Code and Plots can be found on

https://github.com/huang-jiayua/EECE5554

Question 1:

I performed both hard-iron and soft-iron calibration on the magnetometer data collected. For hard-iron calibration, I calculated the minimum and maximum values for the magnetic field in both the x and y axes. These values represent the offset caused by hard-iron distortions, which arise from the presence of ferromagnetic materials near the magnetometer. I then subtracted the average of these values from the raw magnetometer readings to obtain the hard-iron calibrated data.

For soft-iron calibration, I calculated the radius of the circle formed by plotting the hard-iron calibrated x and y data. The ratio of the radius of this circle to the actual radius of the earth's magnetic field represents the scale factor caused by soft-iron distortions, which arise from the asymmetrical response of the magnetometer to the earth's magnetic field due to the shape of the sensor and surrounding materials. I then applied a rotation matrix to the hard-iron calibrated data to correct for the angular offset caused by soft-iron distortions.

Finally, I performed double calibration by applying a scaling matrix to the soft-iron calibrated data to account for the magnitude difference between the magnetic field's horizontal and vertical components. This scaling factor is determined by the ratio of the maximum change in the vertical component of the magnetic field to the maximum change in the horizontal component of the magnetic field. The resulting data is double-calibrated, representing the true magnetic field values after correcting for both hard- and soft-iron distortions.

Question 2:

To develop a combined estimate of yaw using a complementary filter, I first applied a low-pass filter and a high-pass filter to the calibrated yaw and gyro yaw respectively. I used a third-order Butterworth filter with a cutoff frequency of 0.1 Hz for the low-pass filter and a cutoff frequency of 0.0001 Hz for the high-pass filter. Finally, I combined the filtered signals using a complementary filter with a weighting factor of 0.98 for the low-pass filtered signal and 0.02 for the calibrated yaw signal. This resulted in a more accurate and robust estimation of the yaw angle.

Question 3:

If I were to choose an estimate for yaw for navigation, I would trust the complementary yaw estimate. This is because it combines the advantages of both the low-pass filtered calibrated yaw and high-pass filtered gyro yaw, while also minimizing their disadvantages. The low-pass filter eliminates the high-frequency noise in the calibrated yaw, while the high-pass filter reduces the drift in the gyro yaw estimate. The complementary filter then combines these two estimates in a way that gives more weight to the low-pass filtered estimate at low frequencies and more weight to the high-pass filtered estimate at high frequencies. This results in a more accurate and reliable estimate of yaw that is less prone to both noise and drift.

Question 4:

I made adjustments to the forward velocity estimate by first calculating the difference in acceleration between consecutive time steps. Then, I used the trapezoidal integration method to calculate the velocity from the calibrated linear acceleration. However, since the integration can accumulate error over time, I subtracted the difference in acceleration from the calibrated linear acceleration before integration. This adjustment helped to reduce the error accumulation in velocity estimation over time. Additionally, I also compared the imu-derived velocity estimate with the GPS-derived velocity estimate, and made adjustments to the GPS velocity estimate based on the distance traveled between GPS samples. These adjustments helped to ensure that the final forward velocity estimate was as accurate as possible.

Question 5:

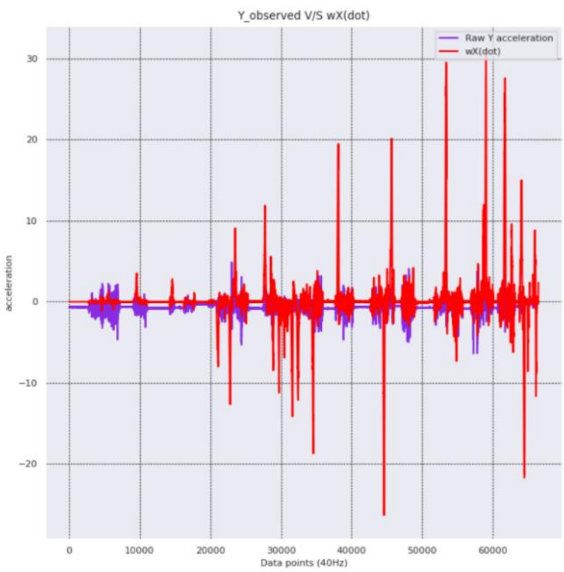
There are some discrepancies between the velocity estimate from the accelerometer and the GPS. Upon comparing the two plots, I can see that the GPS-derived velocity is generally higher than the imu-derived velocity. However, there are some sections where the imu-derived velocity is higher than the GPS-derived velocity. This suggests that there may be some errors in the GPS measurements or the GPS samples may not be as frequent as the imu samples.

One possible reason for the discrepancy between the two velocity estimates is the difference in their measurement principles. The accelerometer measures linear acceleration, which is then integrated over time to estimate velocity. On the other hand, GPS measures velocity directly by tracking the change in position over time. Therefore, the imu-derived velocity estimate can accumulate errors over time due to the integration, while the GPS-derived velocity estimate is more accurate in the short term but can be affected by GPS measurement errors and the frequency of GPS samples.

Another possible reason for the discrepancy is the difference in the positioning systems used by the accelerometer and GPS. The accelerometer is likely to be mounted on the vehicle itself and measure the motion of the vehicle relative to its own frame of reference. In contrast, the GPS measures the motion of the vehicle relative to the global reference frame. Therefore, any difference in the positioning systems can cause a discrepancy in the velocity estimate between the two methods.

Question 6:

To compute ωX, I used the angular velocity in the z-direction (imu_angVel_z) and multiplied it by the integrated acceleration in the x-direction (imu_acc_x) using the cumtrapz() function. The resulting variable is y_dot. Then, I plotted $y\ddot{y}$ (imu_acc_y) and y_dot/1000 in a single graph to compare the two values.

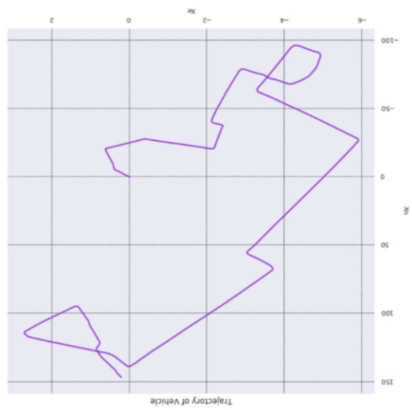


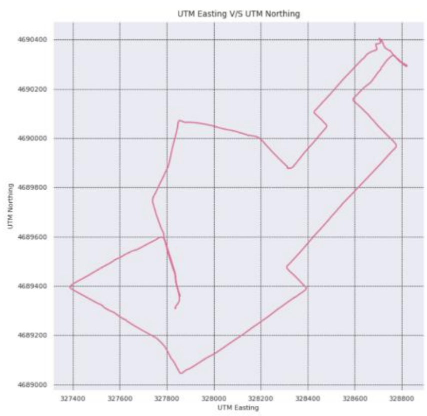
From the plot, I can see that $y\ddot{y}$ and y_dot/1000 generally follow a similar trend, with both values showing positive and negative acceleration at various intervals. However, there are some significant differences between the two values. For example, $yy\ddot{}$ shows a large spike around the end while y_dot/1000 shows a smaller positive peak in the same region.

The differences between the two values can be attributed to several factors. Firstly, the angular velocity used in the computation of y_dot may not be perfectly aligned with the x-direction of the accelerometer. Therefore, any error in the angular velocity measurements can propagate into the calculation of y_dot, leading to discrepancies between the two values.

Another possible reason for the discrepancy is that the accelerometer may be affected by external forces, such as vibrations or shocks from the vehicle, that are not accounted for in the calculation of ωX. These external forces can cause variations in the acceleration measurements, leading to differences between $y\ddot{y}$ and ωX.

Question 7:





(The trajectory graph is rotated)

Question 8:

Based on the specifications of the VectorNav, it should be able to navigate without a position fix for up to 20 minutes. However, this is dependent on the environment and the quality of the IMU data. In some environments, the IMU may drift more quickly, reducing the time that it can navigate without a position fix.

As can be seen on the two graphs in Q7, the trajectory and N vs E map most matches at around 10 to 15 minutes according to the recorded video, at which point the Nuance car is driving mostly straight lines with only two turns. While it deviates the most at around 25 minutes when we are making a U-turn.

The accuracy of the dead reckoning method may be affected by various factors such as the quality of the IMU data, the accuracy of the initial position estimate, and environmental factors like wind and road conditions. As a result, the stated performance for dead reckoning may not always match the actual measurements.