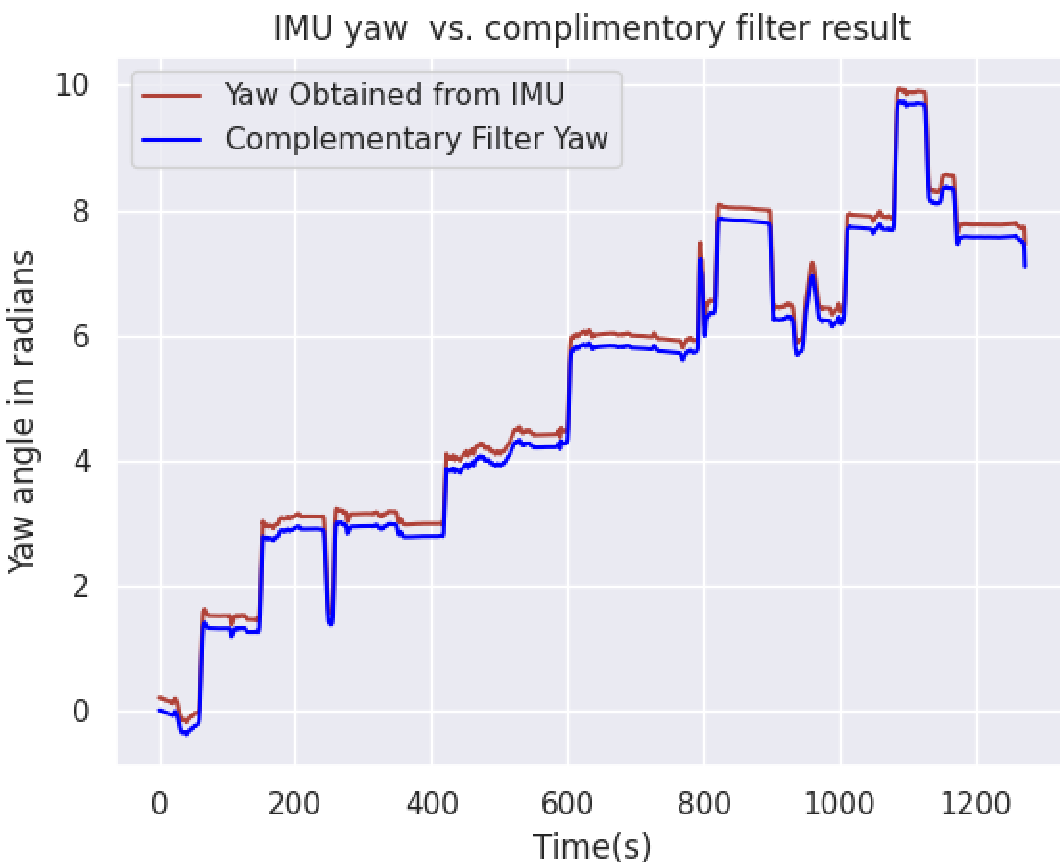


The yaw calculated from the gyroscope data is relatively smoother and less sensitive compared to the IMU yaw, while the yaw derived from the magnetometer data is relatively less smooth. The magnetometer derived yaw angle sees very frequent variation compared to the yaw angle derived from the gyro, the plot seems to mostly match, and the gyro rates yaw looks more stable. The magnetometer is well suited for steady measurements over a long time but lacks the ability to pick up quick movements. The gyro on the other hand is better suited for measurement abrupt movements but this comes with an associated drift over time.

Its is to overcome these errors in the two sensors is to perform a complementary filter on the two measurements. A low pass filter is used on the magnetometer data to keep its steady low drift but remove any high frequency noise while a high pass filtered is used on the gyro data to keep high frequency measurements but remove the bias from low frequency drift being integrated. The High Pass filter filters out almost all the gyroscope-derived yaw and the Low Pass filter almost all the magnetometer-derived yaw, so the complementary filter remains very close to the magnetometer-derived yaw.

The below figure shows the yaw obtained from the IMU and the complimentary filter Yaw. Here we can see’s an improvement over the original data as our magnetometer data was free of noise and the gyro data was mainly free of bias. the complimentary filter stars from zero and propagates where IMU yaw angle is offset by nearly 0.1 radians and follows nearly identical path as the complementary filter. To plot the graph below a cutoff frequency of 0.1 Hz was used in the Low pass filter and no high pass filter was used. Using the complementary filter where a weightage of 0.2 for magnetometer yaw reading and 0.8 weightage for gyro yaw angles reading as the gyro yaw angles look more stable and has less drift.

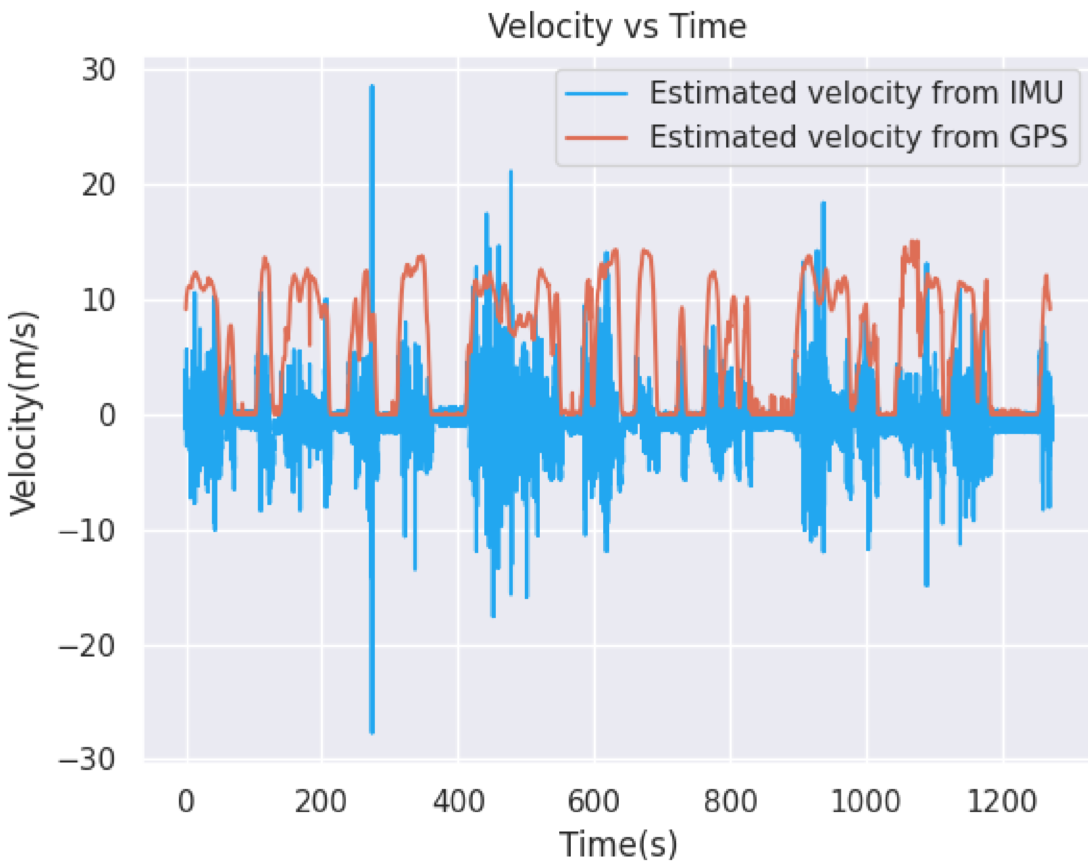
The measurements from the gyroscope, accelerometer, and magnetometer are combined to provide an estimate of a system's orientation, often using a Kalman filter. This estimation technique uses these raw measurements to derive an optimized estimate of the attitude, given the assumptions outlined for each individual sensor. The Kalman filter estimates the gyro bias, or drift error of the gyroscope, in addition to the attitude. The gyro bias can then be used to compensate the raw gyroscope measurements and aid in preventing the drift of the gyroscope over time. By combining the data from each of these sensors into a Kalman filter, a drift-free, high-rate orientation solution for the system can be obtained.



The yaw from magenetometer can’t be trusted if there is high magnetic field. You cannot use a magnetometer because there is a large amount of magnetic interference on the vehicle.

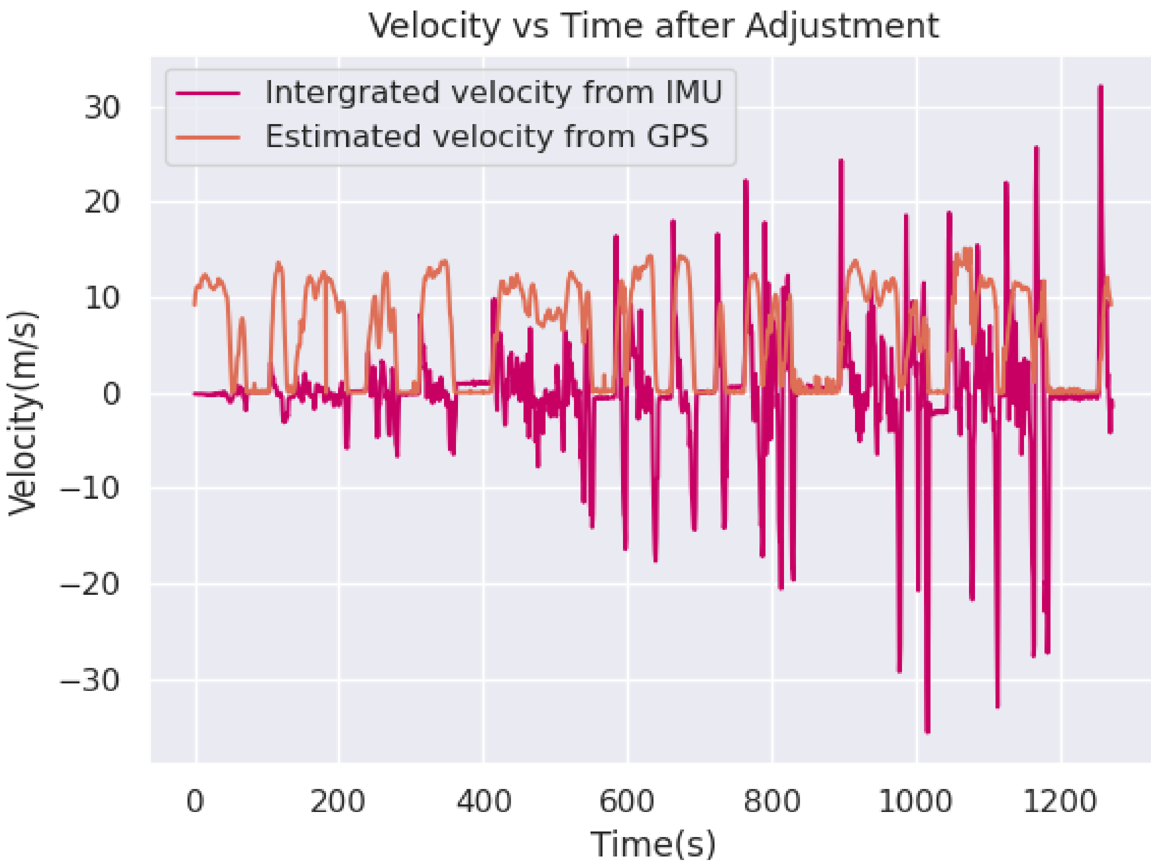
Estimate The Forward Velocity

Velocity was estimated both by integrating forward linear acceleration and by finding the instantaneous velocity of each point of GPS data. Both graphs are similar in form, but the IMU/accelerometer-derived velocity tends to drift over time, suggesting a bias. There are also higher peaks for the estimated velocity from IMU.

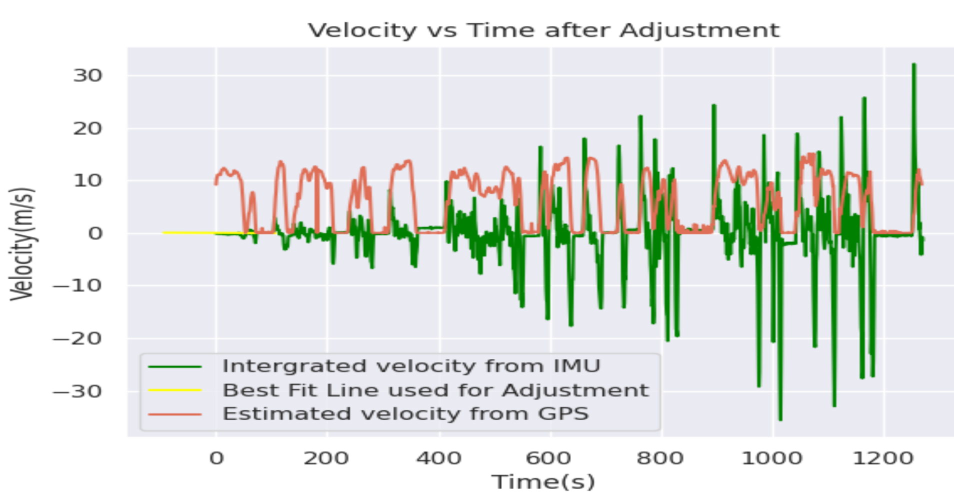


The main change made here was subtracting the mean from the integrated acceleration. This is necessary because bias in the accelerometer data causes a non-zero velocity during integration. We know this is noise / bias because we know when the car is stopped the acceleration should be 0. The error could be due to deacceleration data from imu which converts velocity to negative.

The below table shows the velocity vs time graph after adjustment. There are less peaks here from the IMU as the bias is removed.



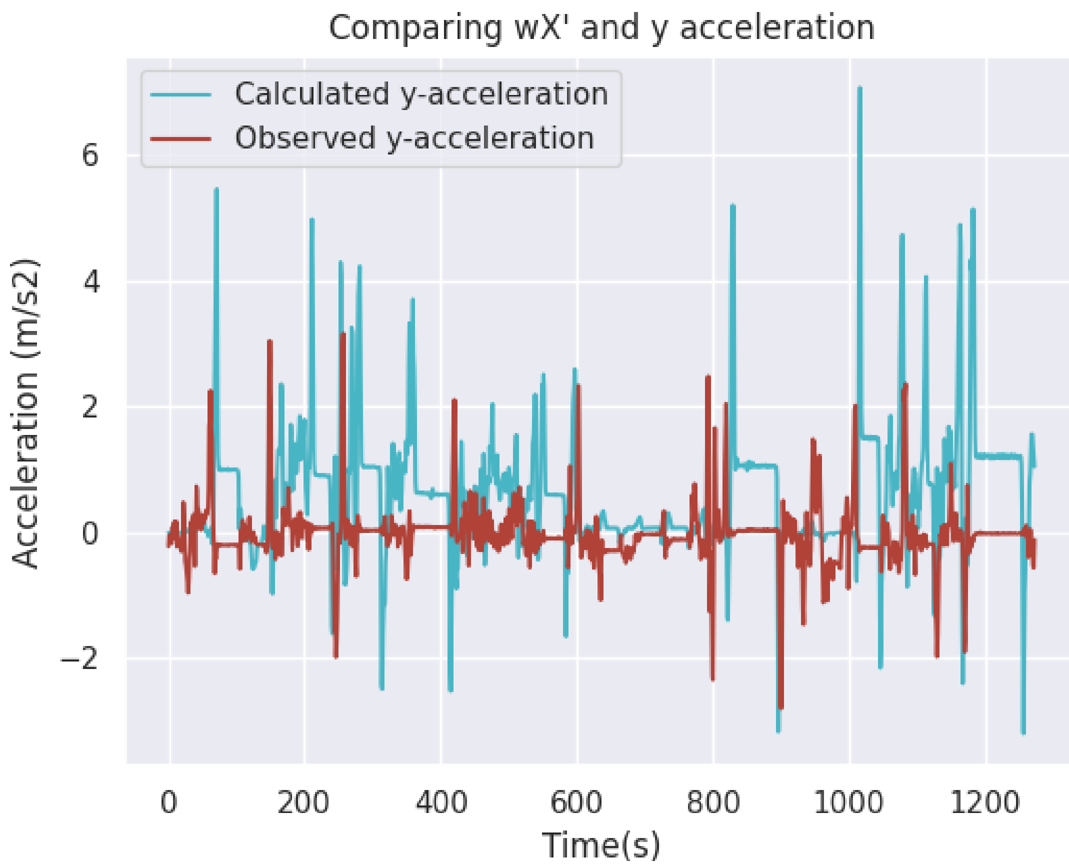
Another method used here can be the best fit line method. The resulting acceleration was corrected using the Line of Best Fit method and then plotted. We can see that it provides a similar result to the graph.



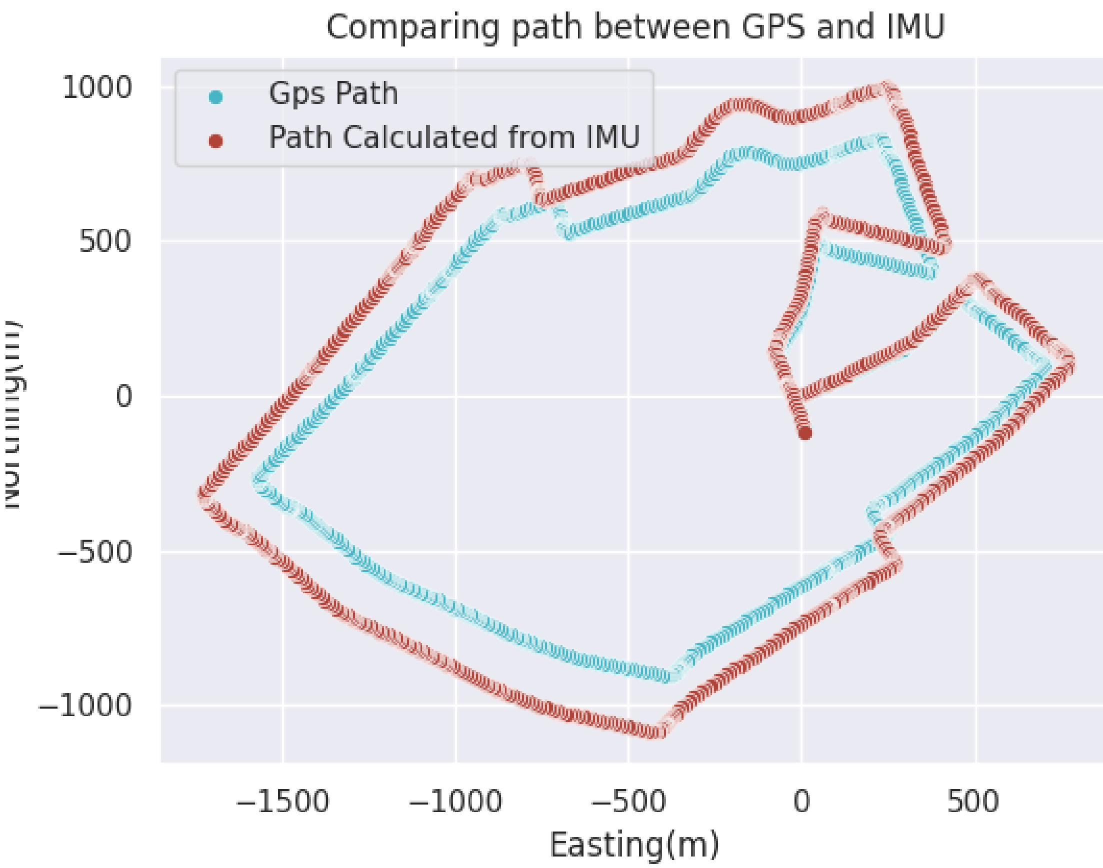
IMU is an electrical device, which can be used to measure angular velocity and acceleration. It combines the sensors of accelerometers, gyroscopes, and magnetometers into one sensor. The accelerometer gives acceleration as a parameter and with time derivative can also be used to give parameters such as velocity and distance. The gyroscope gives the orientation and angular velocity of the sensor. There is discrepancy between the data. The discrepancy is because of the gyro offset.

The discrepancies between the data is mainly due to the motion of the vehicle the magnetometer is much more accurate sensor so it can record values at much close intervals than a GPS. The motion of the vehicle will lead it to connect to multiple satellites at a time and due to presence of building it can lose connection leading to missing values.

<u>Dead Reckoning with IMU</u>



The larges spike are due to turn on the road and can be seen in gps plot. The two graphs coincide, but the magnitude of the two differ. The calculated y-axis acceleration is mostly flat at the beginning, but the peaks increase in magnitude later in the dataset. This appears to a result of gradually increasing bias. The observed and computed acceleration plots looks offset from each other, but the variation of the acceleration is same with offset The observed y acceleration and computed y acceleration are in offset which suggest there may be a bias at the start of the data in IMU. The issue could be due to ignoring offset of the car X_c.



It is seen clear from above graph as time goes on our estimate gets more and more off. We can also see that the starting and ending point of both the plots are the same. Even though the plots look similar there is significant difference between the scale of the plots. This could be due to filter passed and errors in the acceleration due to bias. This indicates that the bias-correction method used is less than ideal. The problems associated with the dead-reckoning method showcase its drawbacks. No scaling was used here but if proper dimension scaling is done the plots could look strikingly similar.

As we can see from the graph the positions of the IMU and Gps matches only in the beginning and the ending. If there is uniform acceleration and deceleration the values of the co-ordinates are matching because during the rest of the ride there is almost zero acceleration or inconsistency in acceleration so we are not getting a fixed position. The performance of the dead reckoning did not meet with actual measurements but we can get a close enough value. The external factors are taken into account here. The errors from the sensors, the traffic,etc.

Finding Xc

An estimate of the angle of rotation of the sensor around the car center of mass can be made by manipulating the equation $v = V + \omega \times r$. Since we can assume that $\omega = (0,0,\omega)$ and $r = (x_c,0,0)$, the equation can be simplified to $v = V + \omega * x_c$.

By simplifying the above equation we get $(v-V)/ \omega$ where V stands for actual linear velocity, v stands for measured linear velocity, and ω is yaw rate measure at the z axis. We can get Xc for every observation of data and taking the mean of all the data can we give us an estimated value.