Analysis Report for LAB-2

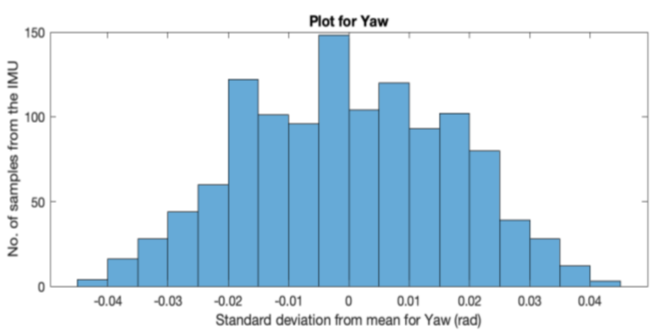
EECE5554: Robot Sensing and Navigation

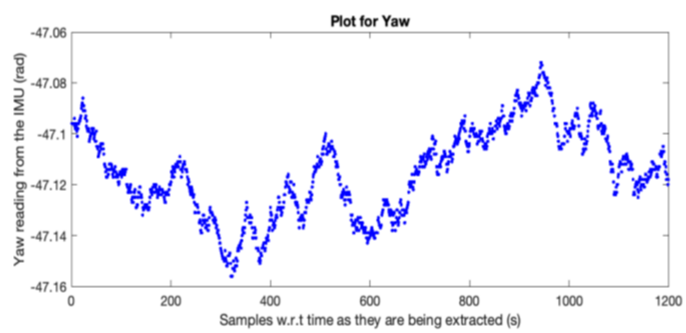
Topic Name: Navigation with IMU and Magnetometer

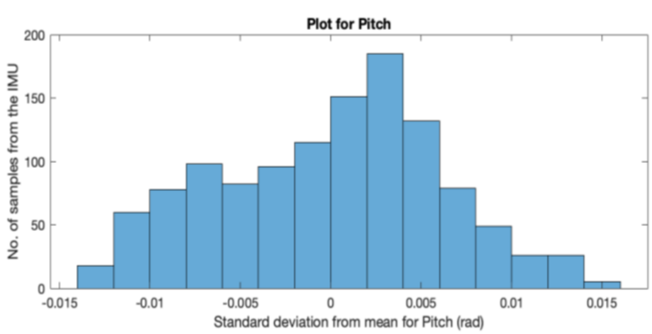
1. Analysis of Stationary IMU Data:

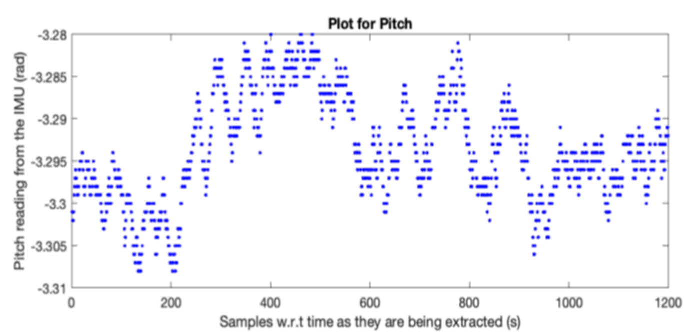
Data was collected by writing a device driver for IMU which would read in the input data using a serial emulator and use that to parse the required components. Reading for Yaw, Pitch and Roll were converted to Quaternions and were published to a predefined IMU message along with data for Angular Velocity and Linear Acceleration in all the 3 axis X Y Z.

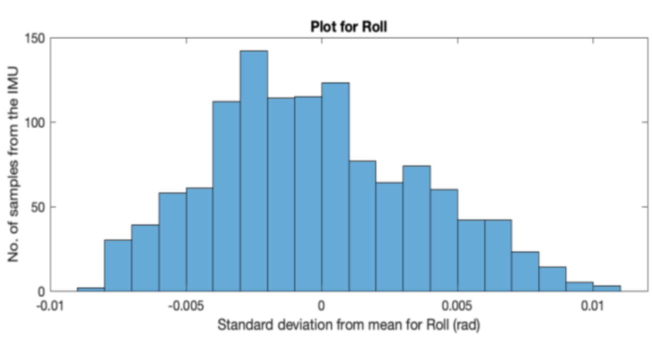
a. Time series plots for the Yaw, Pitch and Roll from the IMU:

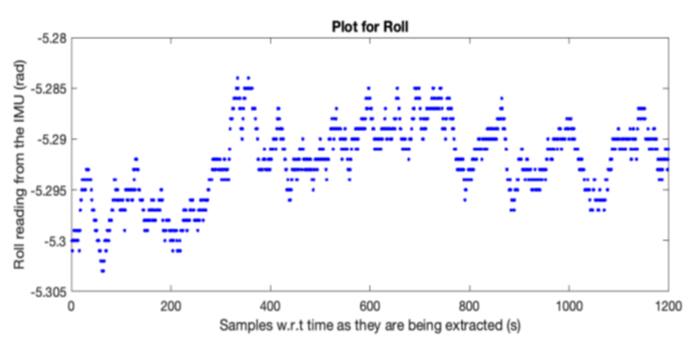








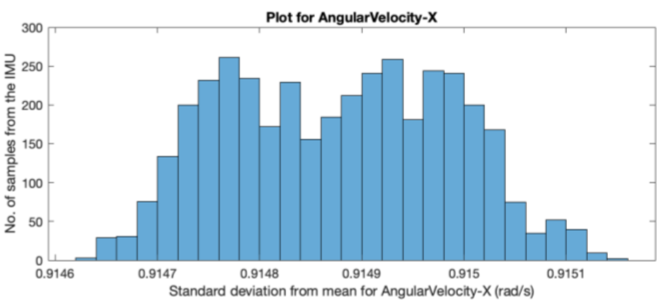


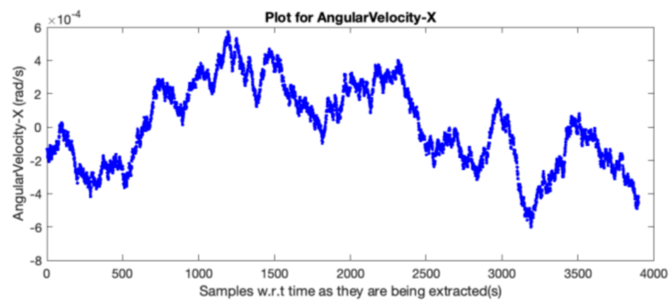


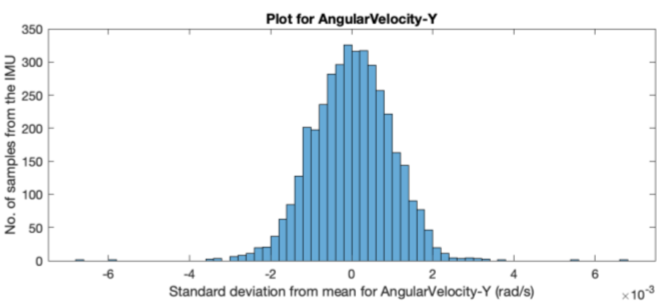
The distribution for the Yaw, Pitch and Roll is comparable to a Gaussian distribution. The output readings are pretty streamlined which shows that there is little deviation when the sensor is kept stationary at one location.

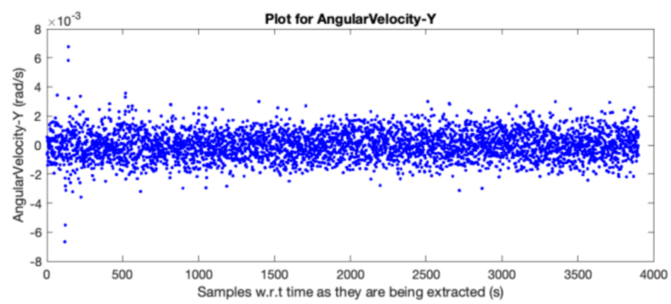
Mean Yaw: -47.11510222 radians
Mean Pitch: -3.293839144 radians
Mean Roll: -5.292108558 radians

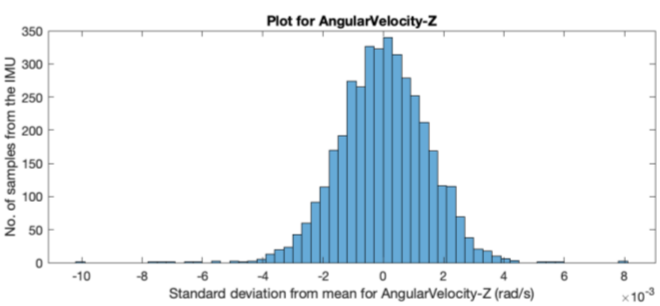
b. Time series plots for Angular Velocity from the IMU:

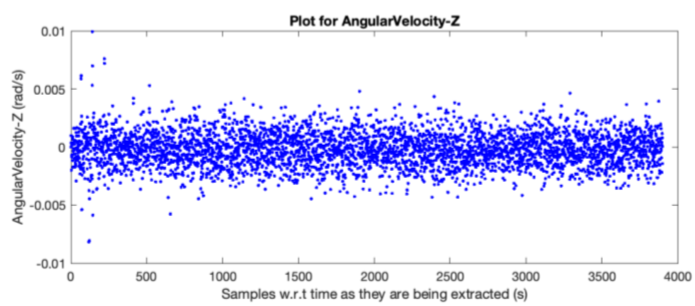








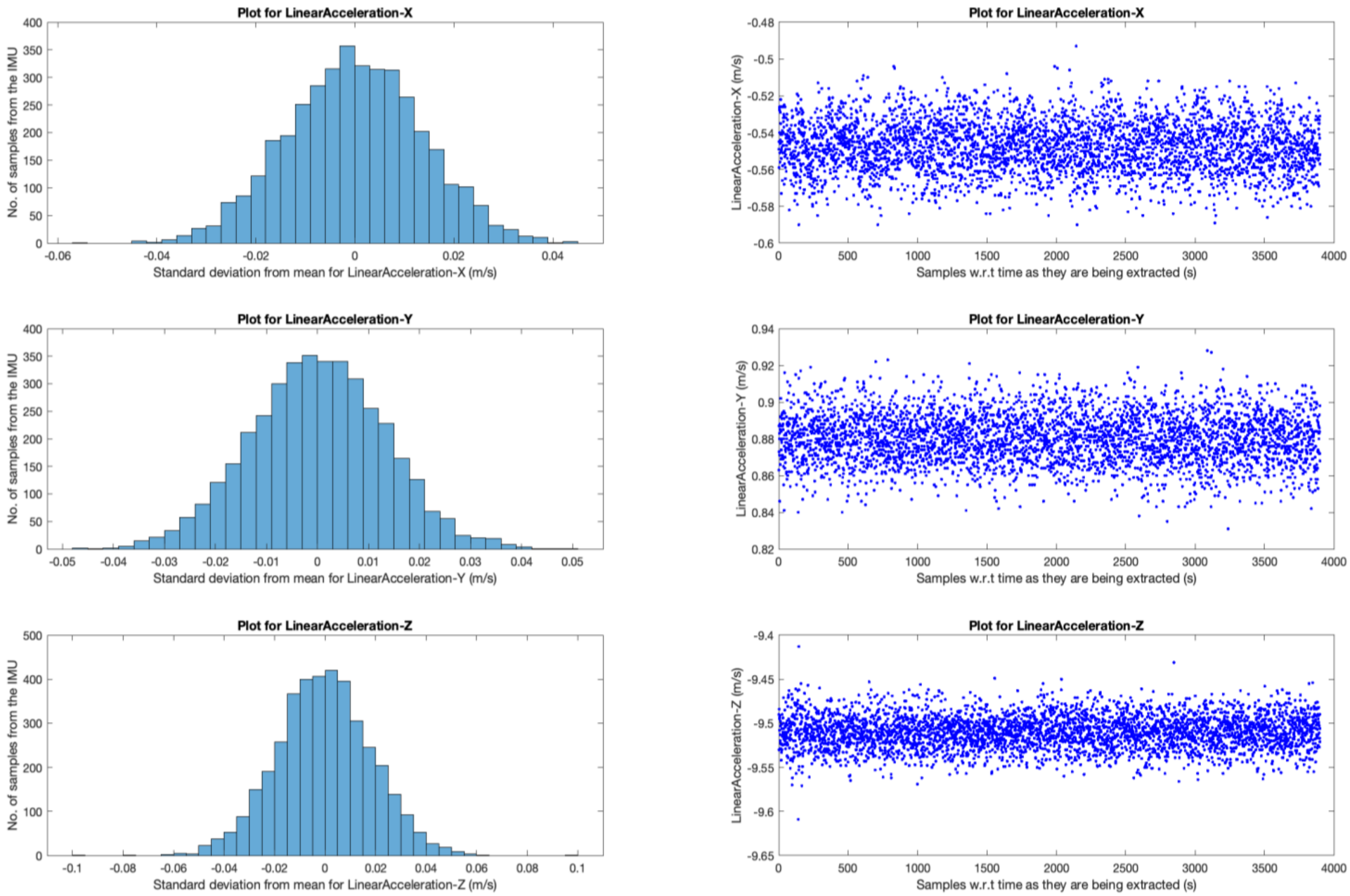




The plots for three axes of accelerators are comparable to a Gaussian distribution. The noise distribution can therefore be attributed as gaussian. It was observed that for the X orientation the noise was spread more vastly and kind off bimodal in nature which might be as a result of some improper placement or disturbance caused in X direction.

Mean Angular Velocity X: 0.000011011 radians/seconds
Mean Angular Velocity Y: -0.000165 radians/seconds
Mean Angular Velocity Z: -0.000165 radians/seconds

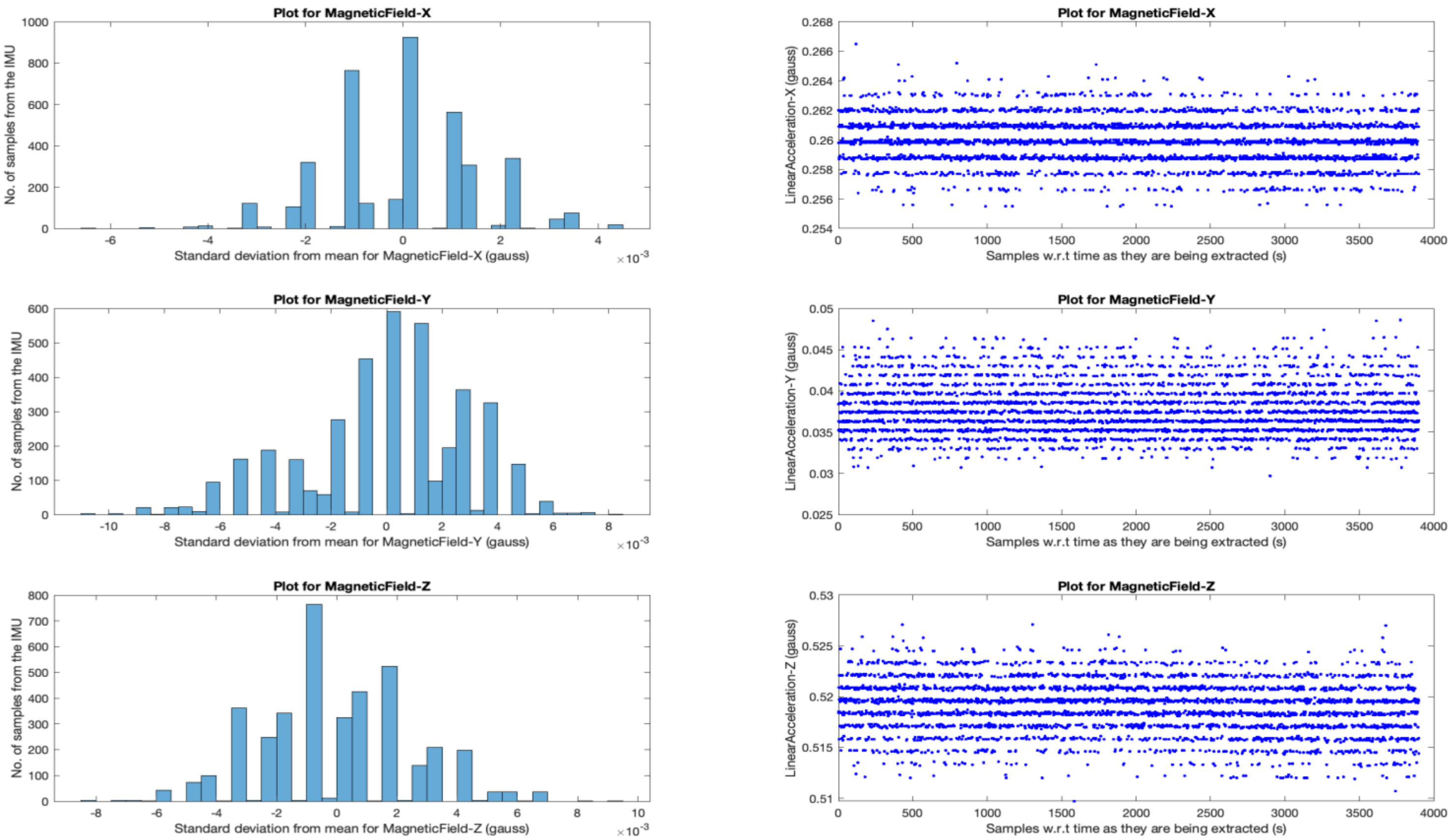
c. Time series plots for Linear Acceleration from the IMU:



The plots for all the three axes for Linear acceleration are also comparable to the ones found for the Angular Velocity. The noise distribution here can also be therefore attributed as gaussian. It was observed that for the Z orientation the noise was spread very minutely as contrast to that of X and Y orientation which are also pretty small with little variation.

Mean Linear Acceleration X: -0.547487512 m/s
Mean Linear Acceleration Y: 0.880382867 m/s
Mean Linear Acceleration Z: -9.510073177 m/s

d. Time series Magnetic Fields from the Magnetometer:

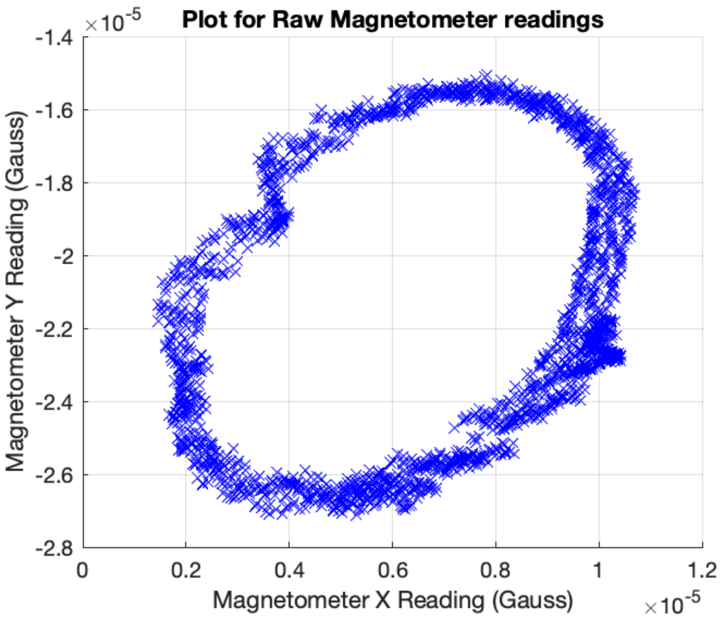


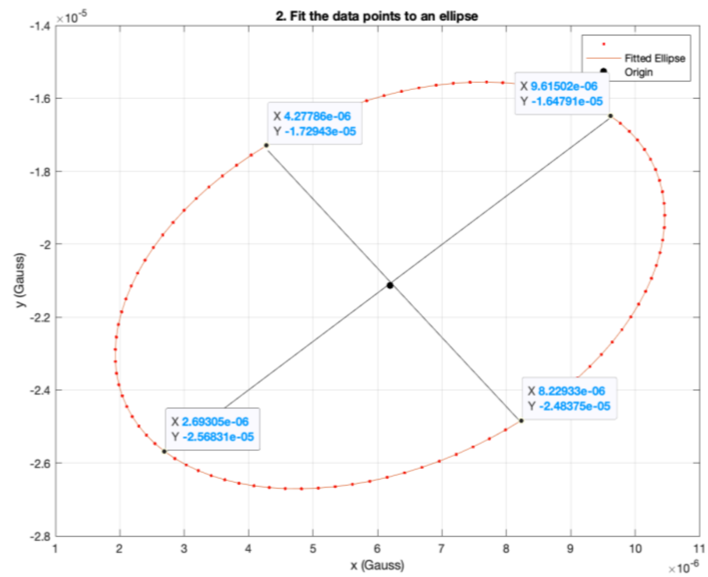
Although not a good way to interpret data for the stationary magnetometer data. The above figure is for the plots shown for Magnetic field in each direction. The deviation is because of presence of soft and hard iron effects that comes into account. These keep on changing continuously and hence the noise and variation in the plots.

2. The Analysis of Moving Data:

The task here was to drive the car around the university to follow some trajectory. The initial starting point and the final stopping point were required to be the same so as to create a closed loop of the path trajectory. The entire data set is for around 83000 readings for an approximate ride time of 34 minutes.

a. Estimate the heading (YAW ANGLE):

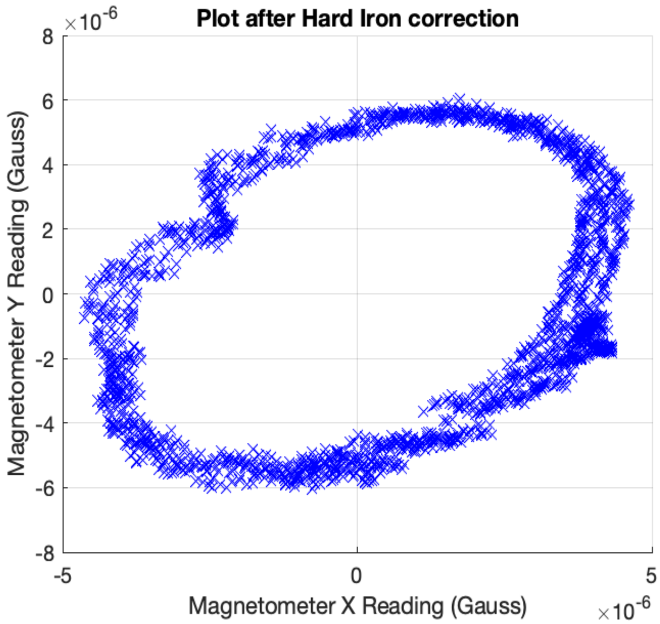




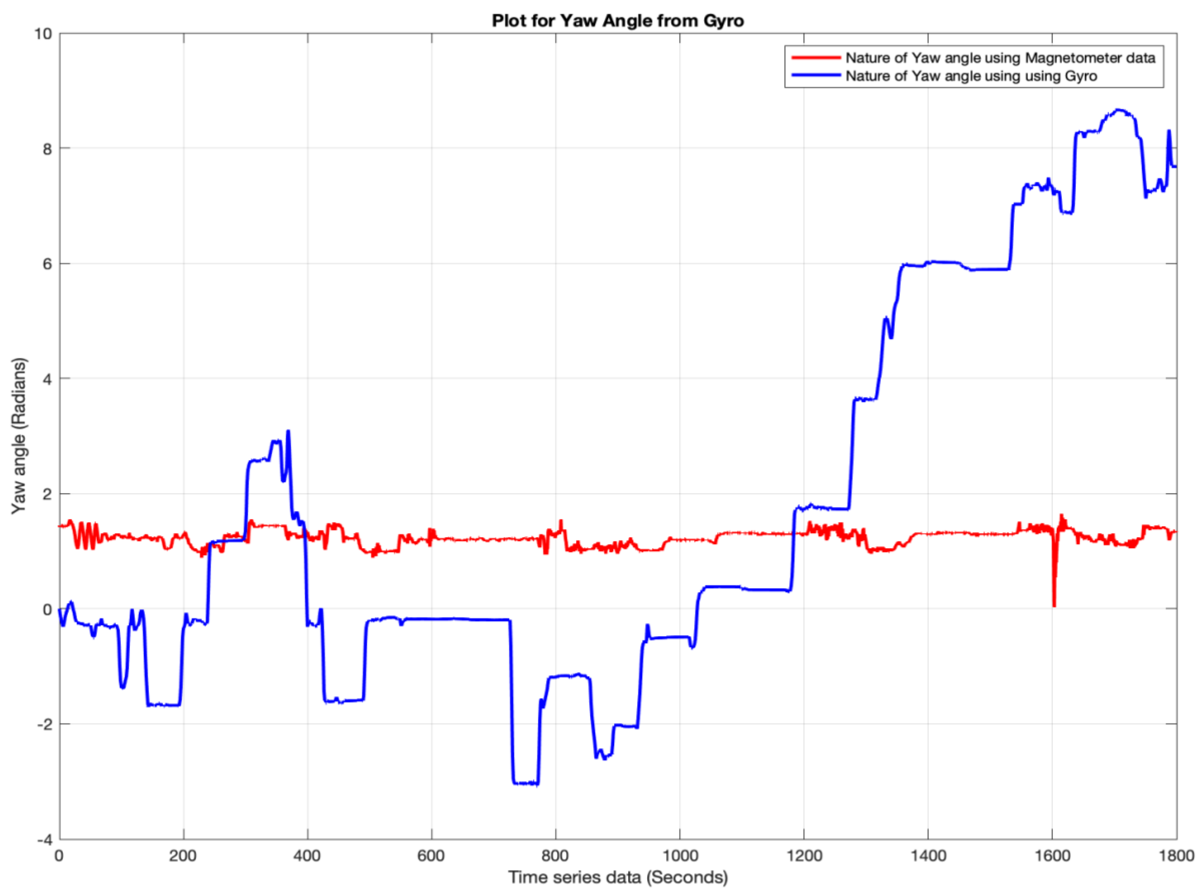
The figure on the left shows the plot for the Magnetometer X vs Magnetometer Y. This is done using the raw data collected directly from the IMU sensor. This are obtained using the data for the driving time in circles. The start point was 1075 and the end point was 3175. It can be seen that the origin is shifted from (0,0) and the orientation also looks a little rotated. This is because of the fact that Hard Iron and Soft Iron effects come in action. So, the next task is to remove the hard iron and soft iron effects and plot the new variations.

The Hard Iron effects were corrected by subtracting the offsets obtained using the minimum and maximum values of each Magnetic field from its original value. After using the new obtained mag_x and mag_y we get the plot as shown on the left in the below figure.

For correcting the Soft Iron effects the points (x1, y1) and (x2, y2) on the respective major and minor axis were taken as derived from the ellipse plotted in the figure next to raw plot. Using these major and minor axes and the rotation matrix we find the new values of mag_x and mag_y and use them to plot the new graph which is shown in the figure on the right in the below figure.

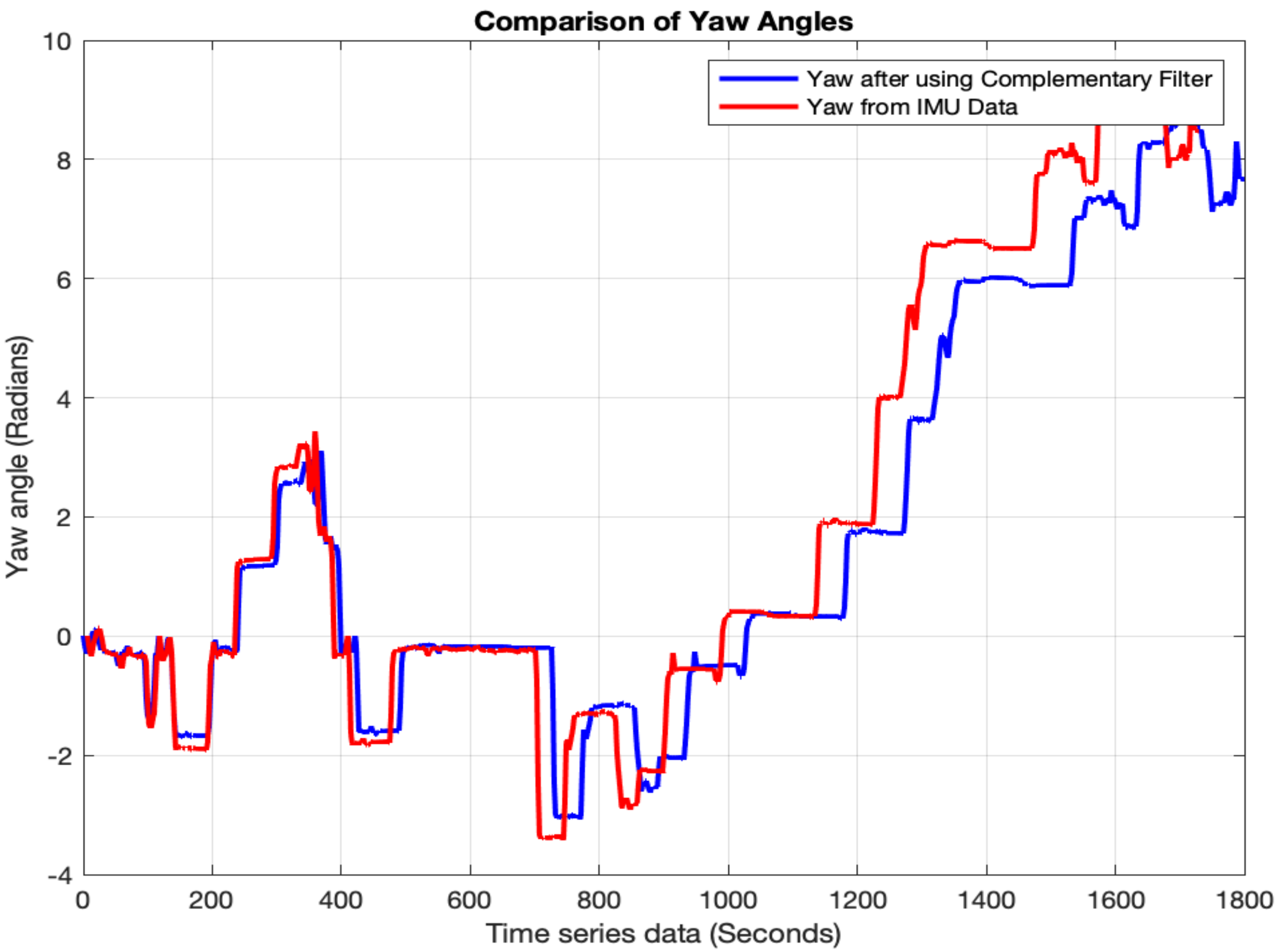


Now the next task is to estimate the heading i.e., the Yaw Angle from the new obtained values of mag_x and mag_y.



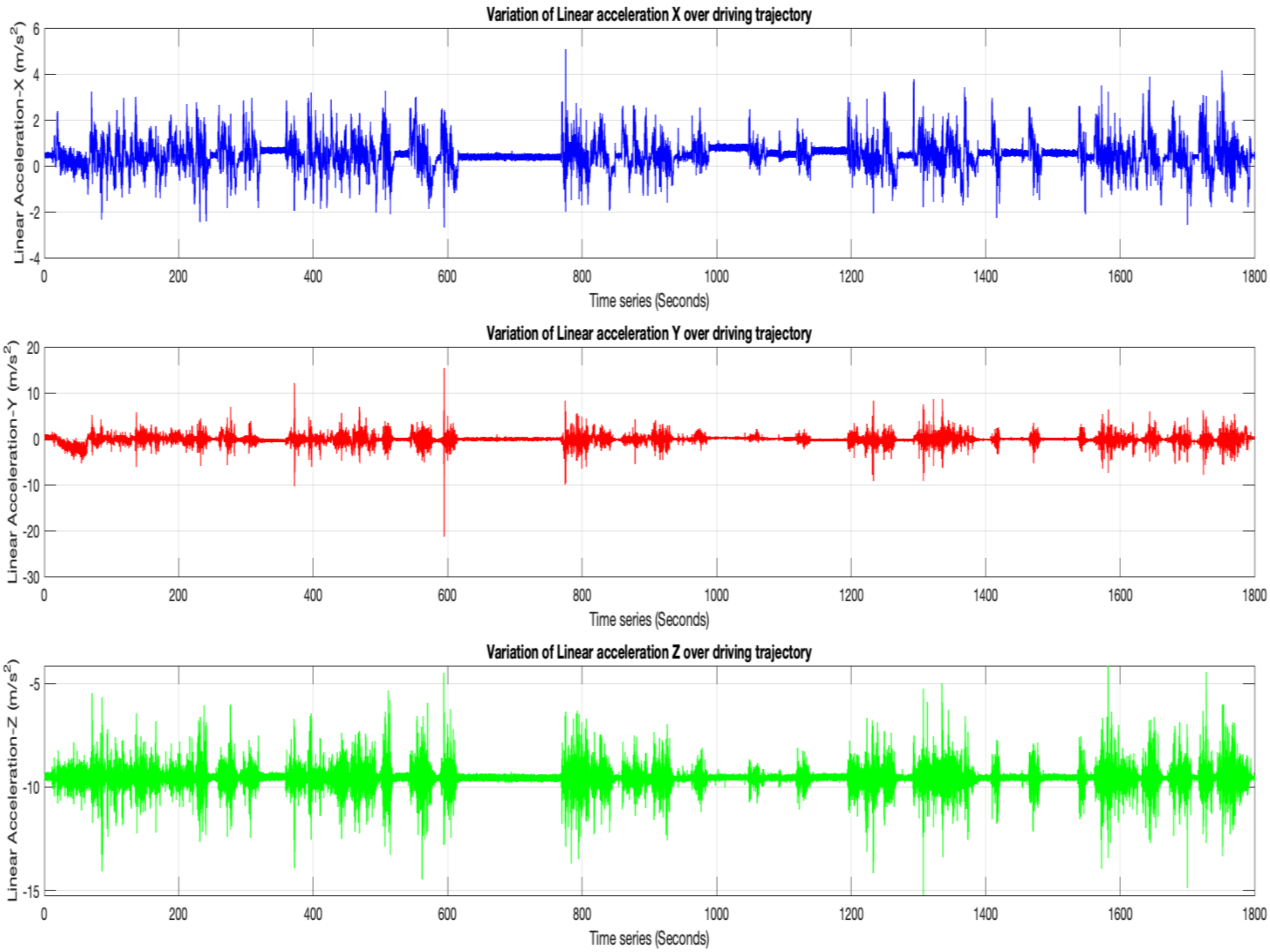
The above plot shows the Yaw Angle obtained by integrating the magnetometer values and the yaw angle from Gyro. When we zoom into the yaw angle obtained from magnetometer it is seen that there is a huge amount of noise present in the plot. This is mainly because of the noise from the sensor and the bias that gradually adds up. Some other reason for large noise could also have been because of the variations during the driving time. There could have also been additional reasons that might have interfered with the sensors and added errors in the data collection.

Next, we design a complimentary filter in which we use a low pass filter to estimate the magnetometer data and we use a high pass filter to estimate the gyro values. This will clear out the noise and be considerably in good shape with the actual Yaw Angle that we obtain directly from the IMU. This is shown in the figure below.



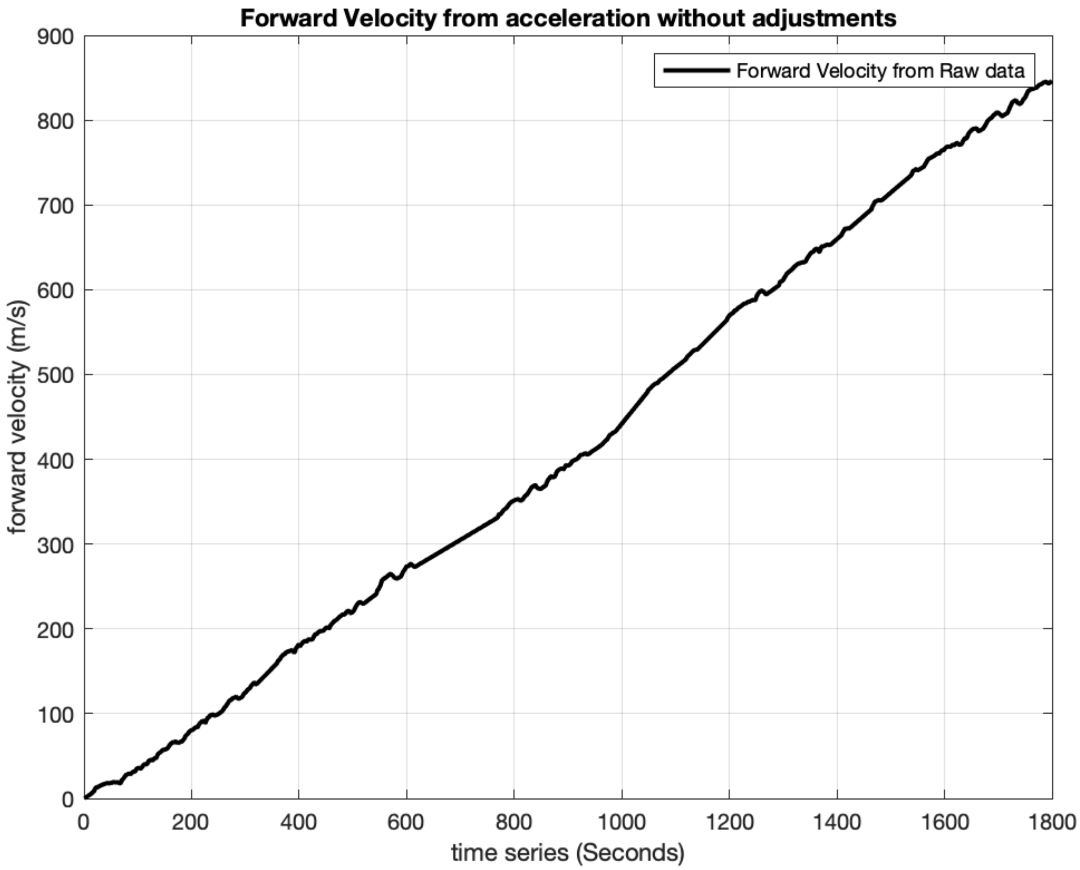
b. Estimate the forward velocity:

The plots for linear acceleration in each of the X-Y-Z axis as a time series are as shown below.



The above shown plots helps us understand the motion of the car to some extent. It tells us the various stops position where the acceleration comes to a halt. As we plot the graphs for velocity from GPS and the gyro, we will see that the same nature is reflected and the position where the acceleration is zero will also have the velocity to be equal to zero.

The aim here is to find the forward velocity which can be obtained when we integrate the acceleration we get from the gyro. The plot after we do this is as shown below.

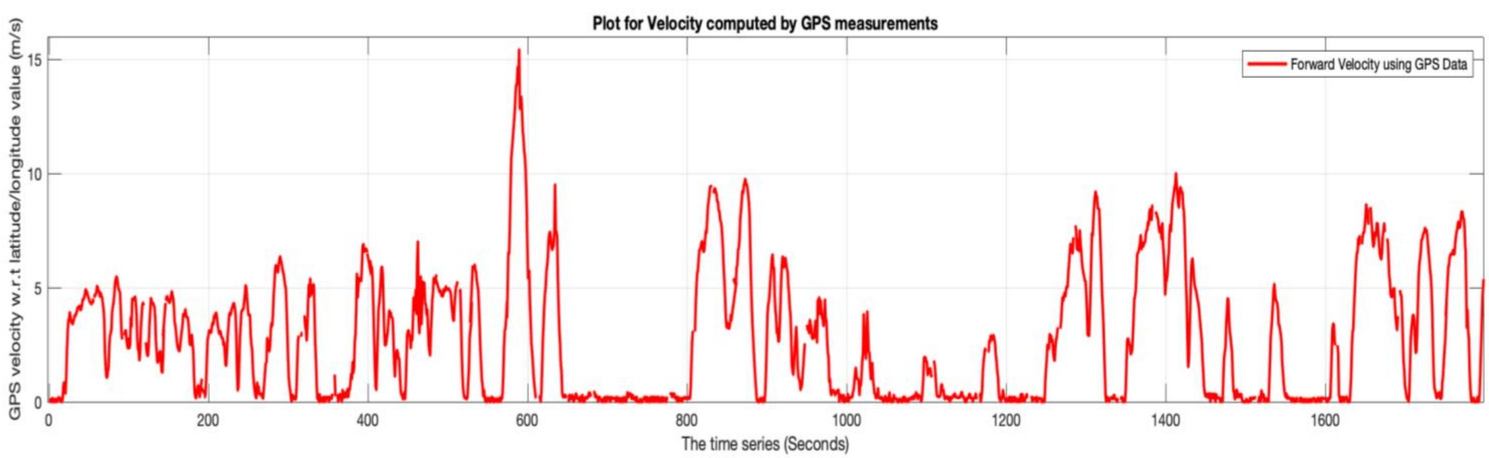


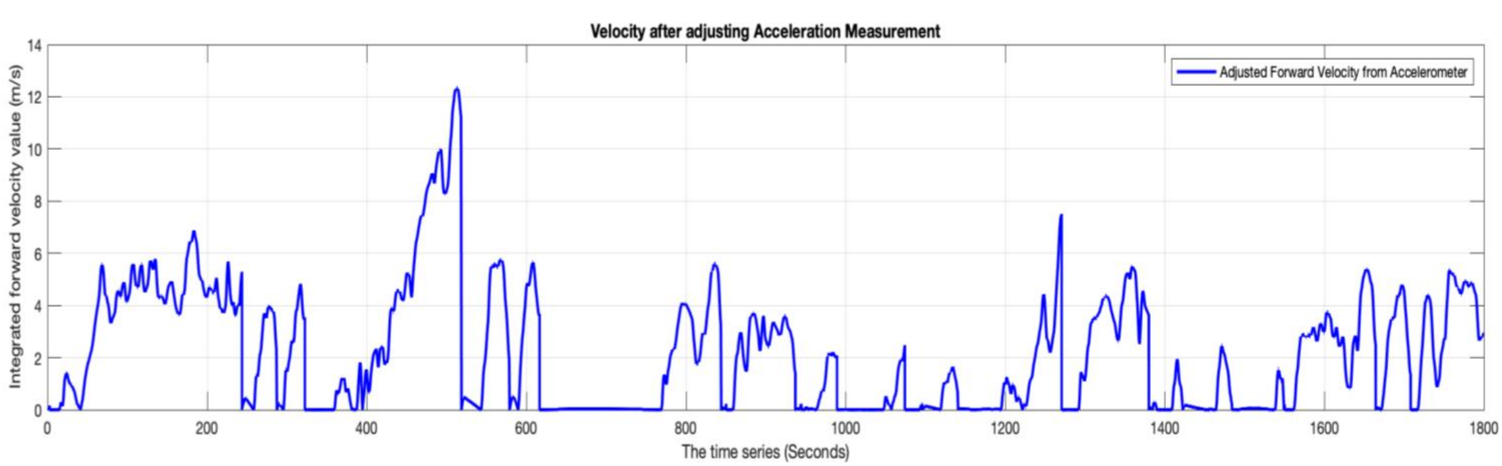
The plot obtained above after integrating the acceleration seems to not make sense. This plot shows a continuous linear nature of increasing velocity which is not an ideal case as there are frequent starts and stops during the entire driving time. One possible reason why we get this kind of plot maybe because the bias and noise from the sensor keeps on adding at each point again and again. This graph is wrong as it is not possible for a car to achieve speeds this high like 500 m/s and beyond.

This velocity obtained by integrating the acceleration from the gyro does not make sense, so we need to make some adjustments to the values in order to obtain a fair value of velocity that makes sense with the real-world scenario. To do this we need to subtract the bias that the sensor has. This can be done by subtracting the mean value of acceleration for the position where the car was at stop or not in motion. This is just the first basic thing that can be done to check it that made a difference to the drift and noise. It was seen that we get a positive feedback about this, so the next step now is to iterate this same thing over the entire course of driving.

Now this is where we can use the raw acceleration plot to interpret the data and find out the points where the car seems to come to a halt. At this point both the acceleration and velocity should come to a zero level.

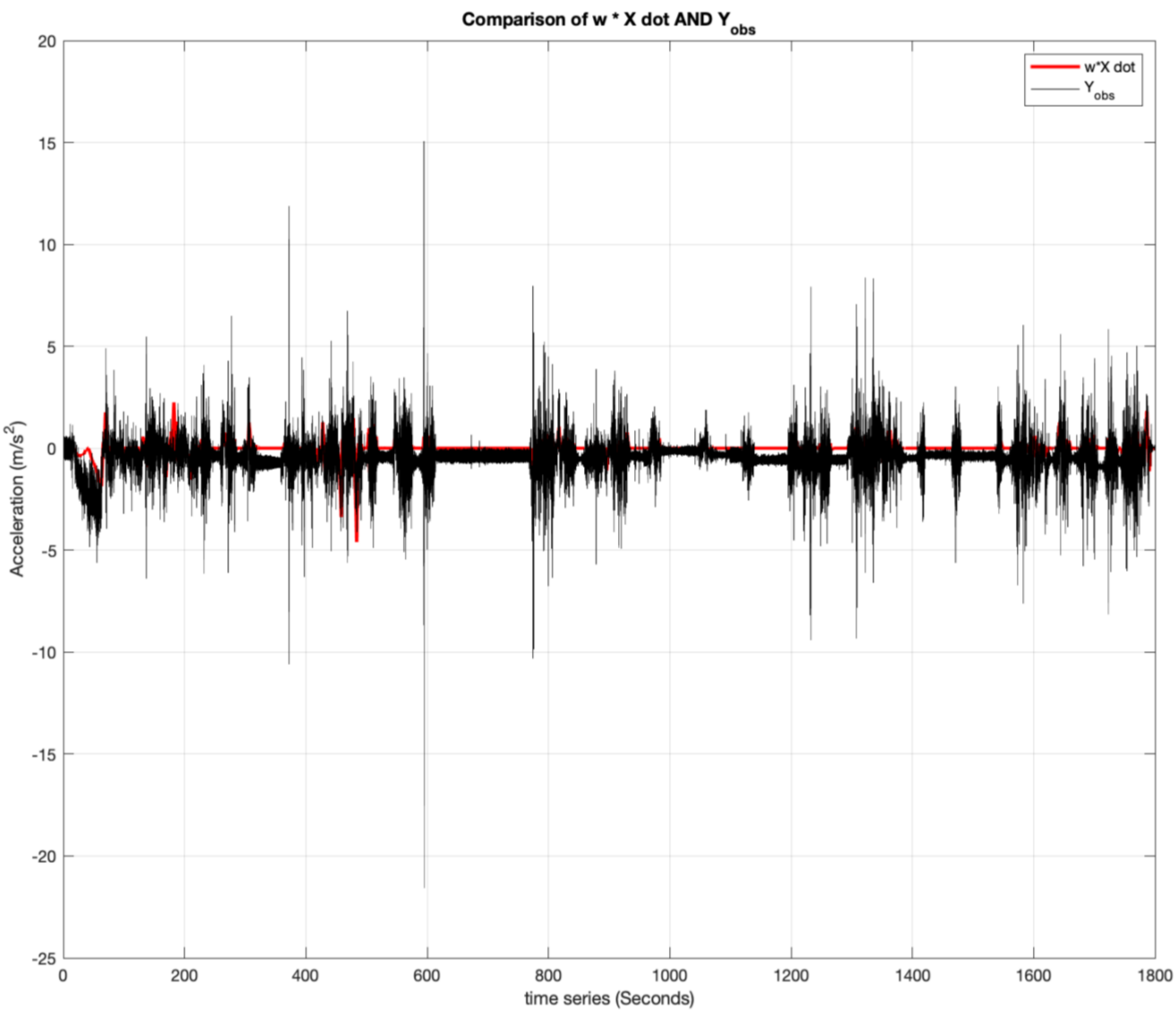
So, for our case the code implements a loop where it checks continuously to find a window where the acceleration seems to be changing and decreasing beyond a particular level for about 200 seconds. If this was the case, then the mean was calculated for all those instances and this mean was then subtracted for all the points that occurred after the constant value window. Finally, after doing this for the entire drive time the plot was then drafted which showed a huge improvement as compared to the one, we got for the raw acceleration data.



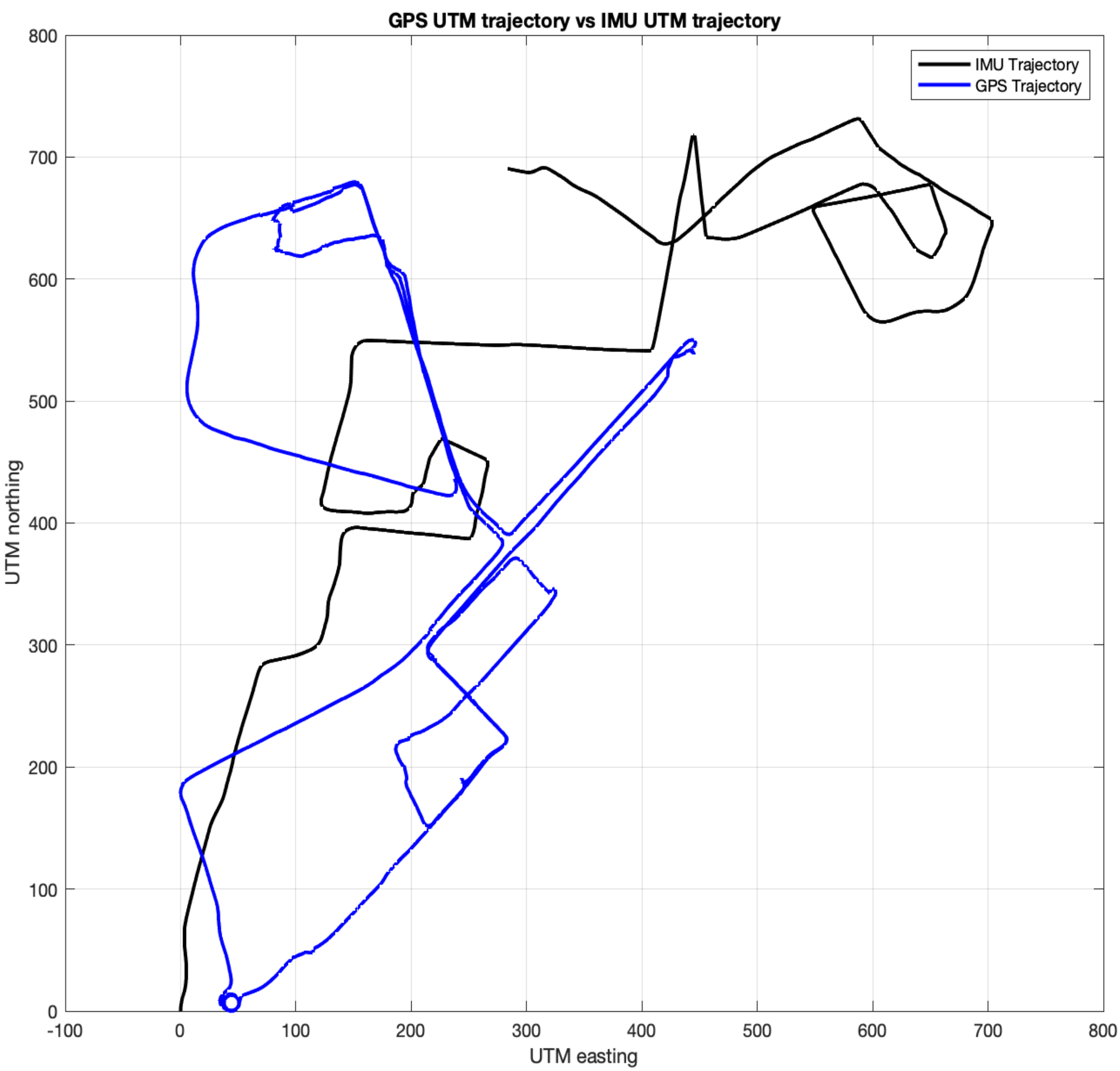


c. **Dead Reckoning with IMU:**

When the graphs were plotted for comparing the acceleration in the two cases it was seen that there was a slight difference when talking about the offset. It was noticed that at all the instances when the car came to rest or whenever there was hard braking it showed up as an offset and difference between the two. It was slowly increasing along the ride as it kept getting added. Another observation made was for the magnitude of both the outputs. There could have been a difference between the calculated value and the observed value because of the offset between Center of Mass of the car and the inertial sensor. The plots are as shown below.

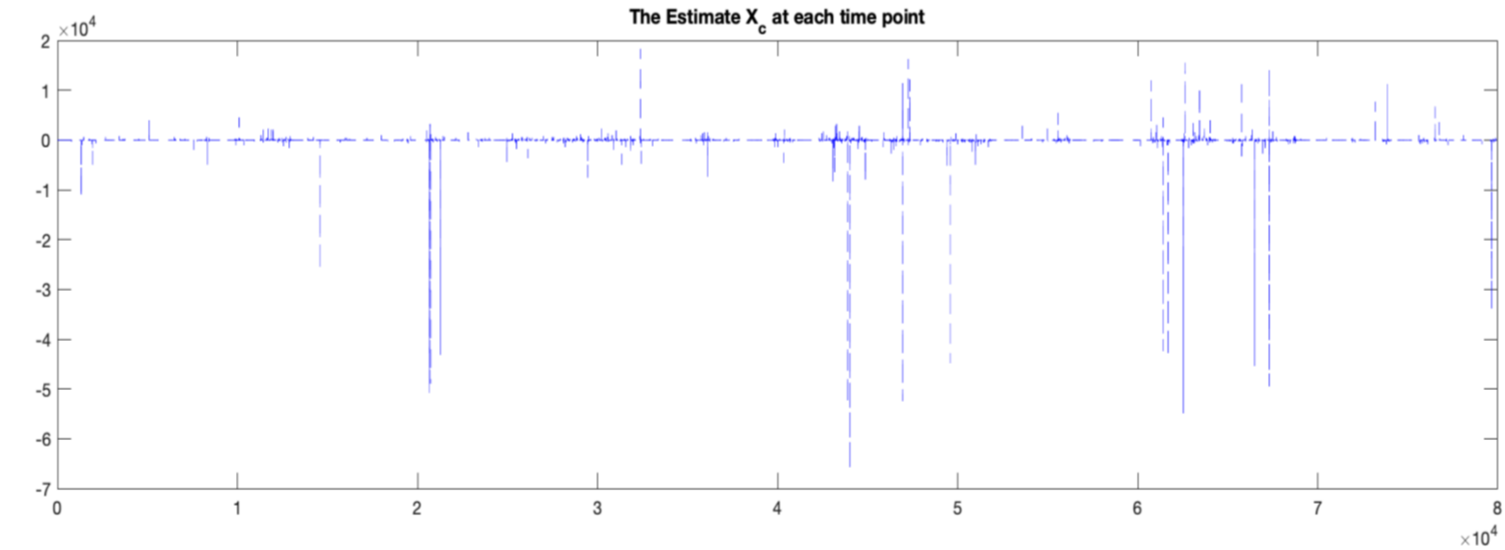


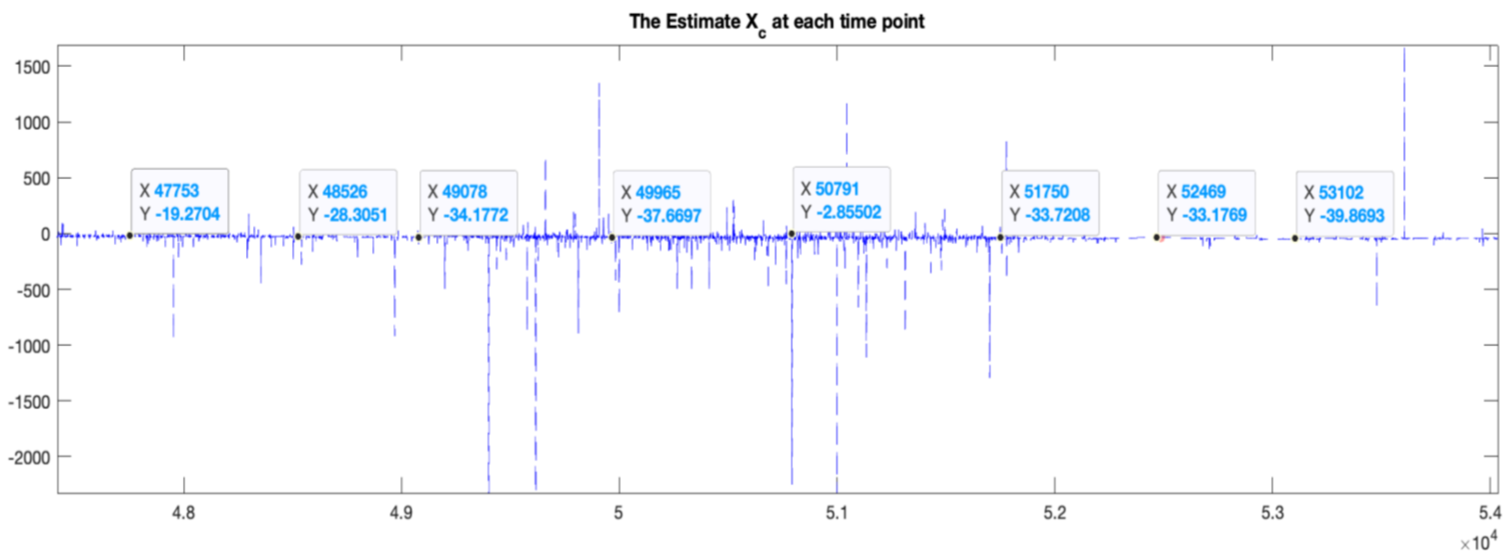
The next thing was to plot and compare the trajectories obtained using the UTM Easting and UTM Northing for the IMU and the GPS sensor. It was well observed that the trajectory obtained from GPS is way more accurate than one obtained from IMU. Because of the high number of loops present in our drive path and also given the complexity of the problem a plot was obtained which was considerably and lightly resembled that of the GPS. The loops and other straight paths could be seen. This data needs to be scaled and rotated to some extent in order to obtain a highly similar trajectory. Considering the complex driving path and the problems associated with them only a plot was obtained which is naive as compared to actual GPS trajectory.



d. Estimate X_C:

An attempt was made to estimate the position of the inertial sensor.

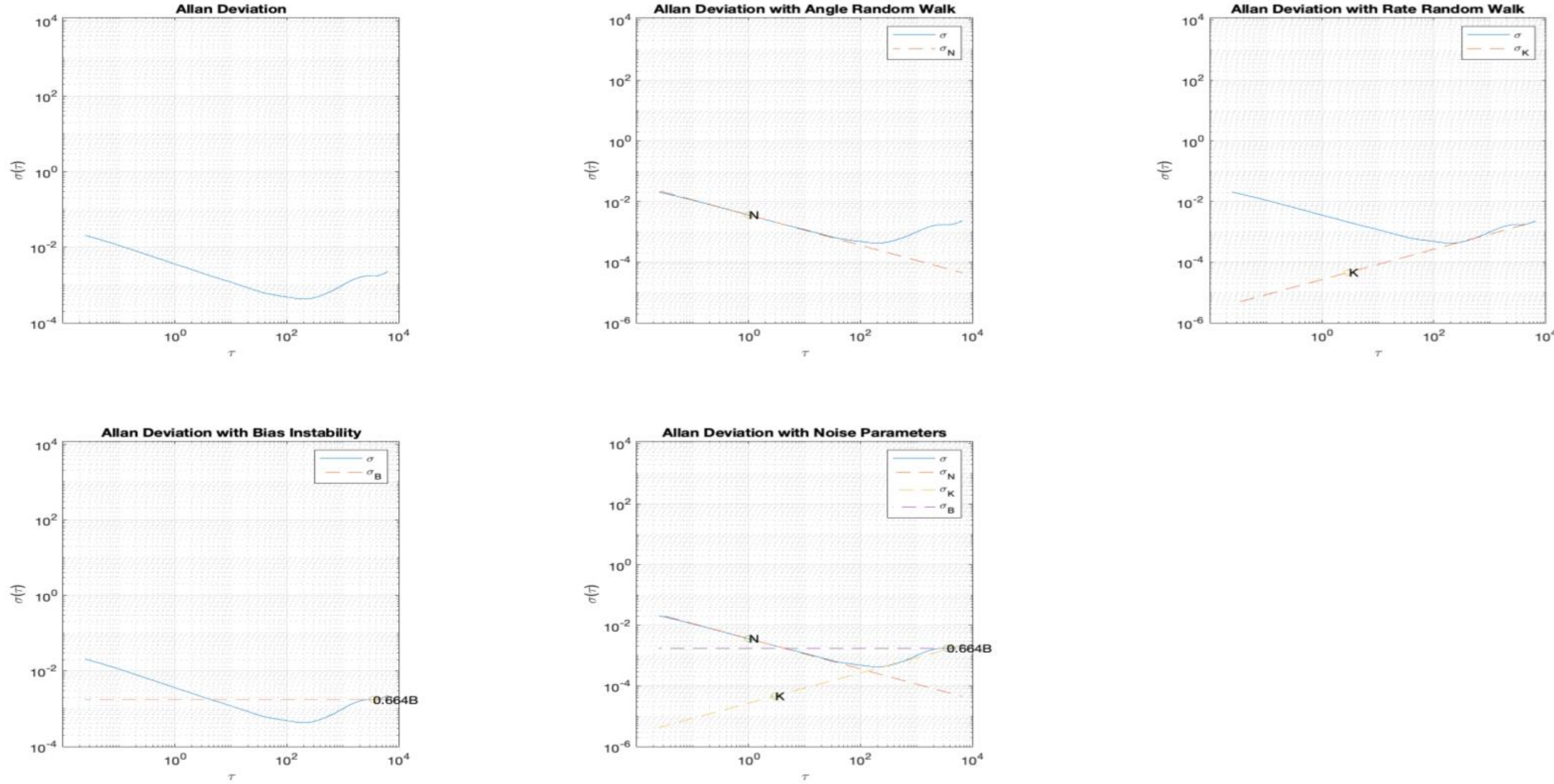




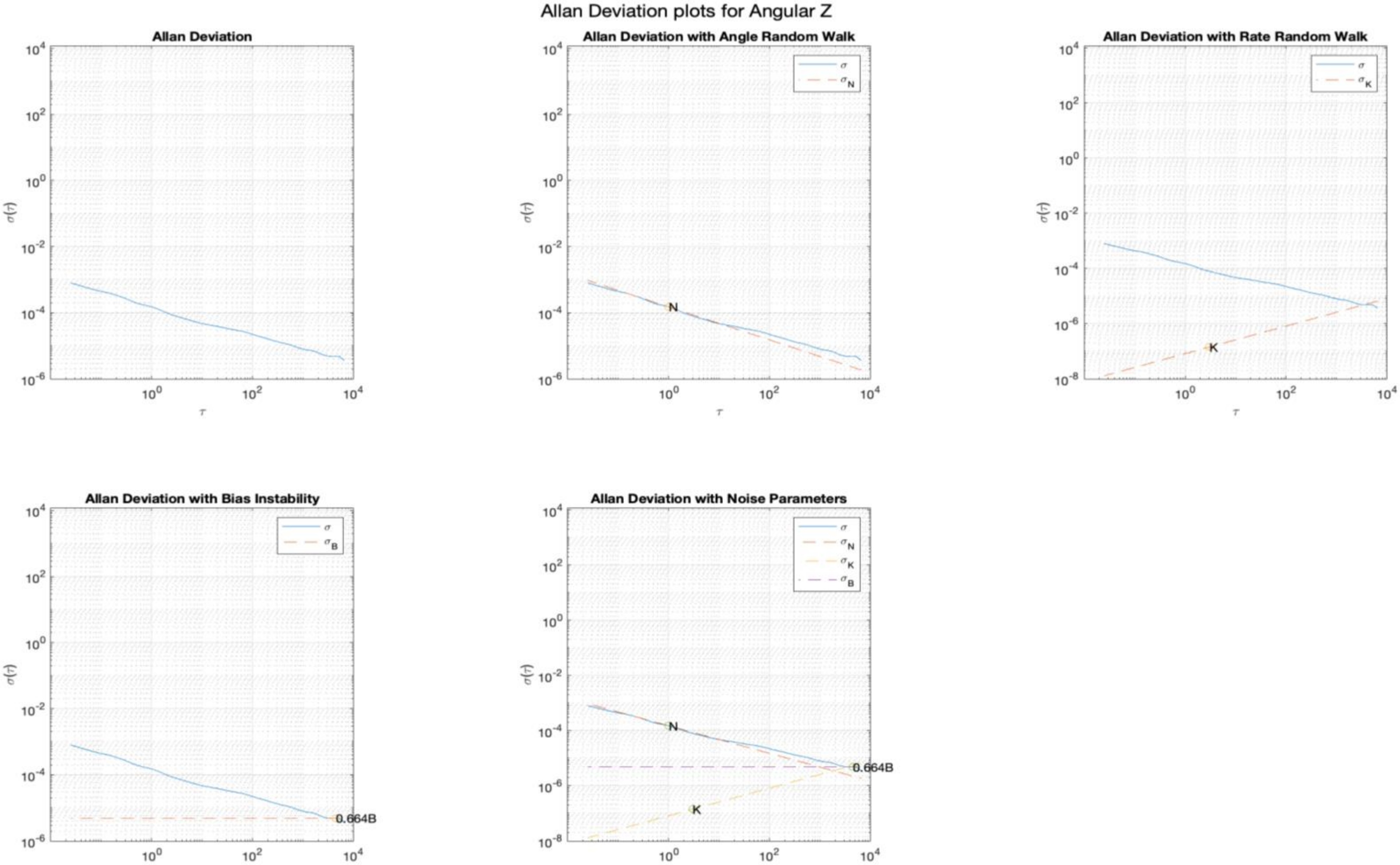
The above of the two plots the entire estimate of X_C for the entire range of the time whereas the one on the bottom shows an enlarged version of the same with the different data tips showing the position estimate.

3. Allan Deviation measurement and analysis:

Allan Deviation plots for Acceleration Z



Allan Deviation plots for Angular Z



The Allan deviation plots are as shown above. The first set of plots if the Allan variance in Acceleration Z axis and the other set is for Allan variance in Angular Z axis.

Allan variance is the method in which the analysis is done w.r.t a time domain. It describes the variance of a signal as a function of averaging time. There are a number of various Asymptomatic properties associated with Allan variance like the Angle Random walk, Rate random walk and the Bias instability.

When there are a number of samples, we can average them all, in this case the noise doesn't necessarily go down by the number of samples, it ideally goes down by the root of those number of samples.

The Angle random walk is a measure of drift due to the noise and the rate random walk is the walk in the bias vs the walk in its first derivative.

Very broadly speaking Allan variance us suitable to investigate the sensor error behavior on different timescales and parameters.