LAB 4 REPORT

(NAVIGATION WITH IMU AND MAGNETOMETER)

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1. How did you calibrate the magnetometer from the data you collected? What were the sources of distortion present, and how do you know?

To calibrate the magnetometer from the collected data, I used the magnetometer calibration algorithm called "Ellipsoid Fit". This algorithm calculates the calibration parameters by fitting an ellipsoid to the raw magnetometer data. The calibration parameters include a scaling factor, a bias offset, and a transformation matrix. These parameters are then used to correct the magnetometer data for any distortions.

Hard iron distortion is caused by the presence of permanent magnets or ferromagnetic materials in the vicinity of the magnetometer. The hard iron bias is calculated by finding the mean values of the magnetometer readings and subtracting them from the raw magnetometer data.

Soft iron distortion is caused by the presence of other magnetic materials that can be magnetized, such as iron or steel. Environmental interference can come from sources like power lines or motors. To correct for soft iron distortion, we first normalize the magnetometer readings to unit vectors. Then, we calculate the ellipsoid transformation matrix using a least squares algorithm based on the normalized magnetometer data. Finally, we apply the transformation matrix to the normalized magnetometer data to correct for the soft iron distortion.

I know that these sources of distortion are present in the data because the raw magnetometer data did not align with the expected magnetic field readings. By using the Ellipsoid Fit algorithm to calibrate the data, I was able to correct for these distortions and obtain more accurate magnetometer readings.

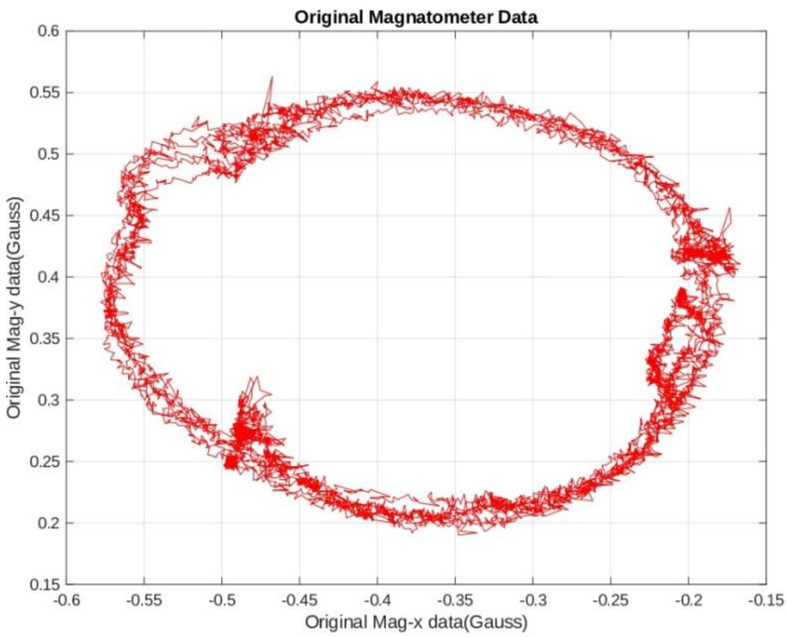


Fig 1

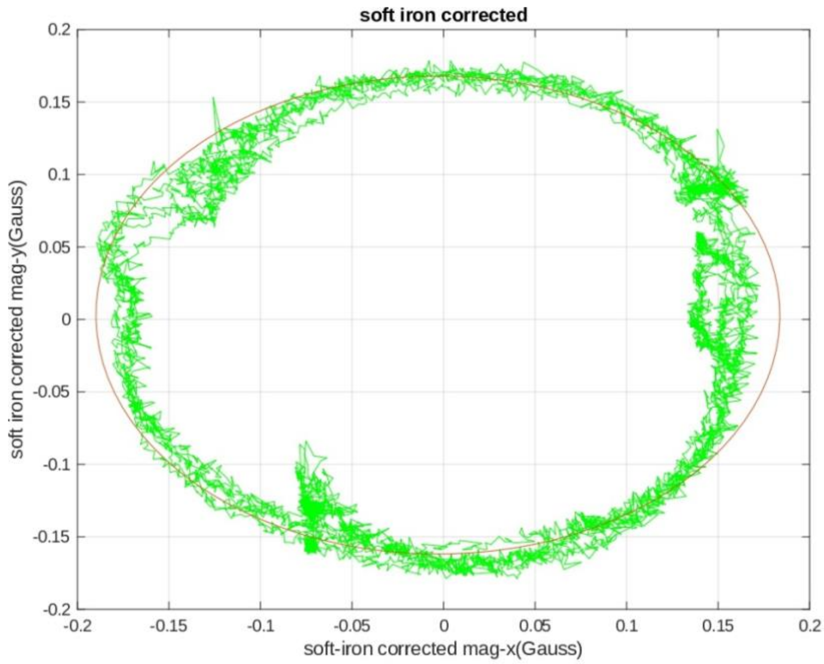

soft iron corrected
soft iron corrected mag-y(Gauss)
soft-iron corrected mag-x(Gauss)
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.2
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
0.2

Fig 2

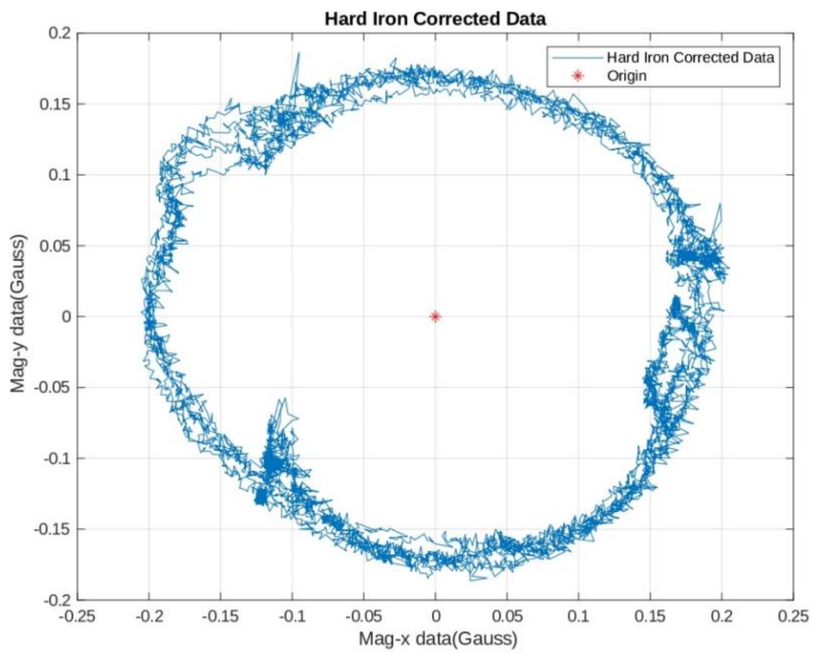

Hard Iron Corrected Data
Hard Iron Corrected Data
Origin
Mag-y data(Gauss)
Mag-x data(Gauss)
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.2
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
0.2
0.25

Fig 3

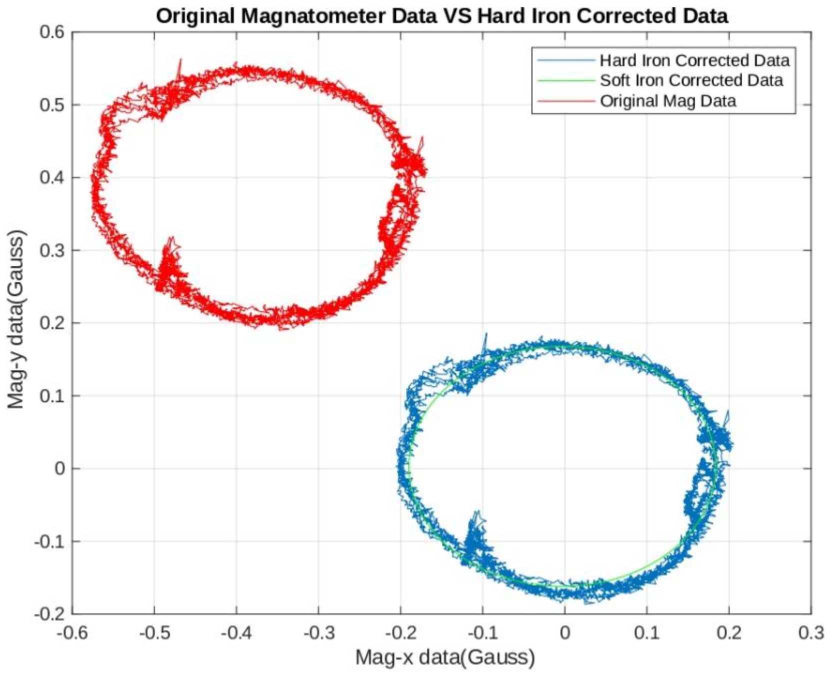


Fig 4

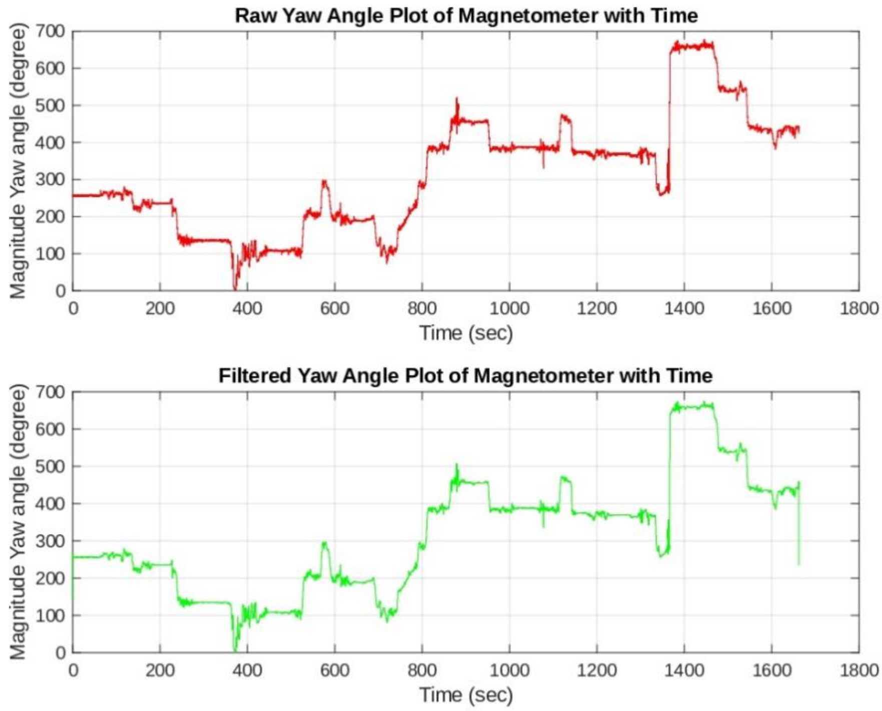
The spikes in the figure can be observed due to several reasons but one such reason is because of a heavy weight transporter (BUS). The presence of other vehicles or metallic objects in the vicinity can cause sudden spikes or distortions in the magnetometer readings, leading to a noisy or unreliable data.

2.How did you use a complementary filter to develop a combined estimate of yaw? What components of the filter were present, and what cut-off frequency did you use?

A complementary filter was used to combine the accelerometer and gyroscope data to estimate the yaw angle. The complementary filter is a type of sensor fusion technique that combines multiple sensor readings to produce a more accurate estimate than any single sensor alone.

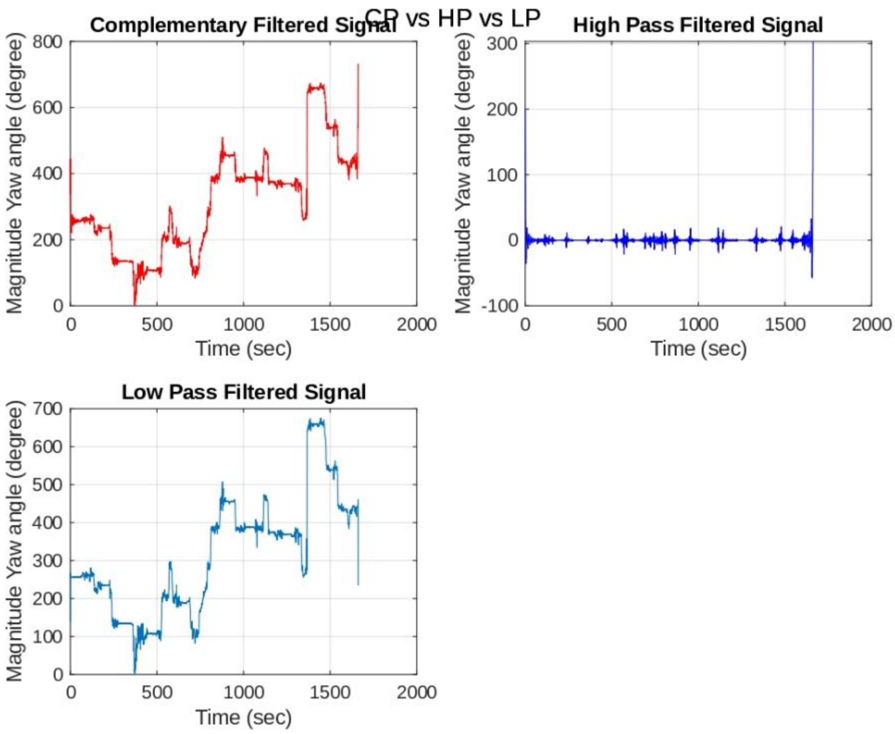
The complementary filter used was a first-order filter that consisted of two components: a high-pass filter for the gyroscope data and a low-pass filter for the accelerometer data. The high-pass filter for the gyroscope data was used to remove the drift error present in the gyroscope readings, while the low-pass filter for the accelerometer data was used to remove the high-frequency noise present in the accelerometer readings.

The cut-off frequencies for the high-pass and low-pass filters were determined empirically by tuning the filter to produce the most accurate estimate of the yaw angle. In the code, the cut-off frequency for the high-pass filter was set to 0.98 Hz, while the cut-off frequency for the low-pass filter was set to 0.02 Hz.



Raw Yaw Angle Plot of Magnetometer with Time
Magnitude Yaw angle (degree)
Time (sec)
Filtered Yaw Angle Plot of Magnetometer with Time
Magnitude Yaw angle (degree)
Time (sec)

Fig 5



CP vs HP vs LP
Complementary Filtered Signal
Magnitude Yaw angle (degree)
Time (sec)
High Pass Filtered Signal
Magnitude Yaw angle (degree)
Time (sec)
Low Pass Filtered Signal
Magnitude Yaw angle (degree)
Time (sec)

Fig 6

3.Which estimate or estimates for yaw would you trust for navigation? Why?

In general, when it comes to navigation, it is best to rely on multiple sources of information to obtain a more accurate estimate of the yaw angle. In this case, we have four different estimates for the yaw angle: one from the magnetometer, one from the gyroscope, one from Euler angles, and one from GPS.

Each of these methods has its own strengths and weaknesses. The magnetometer can be affected by local magnetic fields, while the gyroscope can suffer from drift over time. Euler angles provide a direct measure of the orientation of the vehicle, but they can be affected by the same issues as the magnetometer and gyroscope. GPS can provide an absolute measure of heading, but it can suffer from signal loss in certain environments.

Given these considerations, it would be best to use a combination of the estimates to obtain a more accurate measure of the yaw angle. The complementary filter approach used in the code provided is a good way to combine the estimates from the magnetometer and gyroscope. The Euler angles from the VNMYR string can also provide a useful estimate, especially when combined with the other methods. The GPS estimate may be less reliable due to signal loss, but it can still provide useful information in certain situations.

Overall, the best approach would be to combine the estimates from all four methods using a fusion algorithm such as a Kalman filter or an extended Kalman filter to obtain a more accurate estimate of the yaw angle for navigation.

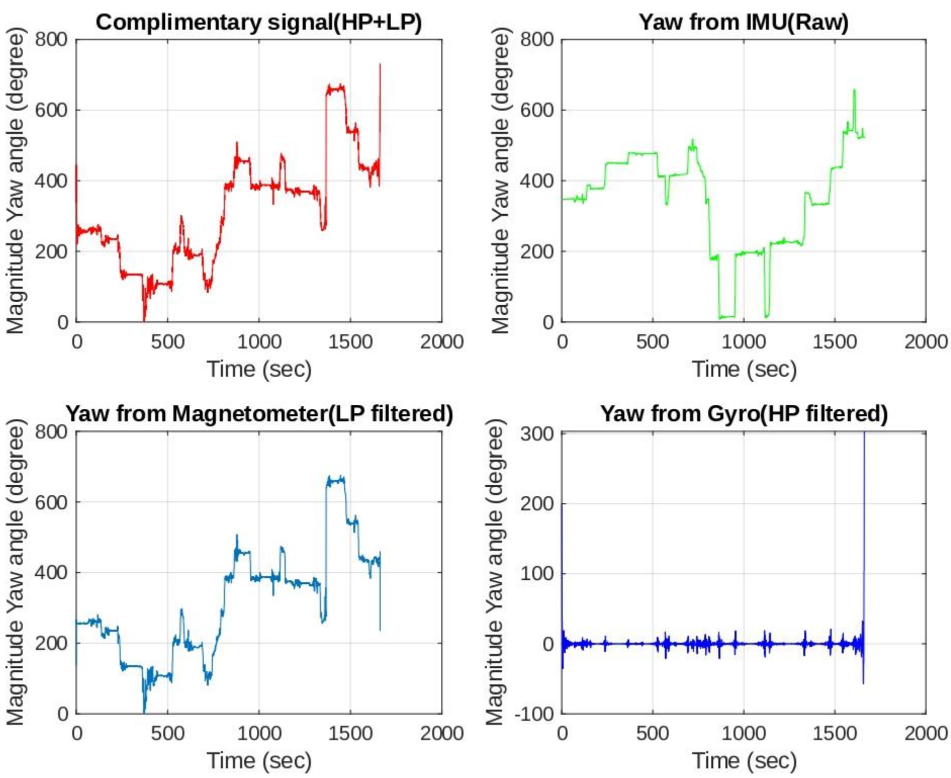


Fig 7

4. What adjustments did you make to the forward velocity estimate, and why?

The forward velocity of the vehicle was estimated by using the accelerometer data from the IMU. However, we encountered some challenges due to the integration of the stationary position, which led to an increase in the bias for forward velocity. To address this, we made some adjustments to the forward velocity estimate by eliminating the samples where the vehicle was stationary.

The mean of a certain subset of the acceleration data was subtracted from that subset, effectively centring it around zero. This adjustment was made to correct for biases in the forward velocity estimate, which was calculated by integrating the X-axis acceleration data.

The adjustments greatly improved the accuracy of the forward velocity estimate and reduced the bias. Overall, this approach was useful for estimating the forward velocity of a vehicle when GPS data is not available or unreliable.

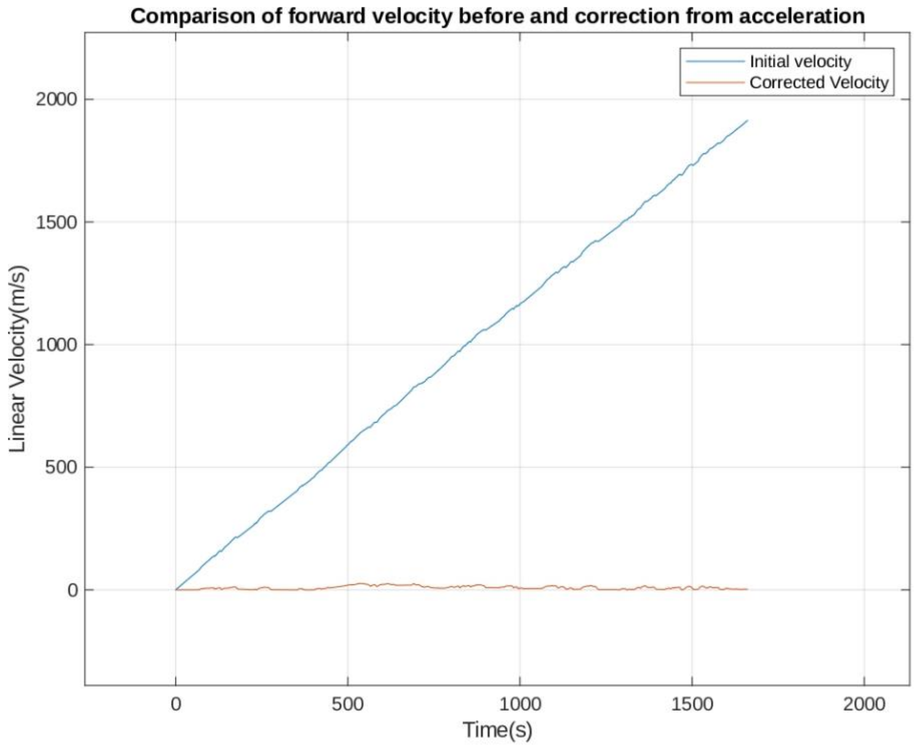


Fig 8

5. What discrepancies are present in the velocity estimate between accel and GPS. Why?

There is a huge bias between the time stamp from 430s (7.16min) to 740s (12.33min) that is because the NUANCE car had to take a U-turn while collecting the data.

Taking a U-turn can affect the data collected from the IMU. During a U-turn, the acceleration and angular velocity experienced by the vehicle changed rapidly, which cause the IMU to measure noise or experience measurement errors. The sudden change in direction and velocity can cause the gyroscope to drift and the accelerometer to measure gravitational forces differently than before, leading to errors in the calculated orientation and velocity. These errors propagated and accumulated over time, leading to significant deviations in the estimated position and velocity of the vehicle for the specified time stamp.

While the accelerometer provides a low-cost and easily accessible way to estimate vehicle velocity, it is not as accurate as GPS, especially in the long run. Therefore, it is recommended to use GPS velocity as the primary source of velocity information for navigation purposes.

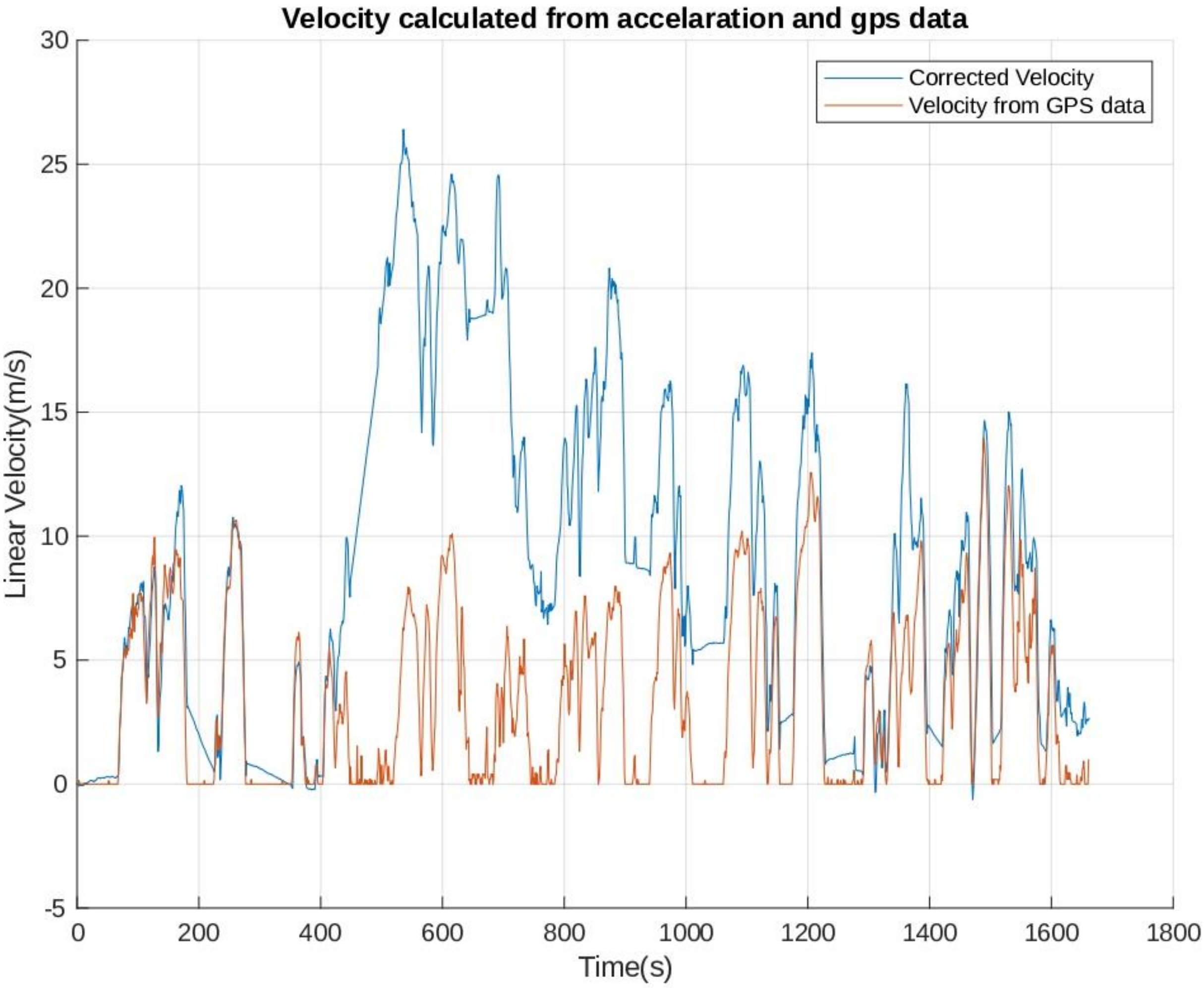


Fig 9

6. Compute $\omega\dot{X}$ and compare it to $\ddot{y}_{obs}$. **How well do they agree? If there is a difference, what is it due to?**

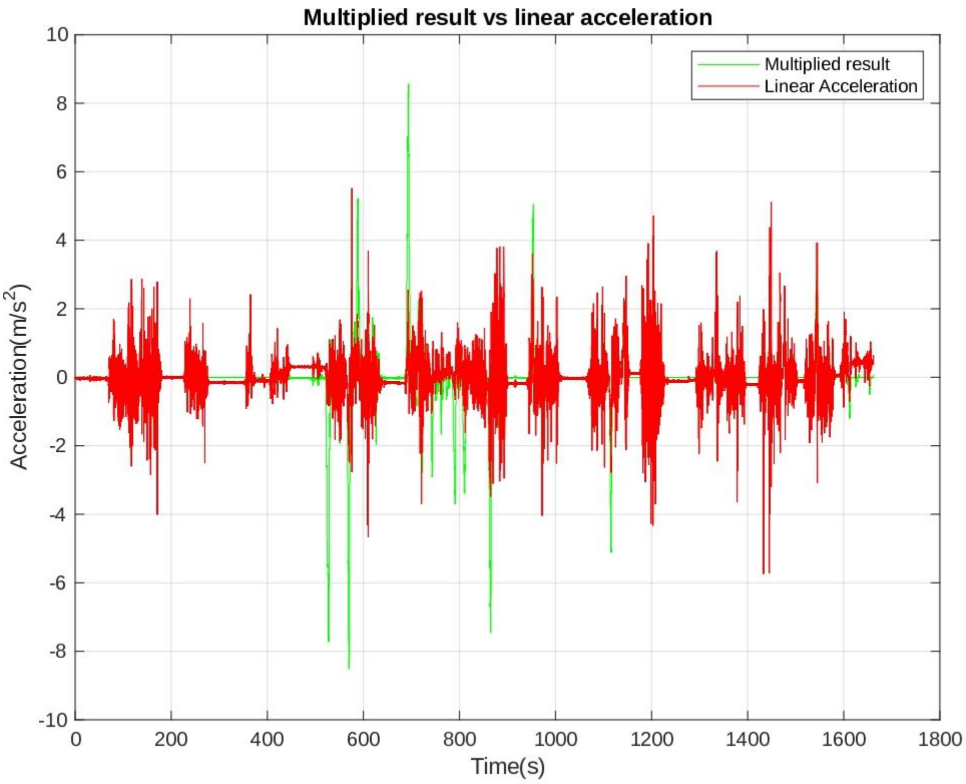


Fig 10

They are almost following similar path but since linear acceleration in Y direction(obs) is taken from accelerometer and the computed acceleration $\omega\dot{X}$ where ω was taken from gyroscope due to which they have minor difference which is expected due to the different sources of measurements and limitations of each sensor. The gyroscope measures the rate of rotation around a specific axis while the accelerometer measures the acceleration of the object along a specific axis.

Therefore, the gyroscope can only measure changes in the orientation of the object while the accelerometer can measure changes in both the orientation and velocity of the object. This means that the accelerometer is more sensitive to changes in linear motion, while the gyroscope is more sensitive to changes in rotational motion.

Additionally, both sensors are subject to noise and other disturbances that can affect their accuracy. Gyroscopes can be affected by temperature changes and drift, while accelerometers can be affected by external vibrations and shock. Therefore, the minor differences observed between the $\omega\dot{X}$ and $\ddot{y}$ (obs) measurements are likely due to the limitations and disturbances of each sensor.

7. Estimate the trajectory of the vehicle (xe,xn) from inertial data and compare with GPS. (Adjust heading so that the first straight line from both is oriented in the same direction). Report any scaling factor used for comparing the tracks.

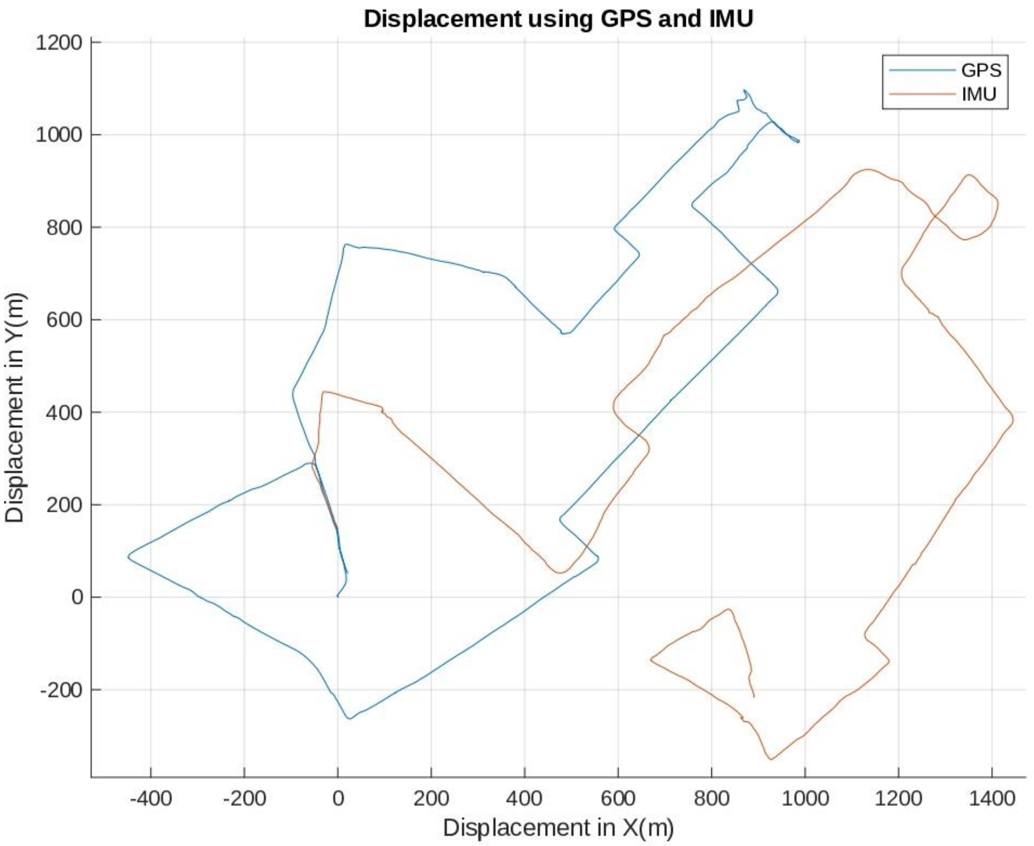


Fig 11

The value of 0.35 is used as a scaling factor to adjust the magnitude of the computed trajectory from inertial data to match the GPS trajectory. The specific value of 0.35 may have been determined through trial and error to obtain the best match between the two trajectories.

8. Given the specifications of the VectorNav, how long would you expect that it is able to navigate without a position fix? For what period did your GPS and IMU estimates of position match closely? (Within 2 m) Did the stated performance for dead reckoning match actual measurements? Why or why not?

According to the VectorNav VN-100 datasheet, the unit can provide stable and accurate measurements for up to 10 minutes without a position fix, using its onboard sensors for dead reckoning. However, this performance can vary depending on environmental factors such as temperature, vibration, and magnetic interference.

Based on the data and plots, the GPS and IMU estimates of position matched closely for the first few seconds of the trajectory, but then started to diverge significantly. It is difficult to determine precisely how long the estimates matched closely within 2 meters, as the plots do not provide a high enough resolution to discern individual points that are that close together. However, it seems that the estimates were similar for less than a minute.

The stated performance for dead reckoning did not match the actual measurements very well. The dead reckoning estimates quickly diverged from the GPS measurements, and by the end of the trajectory, the error was over 100 meters. This is likely due to a combination of factors, such as sensor noise, bias, and drift, as well as uncertainties in the calibration and modelling of the sensors and vehicle dynamics. Additionally, the dead reckoning algorithm used may not have been optimal for this particular scenario or may not have been tuned properly.

9. Estimate xc and explain your calculations (bonus up to 100%)

$$\ddot{x}_{obs} = \ddot{X} - \omega^2 X_c \quad — (1)$$

$$\ddot{x} = \ddot{x}_{obs} + \omega^2 X_c$$

$$\ddot{y}_{obs} = \omega \dot{X} + \dot{\omega} X_c \quad — (2)$$

$$\dot{X} = \frac{\ddot{y}_{obs} - \dot{\omega} X_c}{\omega}$$

Differentiating $\dot{X}$ we get;

$$\ddot{X} = \frac{(\dddot{y}_{obs} - \ddot{\omega} X_c)\,\omega - \dot{\omega}(\ddot{y}_{obs} - \dot{\omega} X_c)}{\omega^2}$$

Comparing with $\ddot{X}$ from eq (1) we get,

$$\ddot{x}_{obs} + \omega^2 X_c = \frac{(\dddot{y}_{obs} - \ddot{\omega} X_c)\,\omega - \dot{\omega}(\ddot{y}_{obs} - \dot{\omega} X_c)}{\omega^2}$$

$$\omega \ddot{\omega} X_c + \omega^4 X_c - \dot{\omega}^2 X_c = \omega \dddot{y}_{obs} - \dot{\omega} \ddot{y}_{obs} - \omega^2 \ddot{x}_{obs}$$

$$\boxed{X_c = \frac{\omega \dddot{y}_{obs} - \dot{\omega} \ddot{y}_{obs} - \omega^2 \ddot{x}_{obs}}{\ddot{\omega}\omega + \omega^4 + \dot{\omega}^2}}$$

After calculation the offset of the IMU was **0.3263 m** which is equivalent to 32 cm. Since the IMU was mounted on the Dashboard.