EECE 5554 Lab 4 Report

Analysis of navigation stack using two different sensors – GPS & IMU

Francis Jacob Kalliath

Drive and Bag file referred from git user: vaidyanathan.sh

1. Estimating the Heading yaw

1.1. Correcting Magnetometer reading for "Hard-Iron" and "Soft-Iron" effect

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

Magnetometer Calibration Steps:

- Hard Iron Correction
  - Subtract the offsets from X and Y axis
- Soft Iron Correction
  - Find the angle theta and rotate the ellipse by angle theta to align major axis of ellipse with reference X axis
  - Scale the major axis to convert ellipse to a circle
  - Rotate the scaled circle back to original position

Hard iron distortions are produced by objects that produce magnetic fields. For example, a loudspeaker or a magnetized piece of iron will cause distortion in hard iron. If the magnetic material is physically mounted in the same reference frame as the sensor, this type of hard iron distortion will cause permanent distortion of the sensor output. Soft iron distortions is viewed as a deflection or change in the existing magnetic field. These distortions stretch or distort the magnetic field depending on the direction in which it acts on the sensor. This type of distortion is usually caused by metals such as nickel and iron. In most cases, hard iron distortion contributes more to the overall uncorrected error than soft irons.

1.2. Plotting the Magnetometer data before and after correction

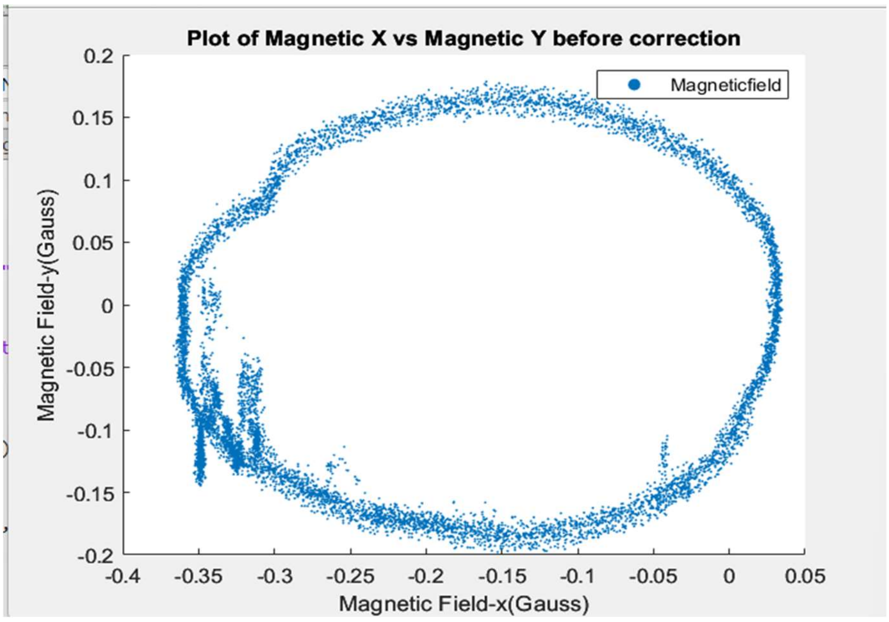

Fig 1: shows the plot of Magnetic X vs Magnetic Y before correction

The plot of Magnetic X vs Magnetic Y before correction is an ellipse and is skewed in shape. Hence, we have to do the Soft-Iron and Hard-Iron correction

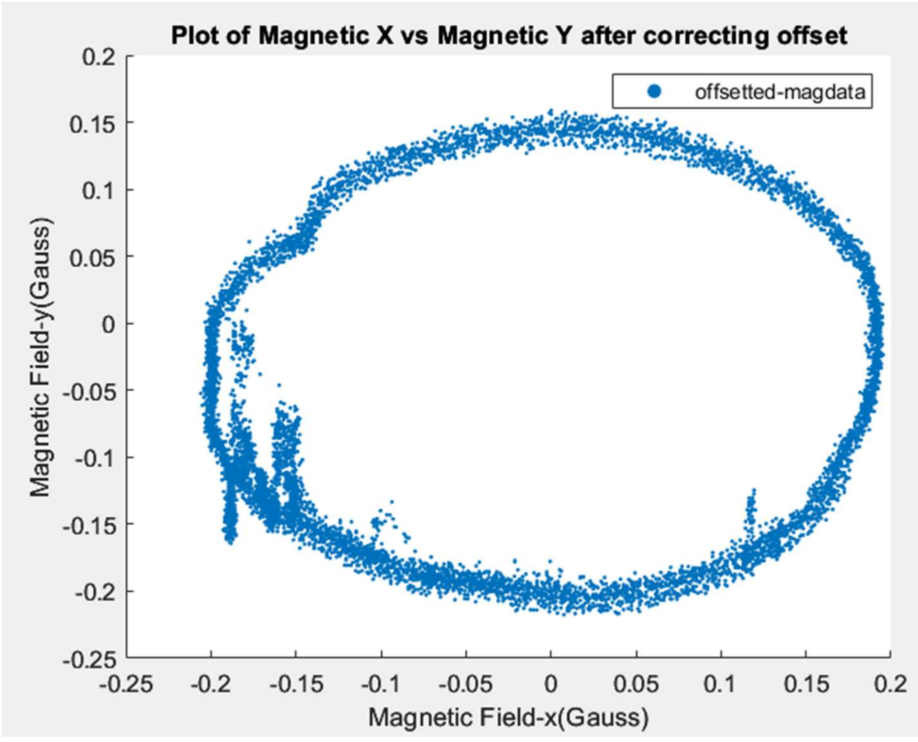

Fig 2: shows the plot of Magnetic X vs Magnetic Y after correction of the offset

Fig 2 shows the plot after hard-iron correction. We can see that the offset that was initially present is now remover

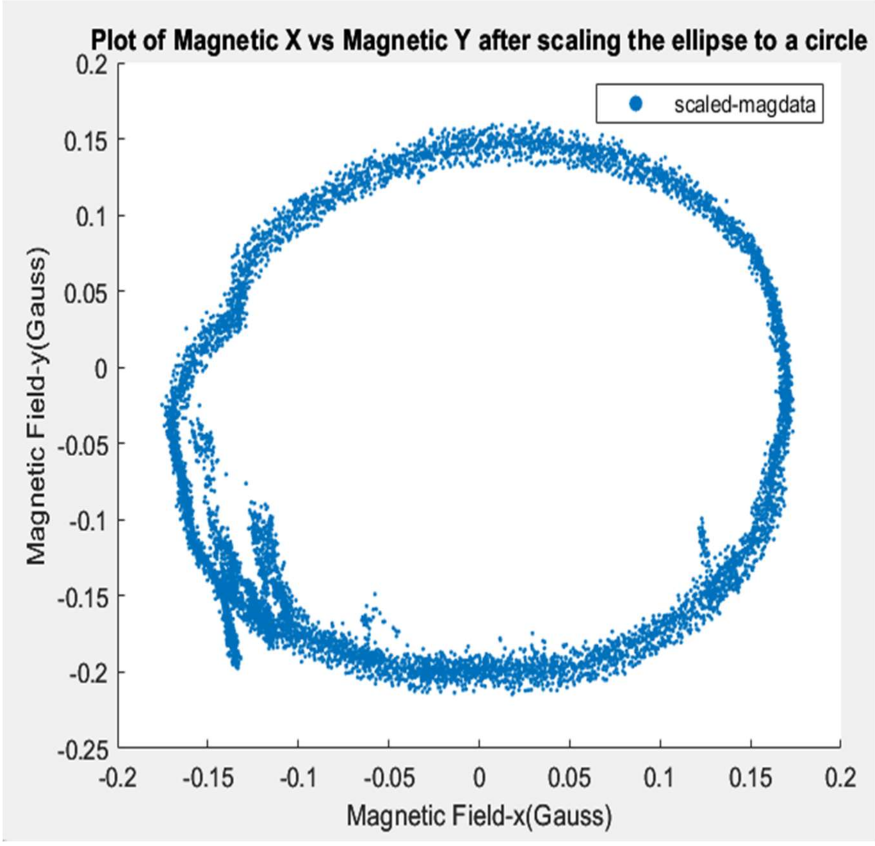

Fig 3: shows the plot of Magnetic X vs Magnetic Y after scaling the ellipse into a circle

The initial plot was observed to be an ellipse but after the scaling operation that we did the ellipse is now converted to a circle.

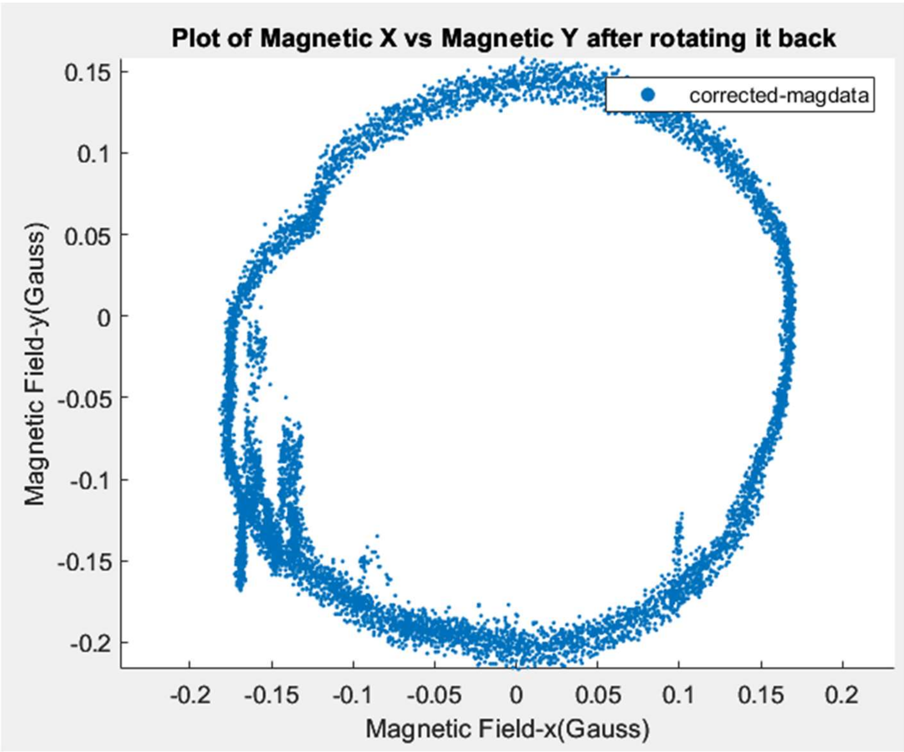

Fig 4: shows the plot of Magnetic X vs Magnetic Y after rotating the circle after correction

After the scaling we are rotating the corrected circle back.

- Soft Iron Correction:

$$\boldsymbol{m_c} = S_I(\tilde{\boldsymbol{m}} - \boldsymbol{b_{HI}})$$

$$\begin{bmatrix} m_{c_x} \\ m_{c_y} \\ m_{c_z} \end{bmatrix} = \begin{bmatrix} C_{00} & C_{01} & C_{02} \\ C_{10} & C_{11} & C_{12} \\ C_{20} & C_{21} & C_{22} \end{bmatrix} \begin{bmatrix} \tilde{m_x} - b_{H_0} \\ \tilde{m_y} - b_{H_1} \\ \tilde{m_z} - b_{H_2} \end{bmatrix}$$

Fig 2: Equation to compensating Hard and Soft Iron Effects

a. Rotation: Rotated offsetted x and y of magnetometer with an angle theta to align with the major axis of ellipse
   $\theta = 0.193615487943903$ rad
   Rotation Matrix= $\begin{bmatrix} 0.981315 & -0.19241 \\ 0.192408 & 0.981315 \end{bmatrix}$

b. Scaling: Scaled the major axis to convert ellipse to a circle
   scale factor = minor axis/ major axis = 0.871228596185692

   Scaled Iron Correction Matrix
   SI= $\begin{bmatrix} 0.875996 & 0.024314 \\ 0.024314 & 0.995233 \end{bmatrix}$

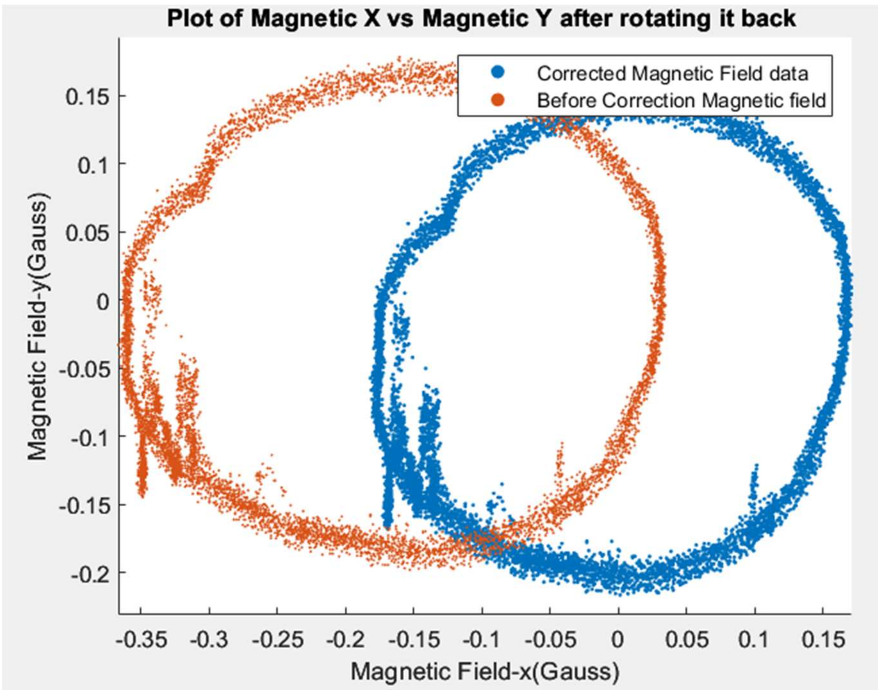

Fig 5: shows the plot of Magnetic X vs Magnetic Y before and after correction

The plot Fig 5 shows that comparison between the Magnetic field plot before correction and after soft iron and hard iron plot.

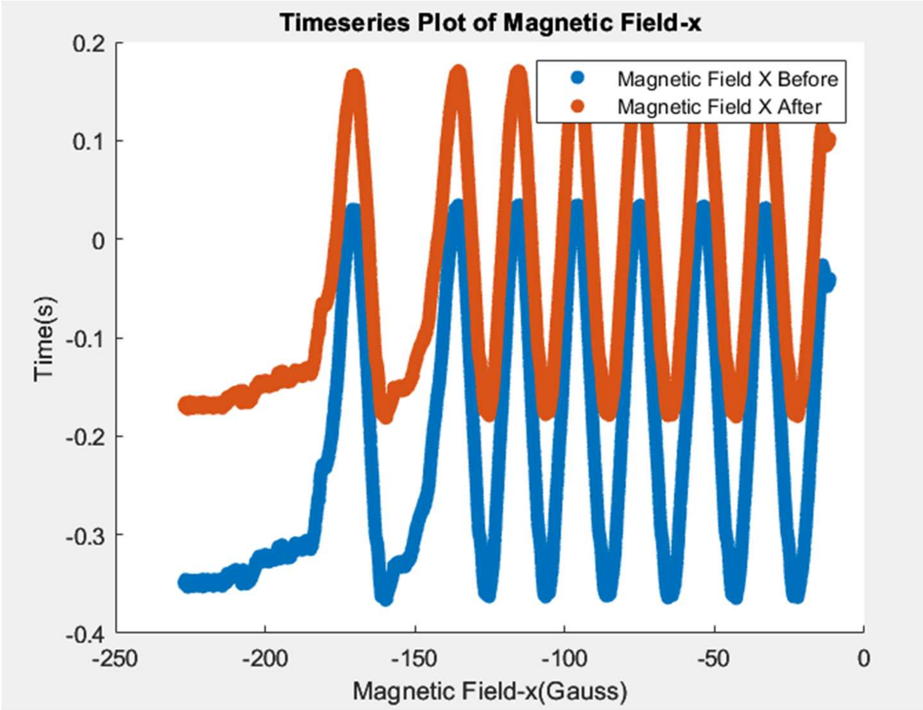

Fig 6: shows the time series plot of Magnetic field X from before and after correction

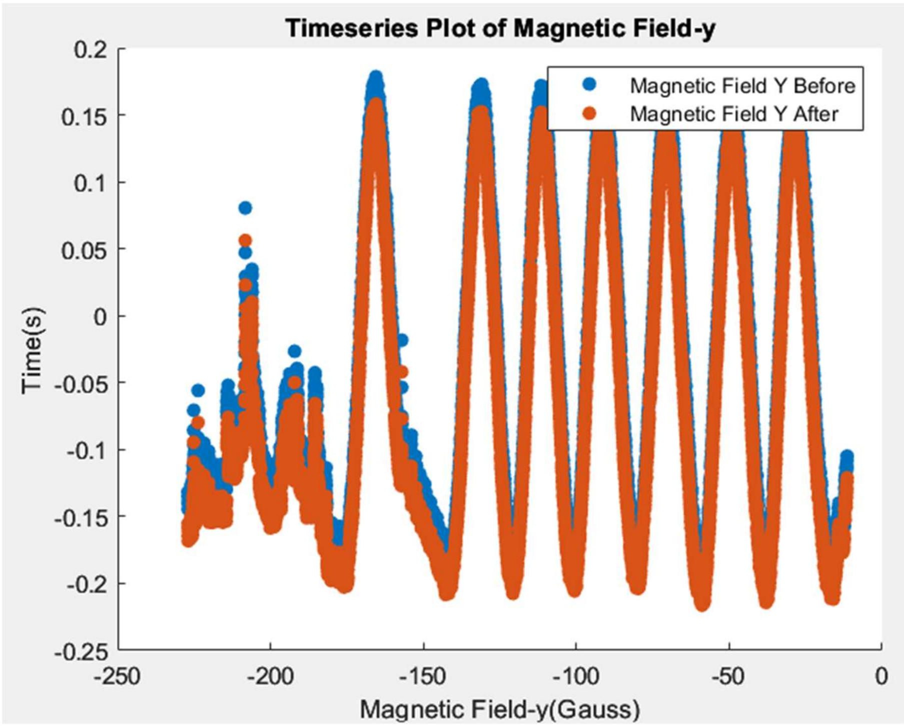

Fig 7: shows the time series plot of Magnetic field Y from before and after correction

1.3. Calculate yaw angle from the corrected magnetometer reading

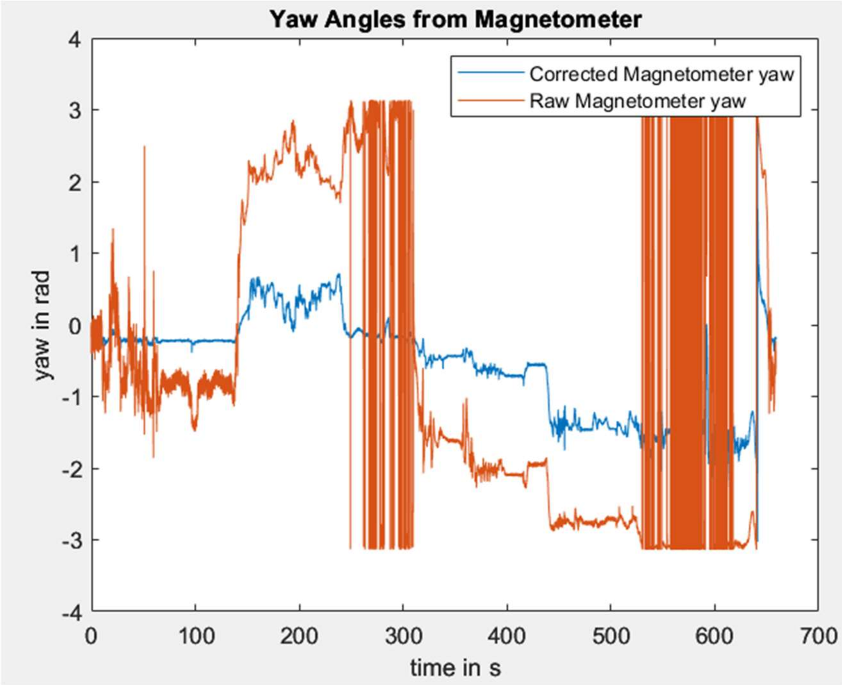

Fig 8: show the plot of raw magnetometer yaw vs corrected magnetometer yaw

1.4. Integrate the yaw rate sensor to get yaw angle

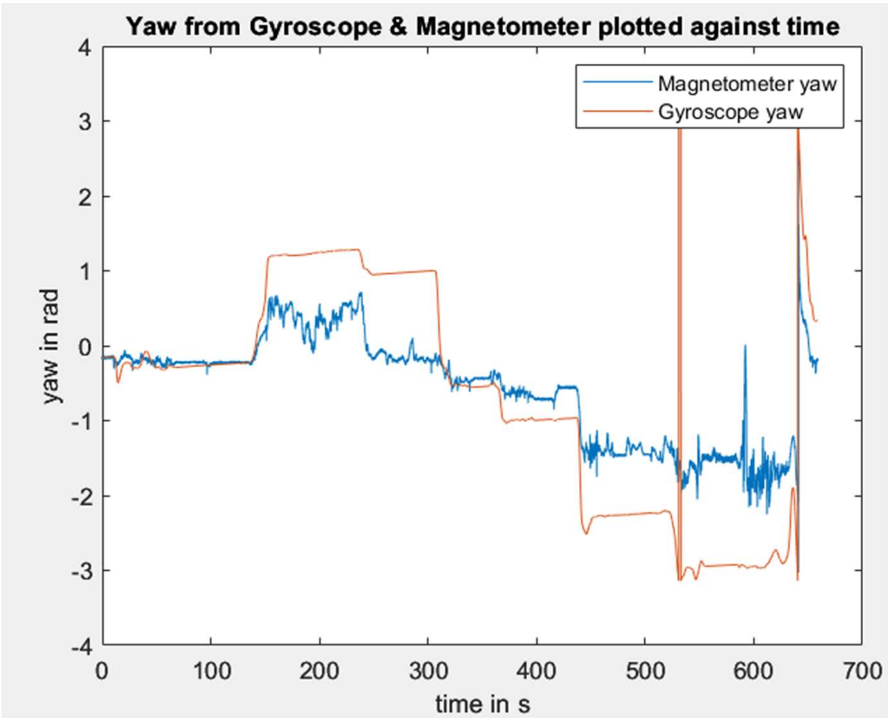

Fig 9: shows the plot of yaw angle in radiant from Magnetometer and Gyroscope

- How did you use a complementary filter to develop a combined estimate of yaw? What components of the filter were present, and what cutoff frequency(ies) did you use?

1.5. Applying the Complementary Filter

- Passing Magnetometer signal through -> low-pass filter

- Passing Gyroscope signal through -> high-pass filter
- Depending on the confidence of the output given from each of the filter a weightage is given to both the Magnetometer signal and Gyroscope signal. The weightage when added up sums to 1

The main components of the filter are Low pass filter and High pass filter

The cut-off frequency we used is 0.001

1.6. Compare the Complimentary filtered Yaw angle to the Yaw from Gyroscope and Magnetometer

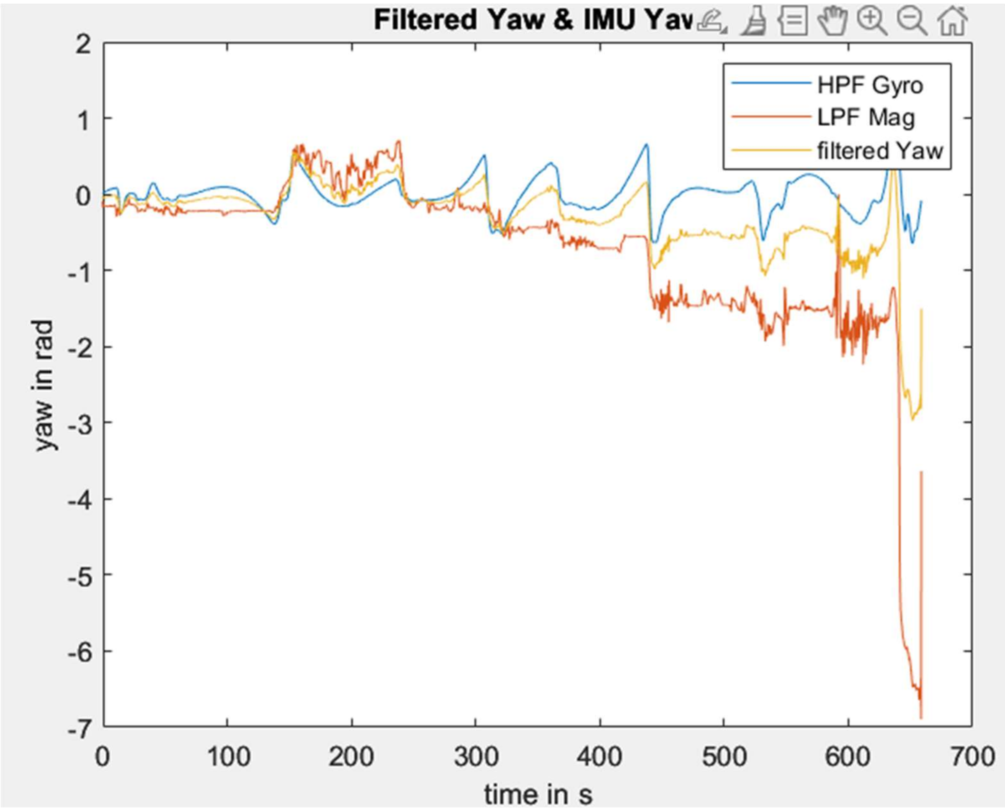

Fig 10: show a plot of HPF Gyro, LPF Mag and complimentary filter against time

The plot shows the comparison plot between the gyroscope yaw passes through High pass filter vs Magnetometer yaw passes through Low pass filter vs Complimentary filter

Complimentary filter is the sensor fusion step of adding

1.7 Compare the IMU Yaw angle to the Complimentary Filtered Yaw

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

The Gyroscope, often known as Gyro, is the initial part of an IMU and it monitors the angular velocity across an axis. Therefore, to calculate angles in three dimensions, you would want three gyros. The best thing about a gyro is that it is unaffected by acceleration and outside forces. When rotational velocities are high, gyros perform remarkably well under dynamic settings, but they drift dramatically over time. Therefore, a high pass filter to eliminate low frequency drift is the simplest filtering operation performed on gyro data.

The Magnetometer, often known as the Mag, it is uses to remove or discard the short-term fluctuation

The complimentary filtered Yaw is the most trust worthy estimated value of Yaw as the complimentary filtered output removes the various noise and error. Gyroscope give most accurate data in static condition and Magnetometer provides accurate values in motion. Since Complimentary filter takes the most accurate data from both gyroscope and accelerometer, we conclude that it provides most accurate data.

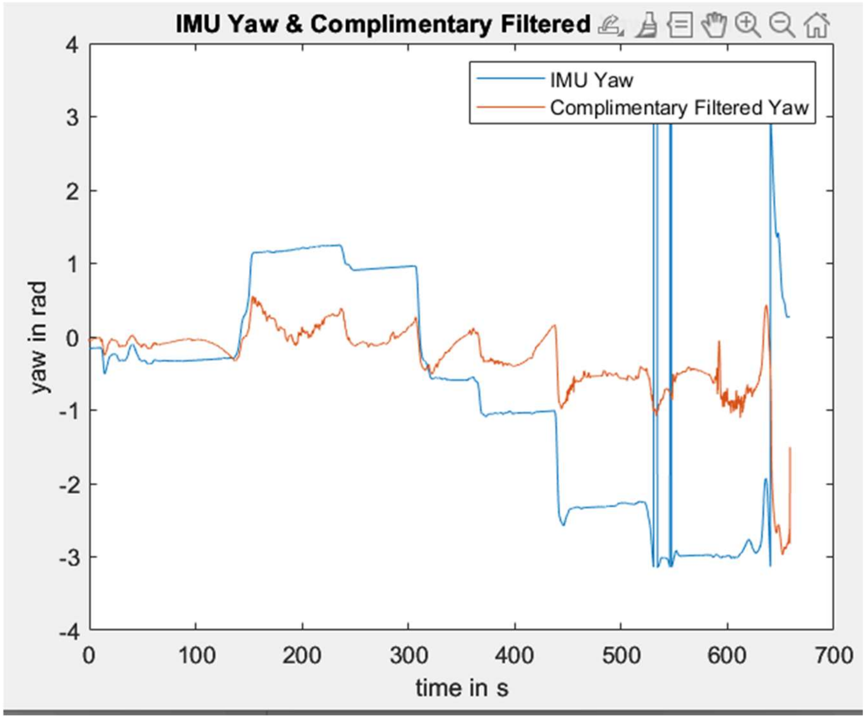

Fig 11: shows the comparison between IMU Yaw and Yaw from complimentary filter

Estimate the forward Velocity

1.1. Integrate the forward acceleration to get velocity

We integrate the forward acceleration of the in X direction to get forward velocity

1.2. Comparing plots of estimated velocity and collected velocity

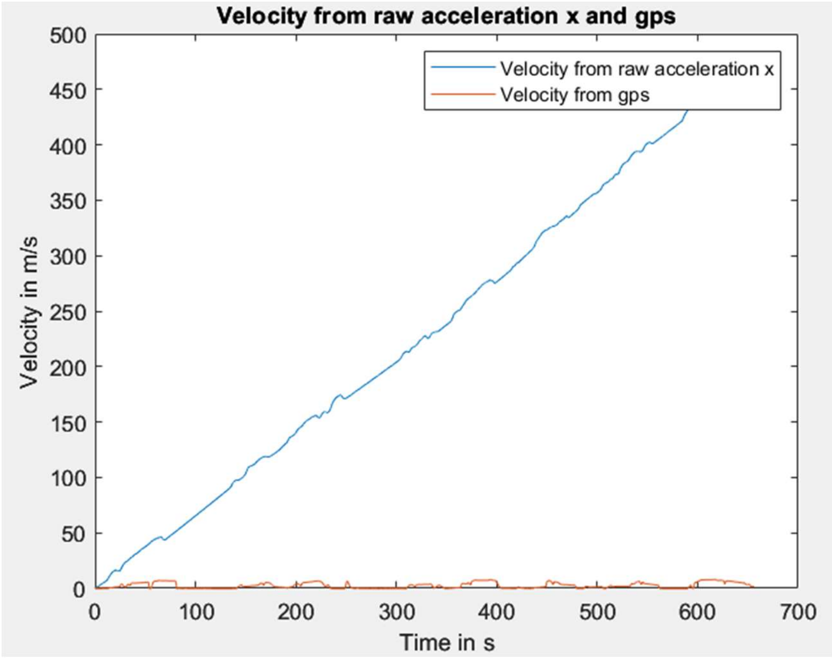

Fig 12: shows the velocity from raw acceleration x and velocity from the gps

The above figure shows the forward velocity by integrating forward acceleration. Due to the presence of noise and drift there is huge error that is observed between observed velocity and calculated velocity

1.3. Adjusting the acceleration measurements

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

The above graph shows an increasing error in the raw acceleration. This is because the raw acceleration has high bias and noise. The bias goes un and down in value during the course of the the collected data. The following are the reasons for the change in bias:

- Bias Instability
- The ground inclination changes with reference to initial point
- Vibration of the car
- The jerks caused due to the movement of the car

The error and noise keep increasing and gets added while performing integration. The value of GPS and IMU velocity should match when the car is in stationary position. The following steps are used to correct the raw acceleration. The originally collected acceleration from IMU is very noisy with a lot of high-frequency components.
After applying low-pass filter using the moving average method. The acceleration value gets smoother. Observing the graph, the small constant value plots have non zero values. **Ideally the values of velocity and acceleration during this period should be zero**. But due to error a non-zero value is provided in the collected data. One of the primary reasons for this issue is because the road might be sloped causing accelerometer to collect a reading even when the car stops.

Hence, we have to bring the constant values to 0
As shown in the figure the drift from all the previous constant value periods was subtracted for the following measured values, then the velocity was calculated through segmented integration of acceleration.

- We are passing the acceleration through low pass filter to cut off frequency of 0.001 Hz.
- Data points with constant acceleration is found with diff function in MATLAB
- A loop is run to iterate to all the data points to check if the GPS velocity corresponds to thw data points that have value 0.
- It the GPS velocity is zero the that acceleration values that that point is considered to be bias. The bias value sis subtracted from the acceleration values till the car stops the next time. The bias is calculated every time and the calculated bias value is subtracted from the acceleration

  This error cannot be solved by adjusting the mean value of acceleration. There may exist a linear or nonlinear relation between the error and input. To smoothen this effect, we need to use the scaling method to scale the measurement and reduce the errors.

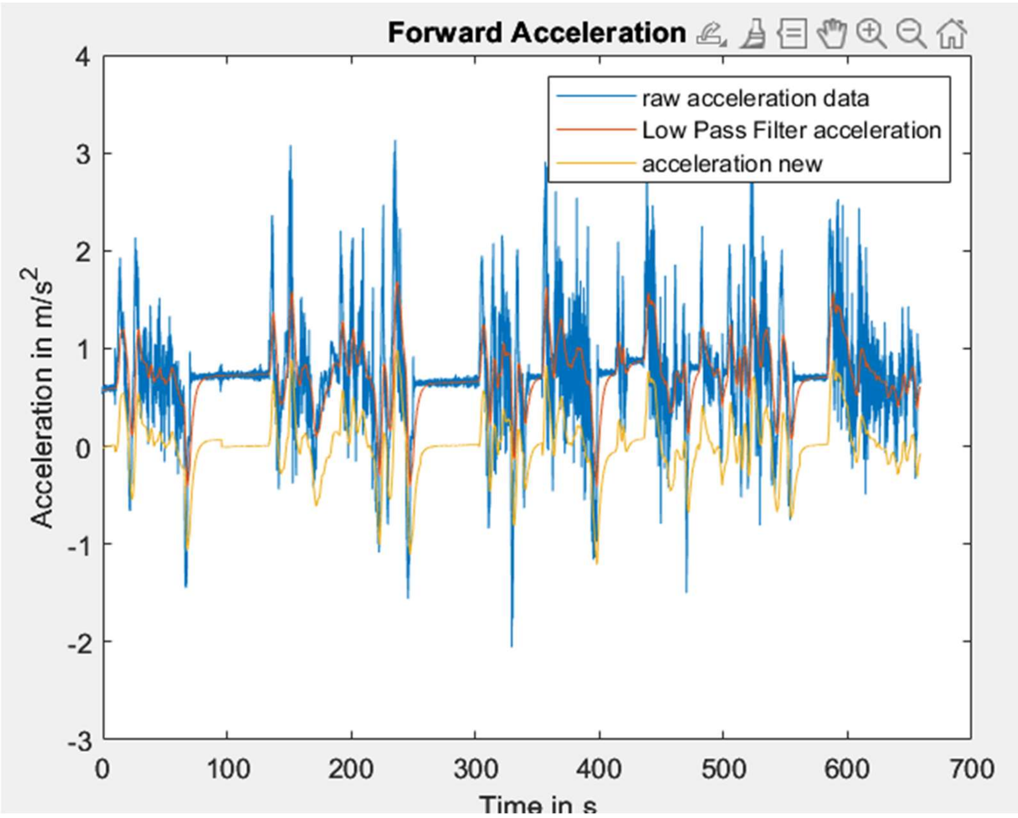

Fig 13: shows that plot of raw acceleration, acceleration corrected through lowpass filter and bias corrected acceleration

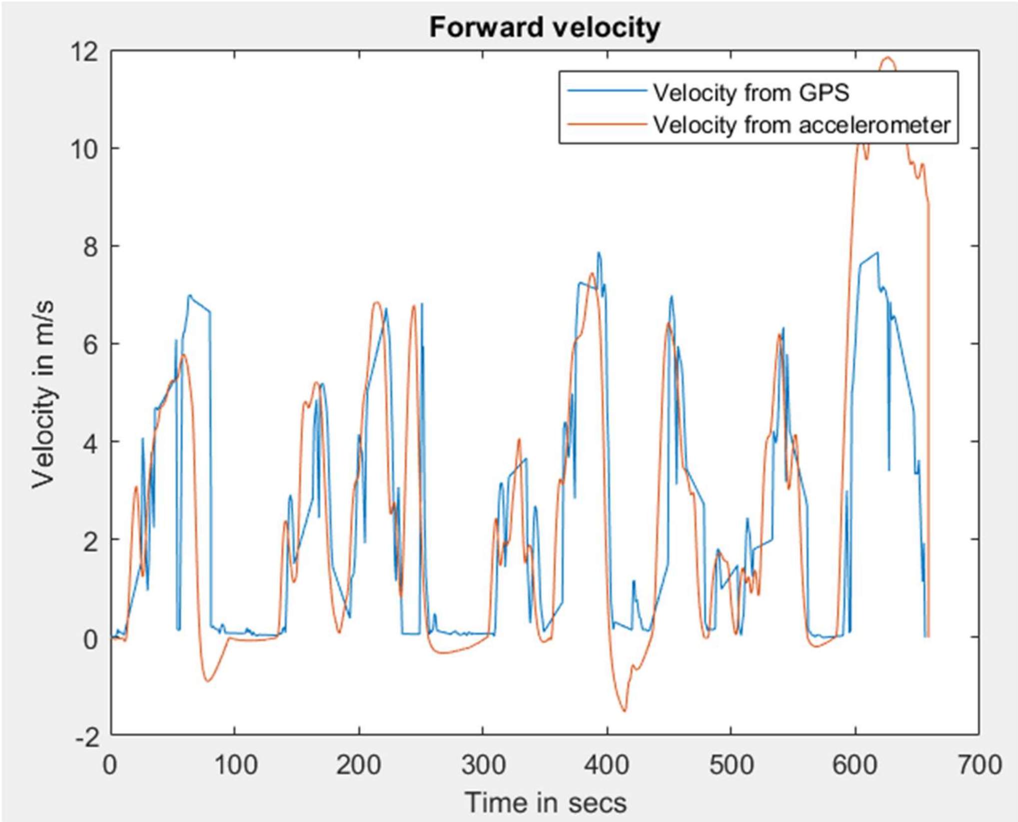

Fig 14: show velocity from GPS and accelerometer

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

While calculating the velocity from accelerometer there might be error because the integration function cumtrapz used might not be taking the exact values. Additionally, there might be loss of decimal values which will lead to error in the calculate velocity from the accelerometer. When the error accumulates then the estimates velocity will show a substantial error in the final graph.

2. Dead Reckoning

- Compute ωX and compare it to $\ddot{y}obs$. How well do they agree? If there is a difference, what is it due to?

2.1. Integrate $\ddot{x}_{obs}$ from IMU to obtain $\dot{x}$ which is the displacement, the compute $\omega\dot{x}$ and compare with $\ddot{y}_{obs}$

$$\ddot{x}\text{obs} = -\omega\dot{Y} - \omega^2 x_c$$
$$\ddot{y}\text{obs} = \ddot{Y} + \omega\dot{X} + \dot{\omega}x_c$$

Assumptions-

vehicle is not skidding sideways i.e $\dot{Y}$= 0

IMU is on the centre of mass of the vehicle- x_c = 0

∴ $\ddot{X}$= $\ddot{x}obs$

$\dot{x}$ = ∫ $\ddot{X}$

Integration errors

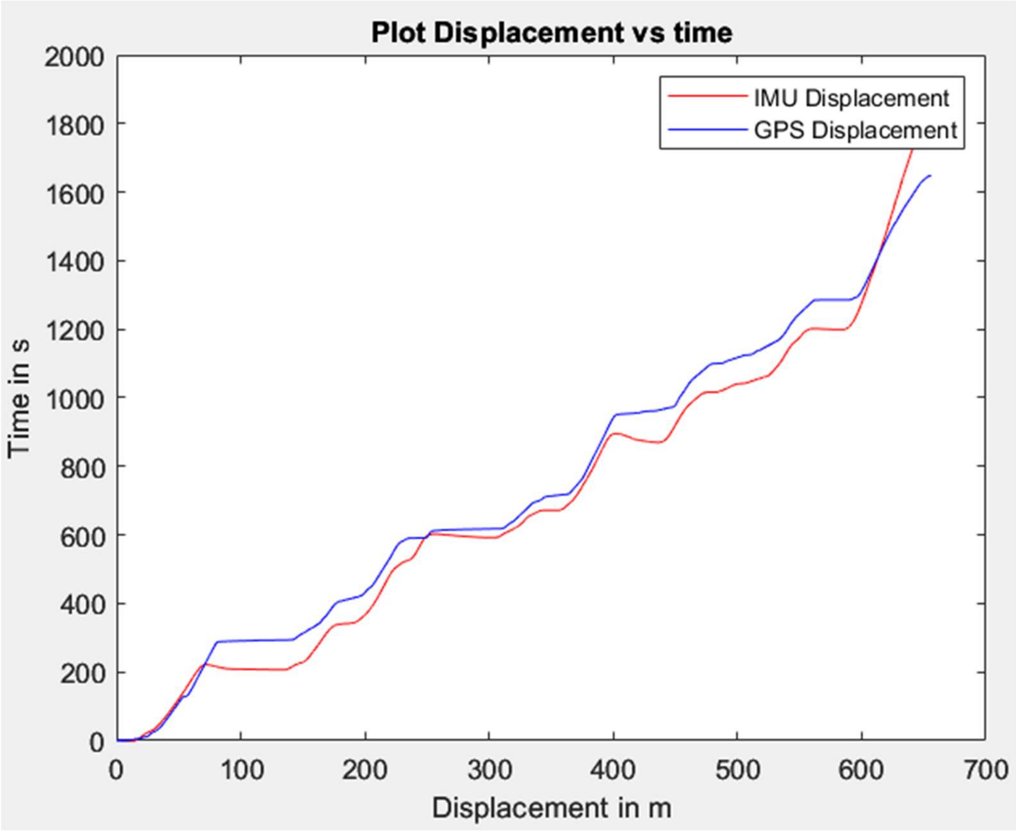

Fig 15: show IMU and GPS Displacement

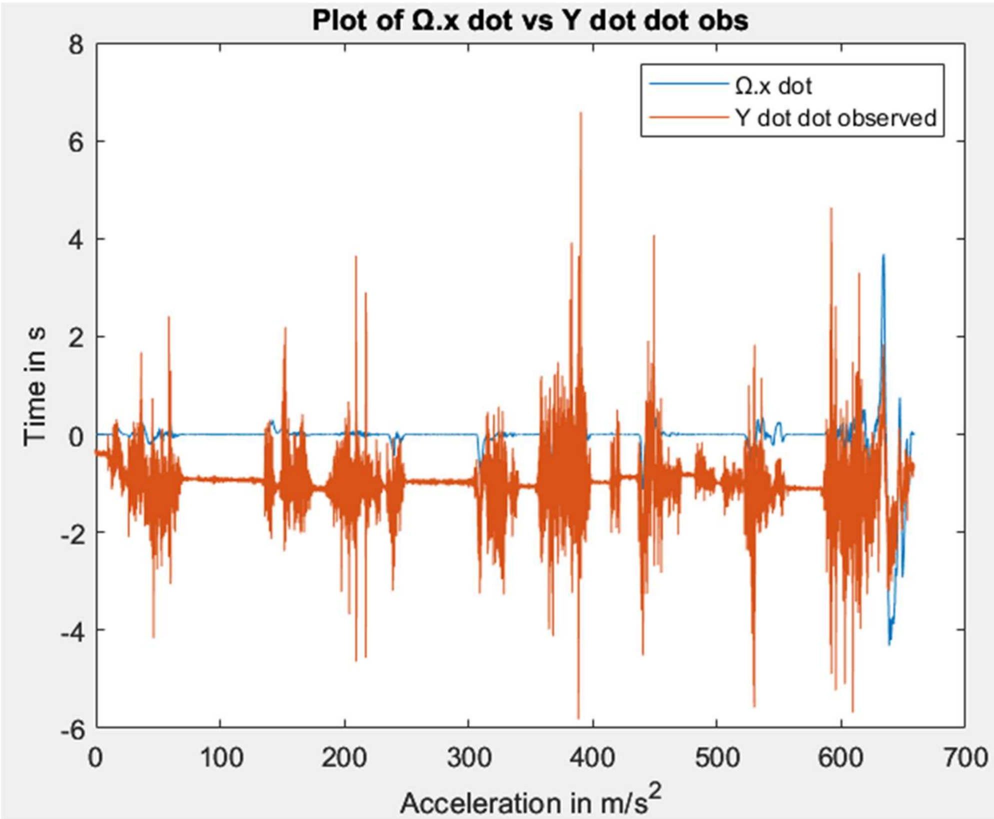

Fig 16: comparing $\Omega.\dot{X}$ vs $\ddot{Y}_{obs}$

Yes there is a difference between a value of acceleration that was calculated this is mainly because of the noise and the errors in the data

❖ Estimate the trajectory of the vehicle (xe,xn) from inertial data and compare with GPS by plotting them together. Report any scaling factor used for comparing the tracks

Use the heading from the magnetometer to rotate the fixed (North, East) to reference frame

- Velocity vector (v_e ,v_n)
- Integrate (v_e ,v_n) to estimate the trajectory of the vehicle(x_e ,x_n)
- Compare the estimated trajectory with the GPS track

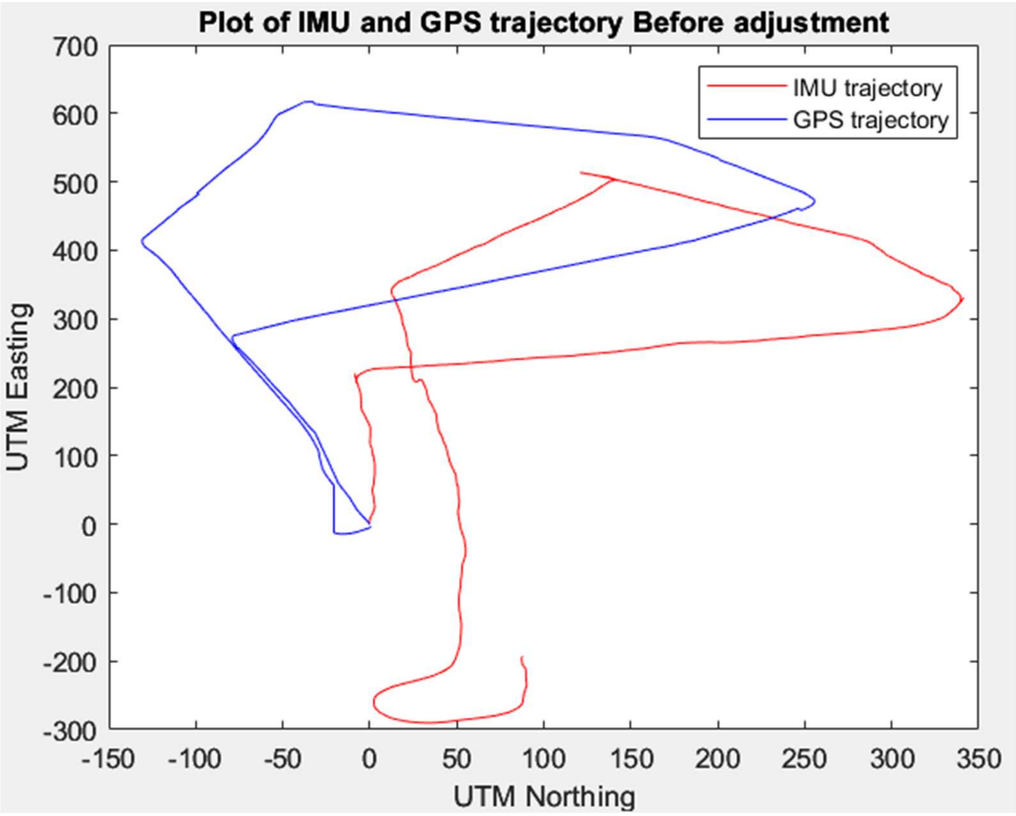

Fig 17 show the IMU and GPS trajectory plot in UTM Northing and Easting before adjusting

The plotted figure is the GPS UTM trajectory and the IMU trajectory is obtained by integrating the IMU velocity.

No scaling was done to the IMU trajectory

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

It can be observed that despite the starting point for both IMU and GPS being from the same location the end point does not match because. There is a slight error in the turn angle that the IMU takes then error adds up to cause a huge error to be observed toward the end of the movement. Hence without a gps fix its very difficult to estimate the collected data. This is the reason the data collected from these sensory are not completely reliable.

$$v_{estimated} = \int acc_{adjusted}, (acc_{adjusted} \text{ was calculated in last part})$$

$$v_a = v_{estimated} * \sin(yaw\_angle_{magnetometer})$$

$$v_b = v_{estimated} * \cos(yaw\_angle_{magnetometer})$$

$$x_a = \int v_a$$

$$x_b = \int v_b$$

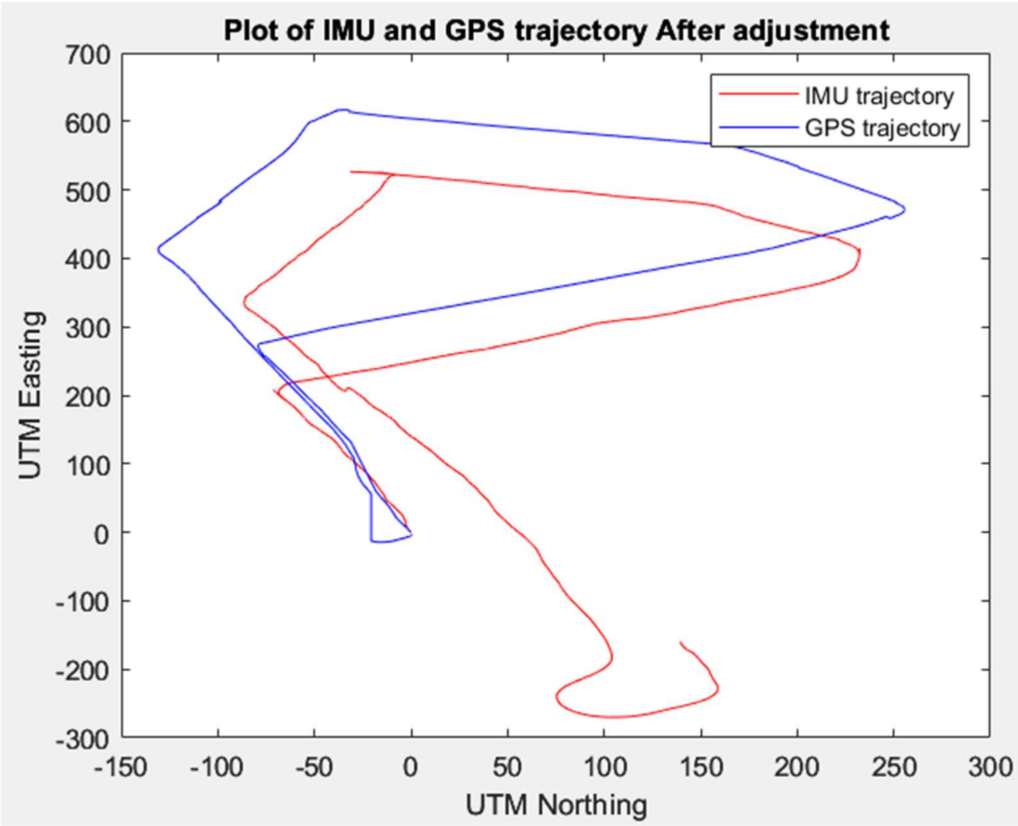

Fig 18 show the IMU and GPS trajectory plot in UTM Northing and Easting after adjusting

Correction was performed in the IMU trajectory to align it with the starting point of GPS trajectory. Then the first path is also aligned with the direction of the first stretch of the trajectory of GPS data. Then the above figure was obtained.

2.2. Estimate x_c

Reference

[1] https://nitinjsanket.github.io/tutorials/attitudeest/imu