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EECE 5554
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IMU Report

Introduction

Inertial Measurement Units (IMU) are used in many present day technologies such as aircraft and spacecraft to help them maneuver. They contain accelerometers, magnetometers, and gyroscopes to calculate linear and angular acceleration, magnetic field, and orientation. Using this information, aircraft and spacecraft are able to make informed decisions about how to maneuver through the air or space.

Methods

The IMU was used to collect a time series data for 3 accelerometers, 3 angular rate gyros, 3- axis magnetometers. The data was collected for about 11 minutes. It was parsed through a ROS IMU driver and analyzed in Matlab.

Analysis

Part 1

The time series data for linear acceleration in the z axis, angular velocity in the x-axis, and orientation in roll is shown in figure 1. Each of these sets of data are similar in shape, however, orientation actually begins to drift a bit as time goes on. Each of these datasets are similar in shape to their counterparts in the other axes and are excluded for that reason. They are not similar in values. For example, accelerometer data in the z-axis is nearly -9.8 m/s^2 where its counterparts when taken the magnitude together are close to gravity. It is evident while looking at these graphs that the data is very noisy. There is not a lot of consistency among the values. The standard deviation for the accelerometer data was about 0.02 m/s^2 and the mean was -9.75 m/s^2.

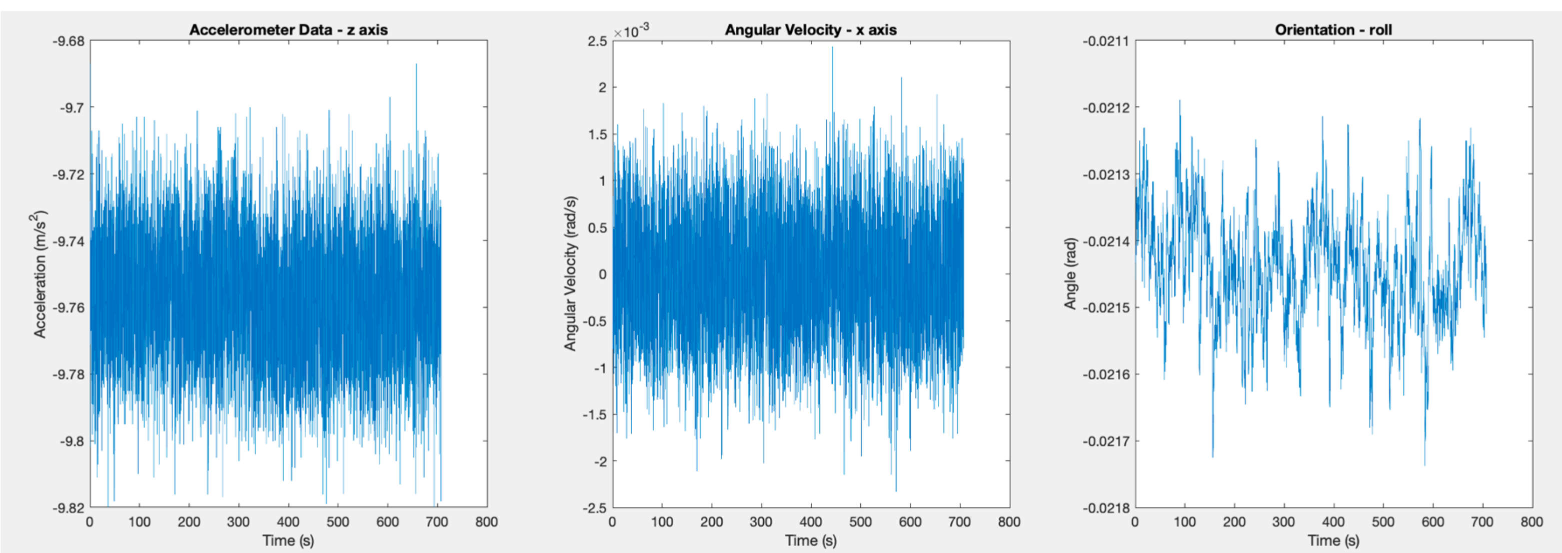

Figure 1: Time series data of z axis linear acceleration, x axis angular velocity, and orientation roll

Since the data was fairly similar across each axis, only the z axis error was calculated, by subtracting each point from the mean, and plotted in a histogram as shown in figure 2. At first glance the error in the plot looks Gaussian. Taking further examination of the data by comparing it to a normal distribution in figure 3, the error can be reasonably concluded to be normally distributed show gaussian noise in the sensor.

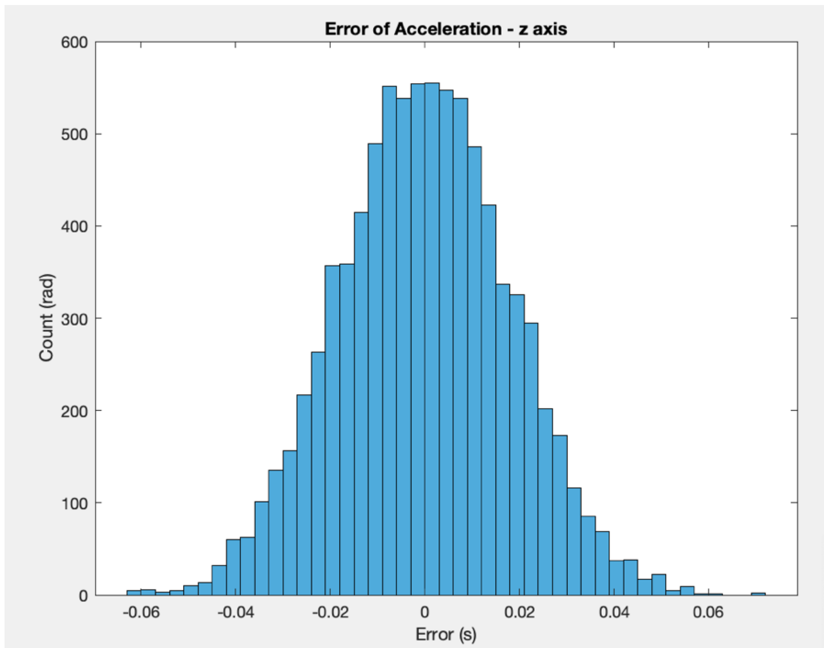

Figure 2: Histogram of error of z-axis linear acceleration

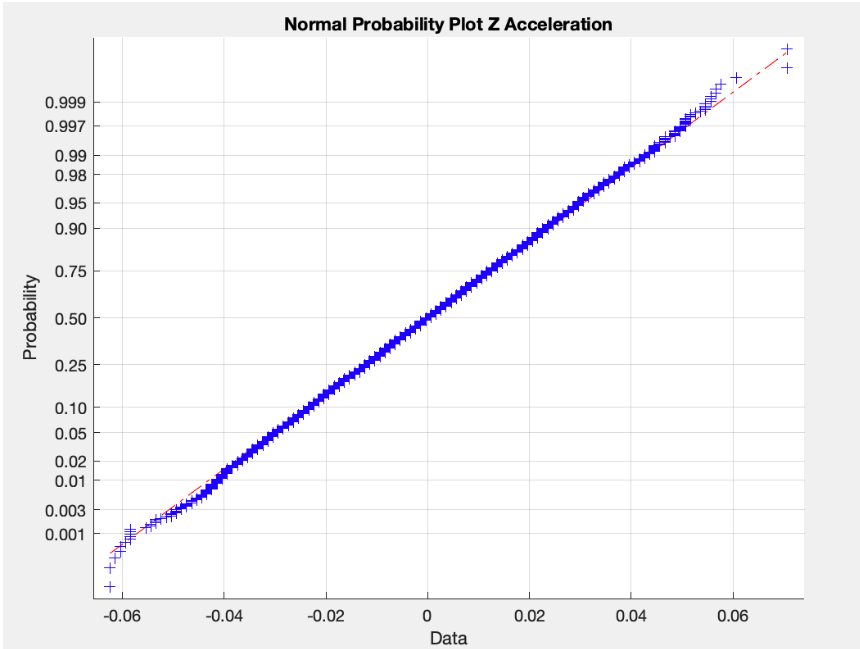

Figure 3: Comparison of error to a normal distribution

Part 2

Data was collected through the path shown in figure 4. The total length of the trip was about 749 seconds.

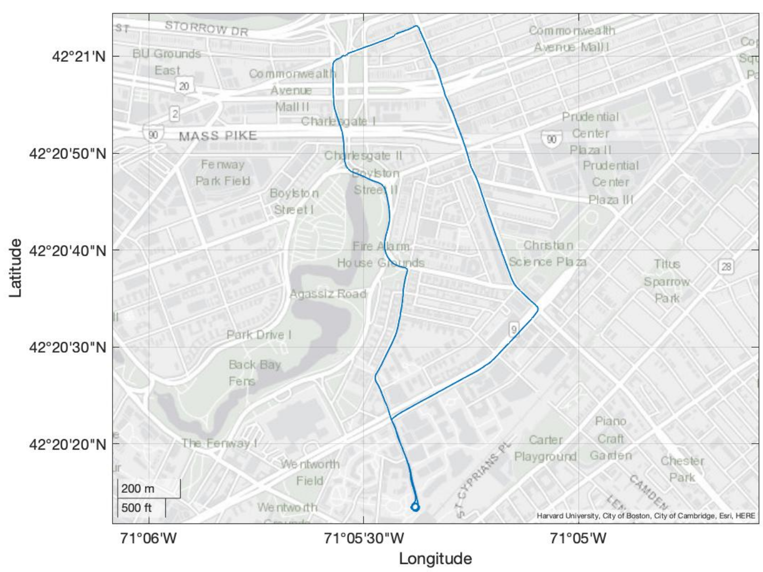

Figure 4: Path of Travel

The magnetometer in the IMU needs to be corrected for hard-iron and soft-iron effects. Hard-iron effects are caused by other metallic objects, typically on the circuit board, which shifts the origin of the more circular ideal data. The soft-iron effects are more subtle and come from other objects which could distort the magnetic field. As shown in figure 5, the data has a more ellipse shape uncalibrated and a circular shape while calibrated. Outliers in the data were taken out as they failed to help create the ellipse shape. These outliers could have been caused by movement of the IMU initially prior to driving in the circles. The data recorded from driving through the circles are then removed from the rest of the data. To eliminate these effects, the x Mag data and the y Mag data were plotted and fitted with an ellipse. The x Mag data and the y Mag data were then subtracted by the offset of the ellipse to center the data at (0,0). As can be seen in figure 5, this now created a more circular shape in the calibrated data.

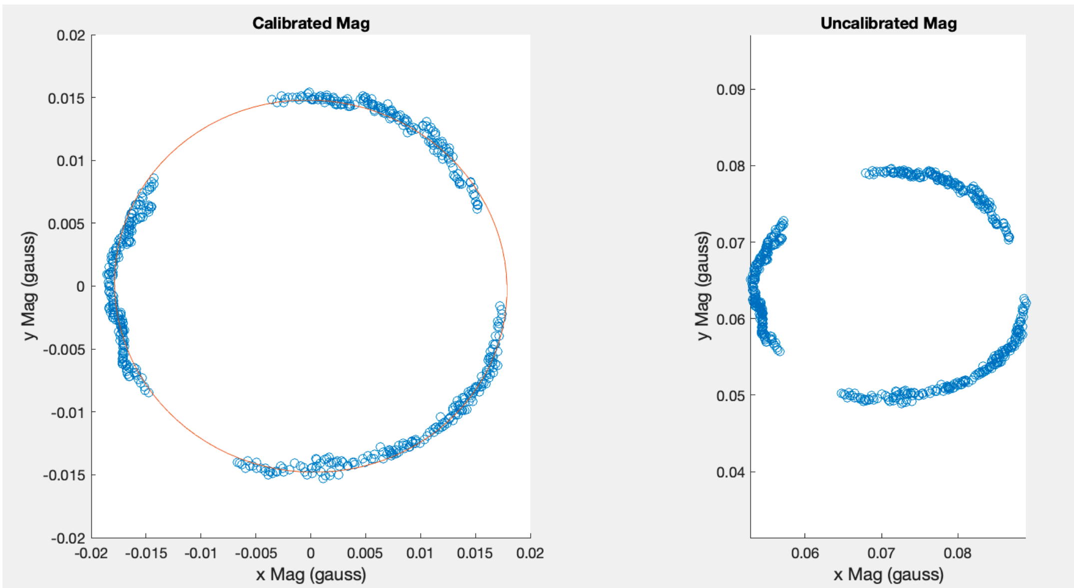

Figure 5: Magnetometer Calibration

Using the newly calibrated data, the yaw angle was calculated from the x and y magnetic field. As seen in figure 6, the Magnetometer Yaw is fairly similar to the Yaw found from the sensor. There is a slight offset in some areas of the data but fits the data well. However, the yaw calculated from gyro is very offset from the data. It slightly follows the data but does not fit the values well. From time 0-200 seconds, the yaw gyro does not follow the data at all but begins to follow it slightly from about 220 seconds and onwards. The integration of the gyroscope data does not give a good representation of the yaw. As we integrate for gyro, there is risk of drift due to noise. However, that does not seem to be the case here since the gyro is least accurate at the beginning compared to the end. I believe the initial error is due to bias instability of the gyroscope, causing the sensor to miss orientation for a brief time.

However, combining both yaw calculation from magnetometer data and gyro data into a complimentary filter yielded the best results. The gyro yaw was filtered with a high pass filter and the magnetometer yaw was filtered through a low pass filter. These were then weighted into a complimentary filter with 98% of the filtered magnetometer yaw and 2% of the filtered gyro yaw. Combining both of these, as seen in figure 7, yielded a closer fit to the sensor yaw than either of the 2 readings independently. However, it seems as though that if only a single sensor were able to be used, a magnetometer would make most sense in 2 dimensions similar to a compass.

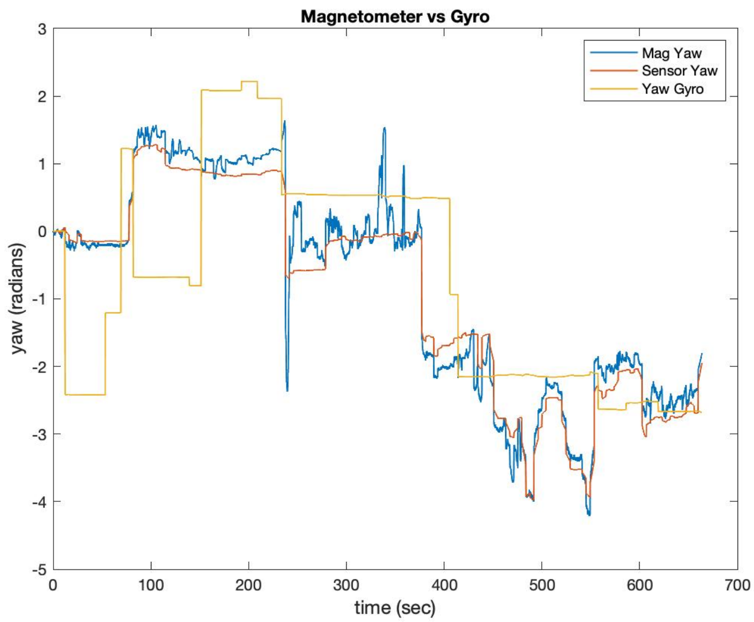

Figure 6: Comparison between yaw found from Magnetometer, Sensor, and Gyro

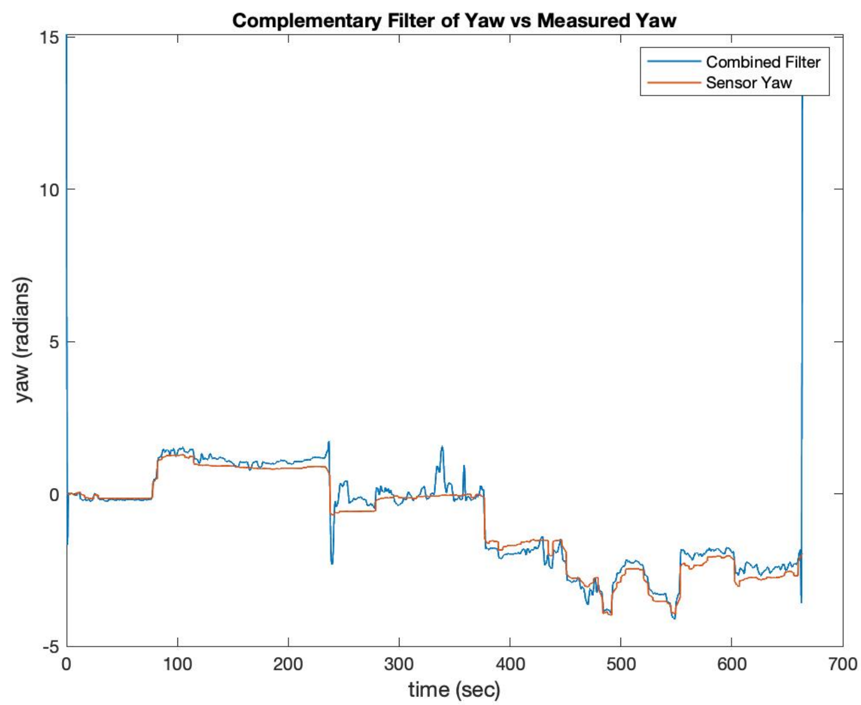

Figure 7: Complimentary Filter

As seen in Figure 8, the Acceleration in the x direction was integrated to find the forward velocity. The shape of the integrated forward velocity seems very similar to the velocity calculated from the GPS by finding the difference between each northing measurement and easting measurement. The magnitude would then be found and then divided by the time between each measurement to find the speed. This integrated forward velocity from x Acceleration makes sense in that if it were rotated up to 0 m/s, it could be very similar to the GPS velocity. However, the values by themselves in figure 8, is not accurate.

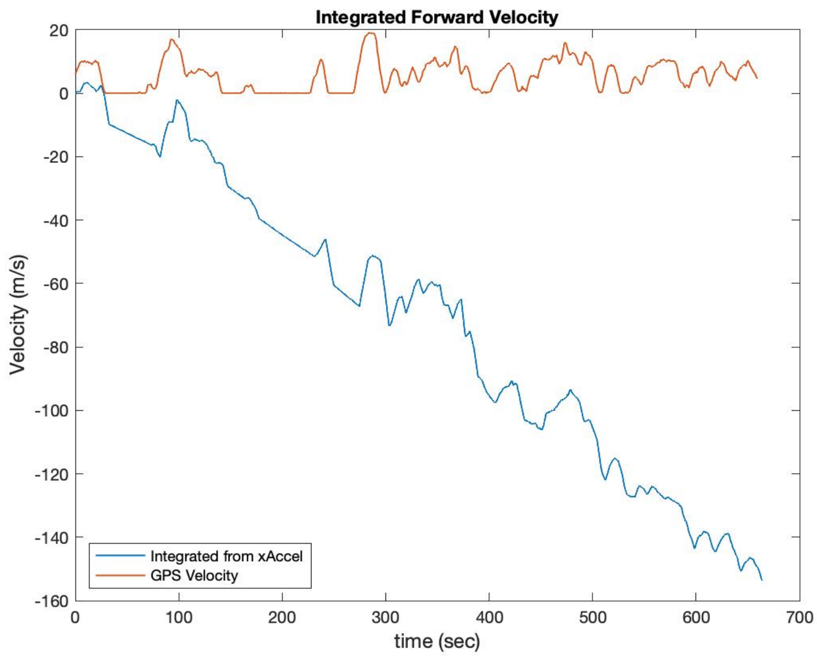

Figure 8: Integrated forward velocity compared to the GPS Velocity

To try and match the velocity of GPS, the x Acceleration was subtracted by its average to get rid of the offset. Then the difference of each point of the x Acceleration was taken consecutively. Then the differences would be searched to find when they equal zero. Consecutive numbers of 0 would indicate that there was no forward acceleration in this time period. I don’t believe our driver, Jack Bauer, was able to drive at an incredibly consistent velocity that there would be no acceleration so this would show that it did not need to be integrated. Each of those indices corresponding to those differences were set equal to 0 in the x Acceleration and then the integral was taken to find an adjusted forward velocity. Each velocity found below 0 was set equal to zero as the car was never driving in reverse. As seen in Figure 9, the adjusted forward velocity is fairly close in shape to the GPS velocity but there are subtle differences between both sets of velocities.

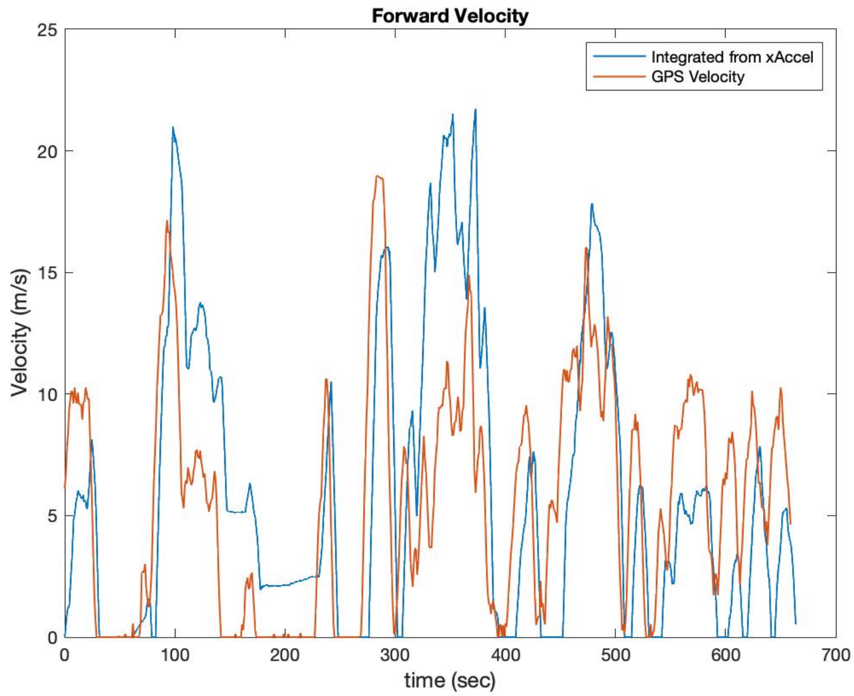

Figure 9: Adjusted Forward Velocity

Dead reckoning was used to calculate the route taken using the sensor information. Using omega and the forward velocity compared to the y acceleration shows some drift within the omega multiplied by the adjusted forward velocity. It is consistently matching up from 0 seconds to 375 seconds until there is an increase in omega multiplied by the adjusted forward velocity. This is caused by the noise in the gyro which showed drift over time and is reflected in figure 10.

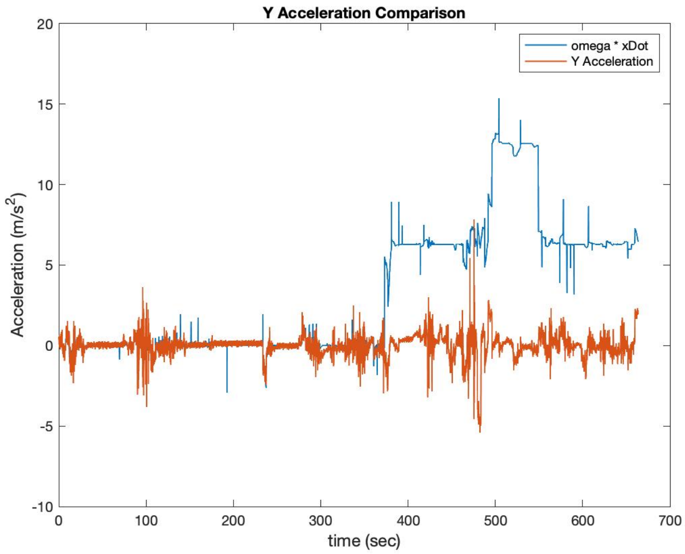

Figure 10: Comparison of Y acceleration

Using the yaw from the sensor and finding v_e and v_n by multiplying the sin and cos of the yaw by the adjusted forward velocity, the estimated trajectory was obtained. The shape of the estimated trajectory seems somewhat similar to the actual GPS track. However, the first turn in the estimated trajectory is too elongated and should be shorter. Furthermore, the last turn is directed in the wrong direction instead of redirecting back towards the direction of the starting point. This is reflected in the inaccuracy of adjusted forward velocity as seen in the rapid jump in the adjusted forward acceleration almost 100 seconds in after the rest where the turn would be made. This could have accounted for the elongated estimated trajectory on the first turn and how it stays increased above the GPS velocity. This could have been caused by the noise in the accelerometer data and sudden brakes and decelerations while driving. Furthermore, centripetal force is a factor in acceleration and could have attributed to the error in the forward velocity. When using the combined yaw to find the estimated trajectory as shown in figure 12, the trajectory follows a similar shape, especially given that the combined yaw followed the shape of the sensor fairly well. However, the difference shown between the 2, indicates that the error in the yaw in the combined filter created a path that did not quite follow the path by using the sensor yaw. Figure 12 demonstrates a much longer first turn while the other turns are much shorter, showing how much a difference can be made when there is still some inaccuracy in the combined filter yaw.

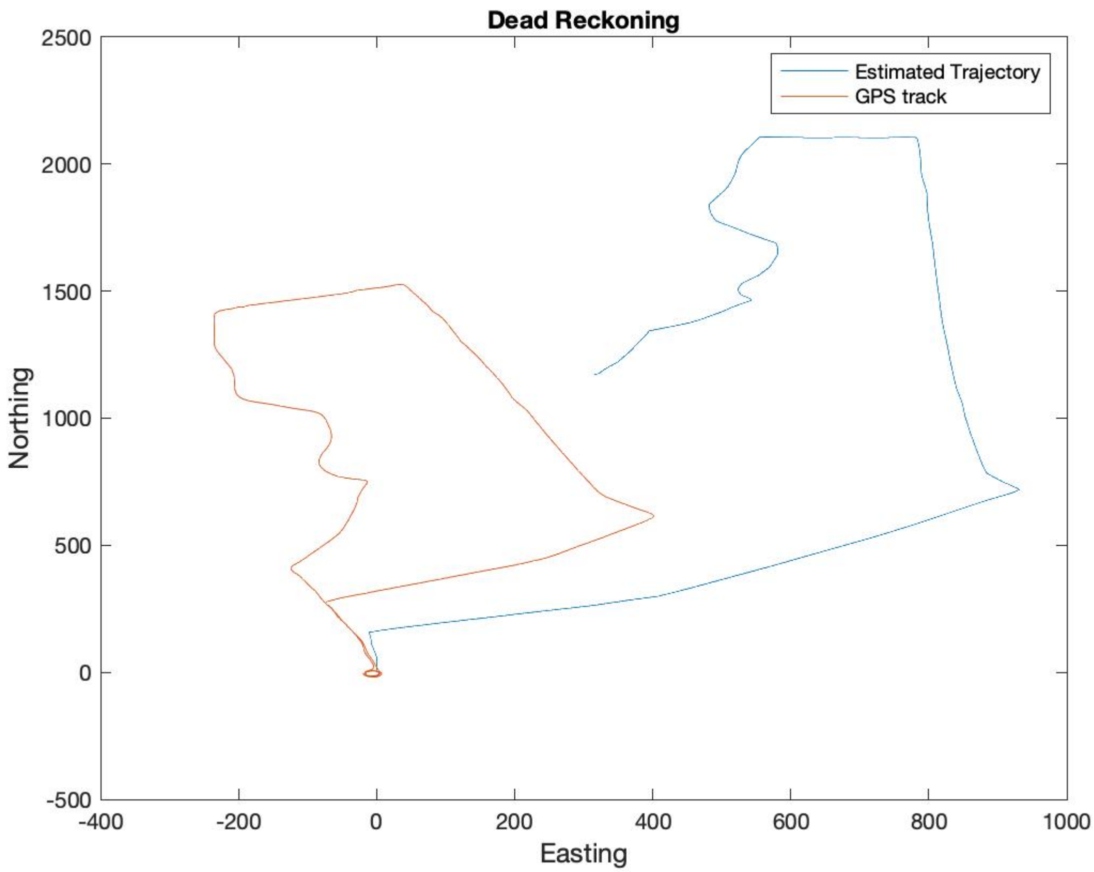

Figure 11: Dead Reckoning Estimation using sensor yaw

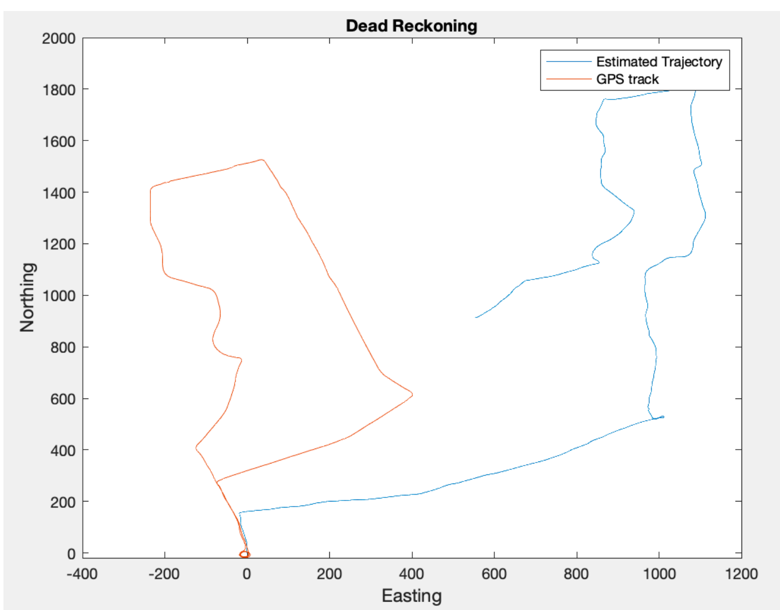

Figure 12: Dead Reckoning with combined filter

Allan Variance is the measure of frequency stability for oscillators or clocks. Oscillators and clocks also possess a white frequency noise. This noise could be characterized in finding the Allan Variance in both the zGyro and x Accel data. Utilizing the Allan Variance the noise can be characterized as shown in figure 13 and 14. The value of N is the angle random walk coefficient. The greater value of N, the larger the white noise spectrum. N was found to be 3.75 for the zGyro and 0.002 for x Accel. This would explain the noise found when finding the integration of zGyro for yaw where the zGyro did not quite correspond to the yaw found by the sensor. K, the rate random walk coefficient, which represents the red or Brownian noise, was found to be 4.32 $*10^{-4}$ for x Accel and 0.0301 for z Gyro. B, the bias instability coefficient, which represents the pink or flicker noise, was found to be .0058 for x Accel and 0.2746 for z Gyro. There is clearly significant noise in the z Gyro as seen in the white noise which would explain why it was not able to follow the calculated yaw. There is significantly less noise in the accelerometer which gave it the capability of following the pattern for the estimated trajectory in dead reckoning but was not fully accurate in estimating the vehicles velocity, which has several factors in estimating the acceleration. The z Gyro was also not calibrated which could explain much of the noise that is seen in it. The soft iron and hard iron effects could be included in the noise found here.

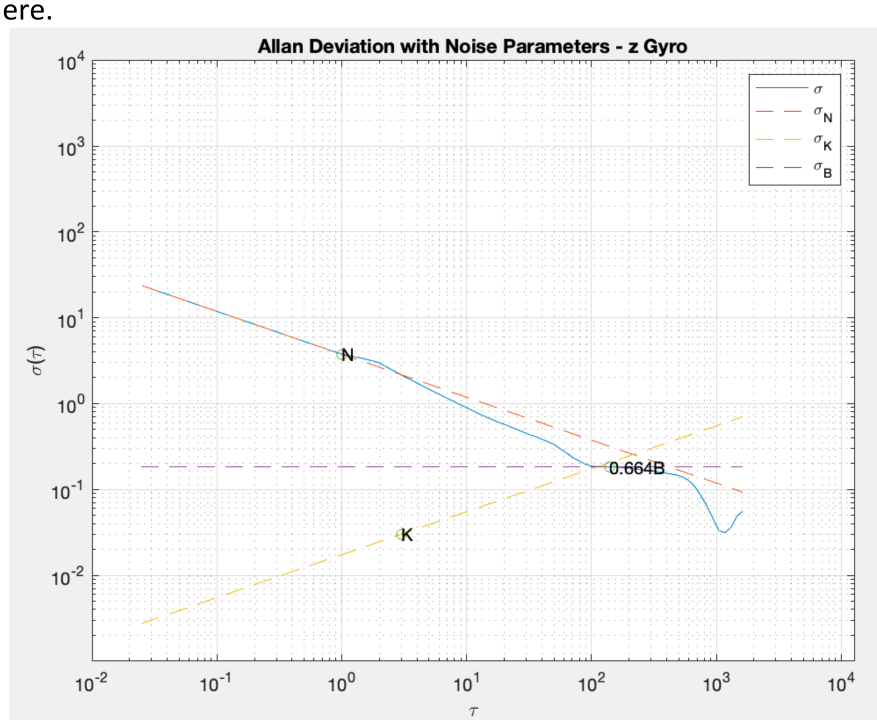

Figure 13: Allan Deviation of zGyro

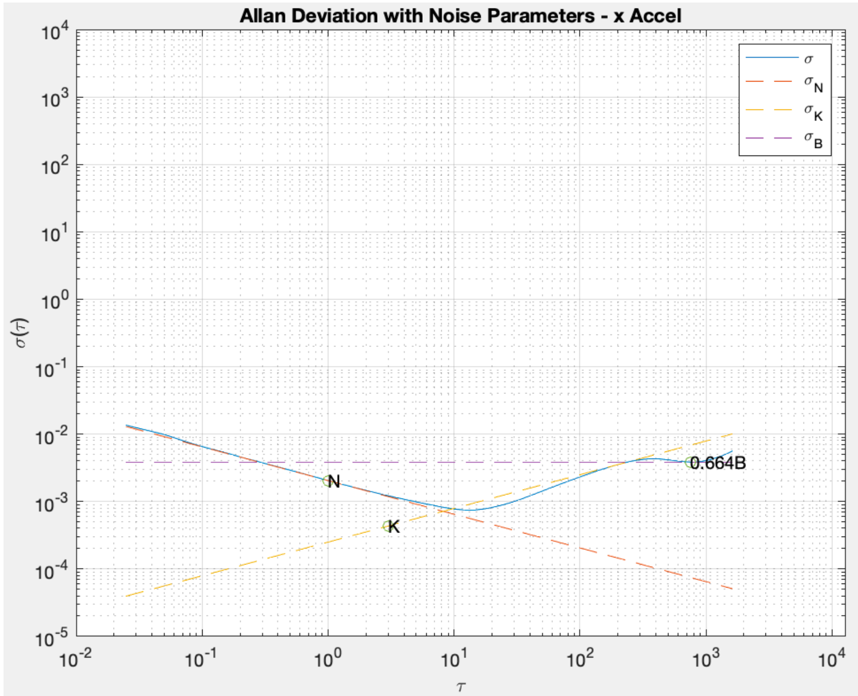

Figure 14: Allan Deviation of x Accel

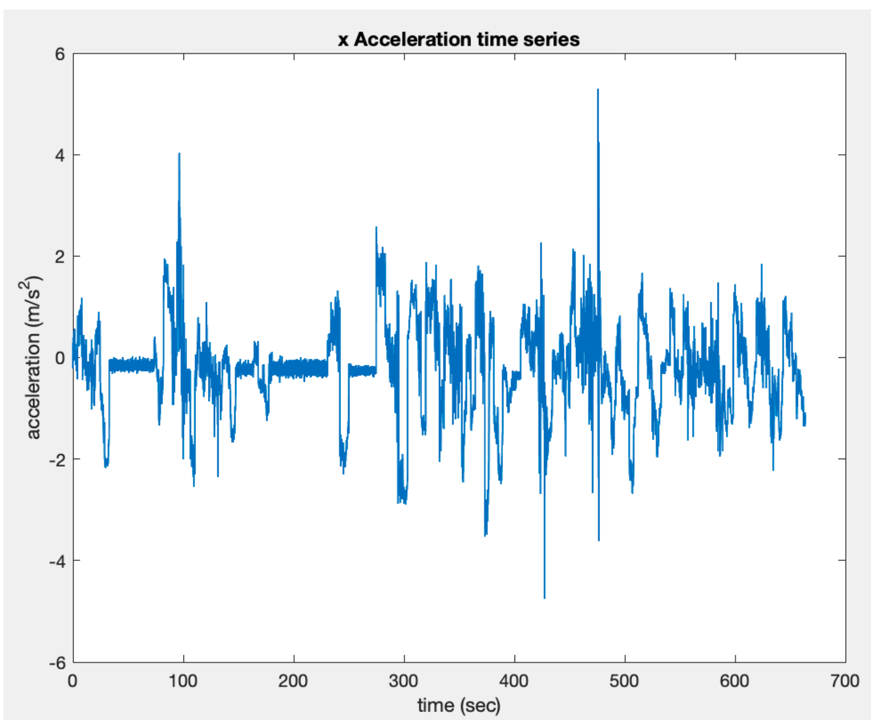

Figure 15: Time series of x acceleration

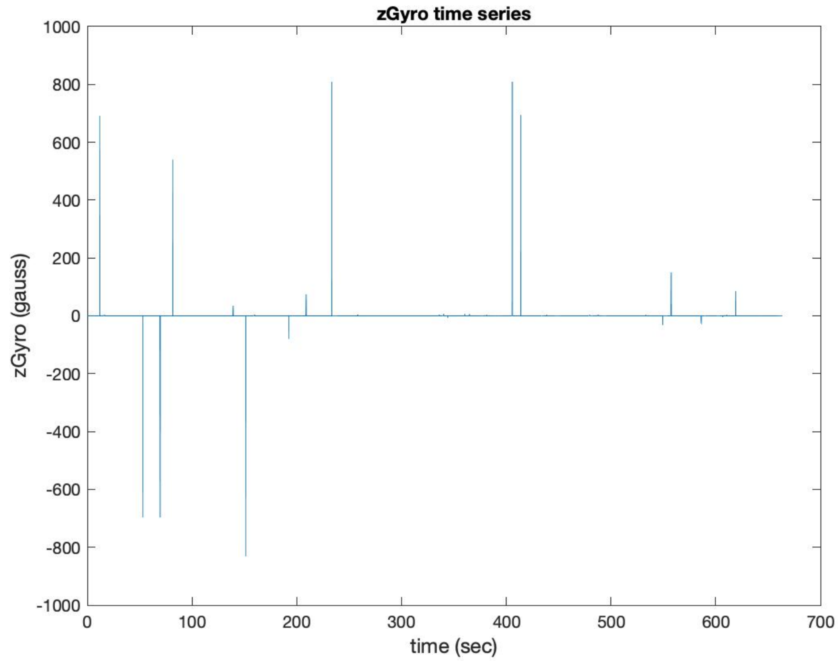

Figure 16: Time series of z Gyro