

Introduction

A 12 DOF Vector Nav 100 IMU was used for measuring magnetic field, orientation, linear acceleration and angular velocity.

1) Driving in Circles

For calibration of the magnetometer, about 4-5 rounds of driving in a same circle was done and readings were collected. Fig 1. shows The graph obtained.

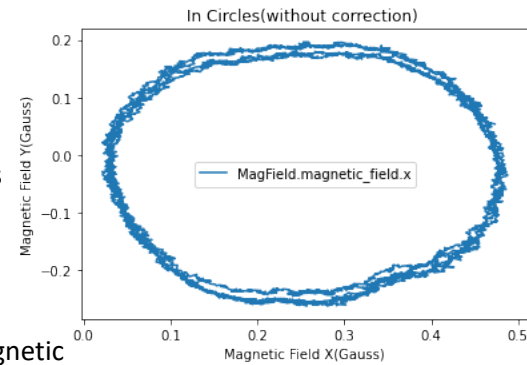


Fig 1.1

A) Hard Iron calibrations

Hard Iron distortions are created by objects that produce a magnetic field. They lead to a permanent bias thus shifting the centre of the circle. They do not distort the shape of the circle.

So to remove them, x and y offsets are subtracted.

An ellipse is first fitted to give the angle as 0.152 radian and Center as (0.253,-0.030) as shown in Fig 1.2

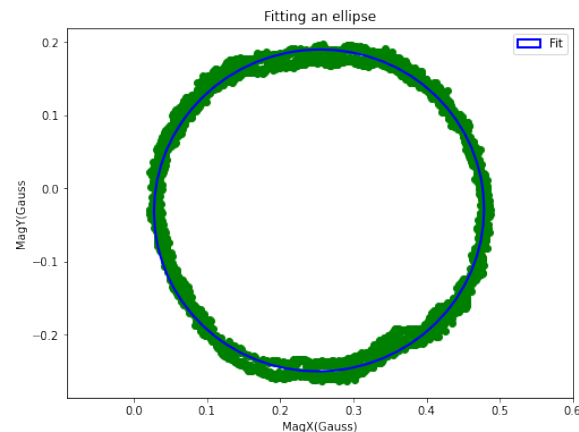


Fig 1.2

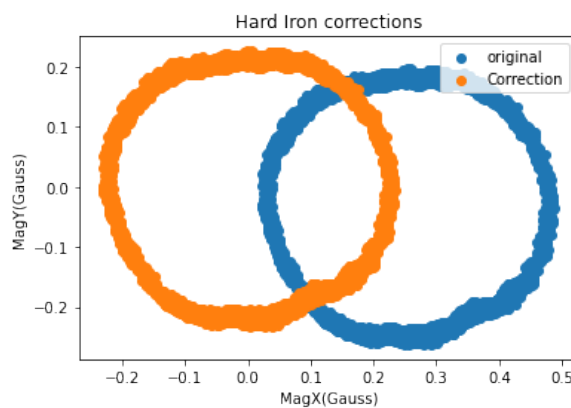


Fig 1.3

Fig 1.3 shows the comparison between original and after performing Hard Iron corrections.

B) Soft Iron Corrections

Soft Iron Distortions are deflections/alterations in the existing magnetic field. These can either stretch or distort the magnetic field. They can also distort and warp the existing magnetic field.

The process involves passing the MagX and MagY through rotation and scaling to fix the errors and centre it at the origin. Rotation was done to make the axis align with X-axis.

Scale factor makes the ellipse look like a shape of a circle

Fig 1.4 shows these corrections

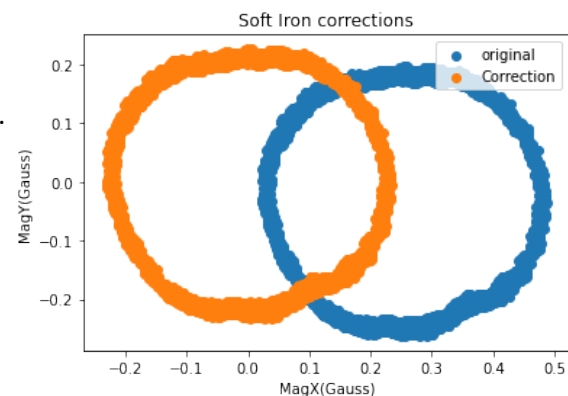


Fig 1.4

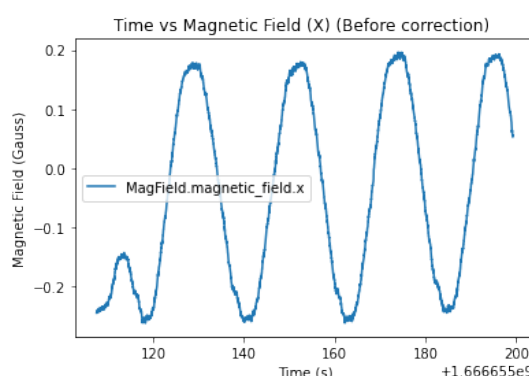


Fig 1.5

Fig 1.5 shows the time series Magnetic Field before correction. The mean of the magnetic field was not About 0 due to presence of the hard iron and soft iron Distortions.

Fig 1.6 shows the time series Magnetic Field after correction. The mean has been centered around 0, which implies that the distortions have been corrected

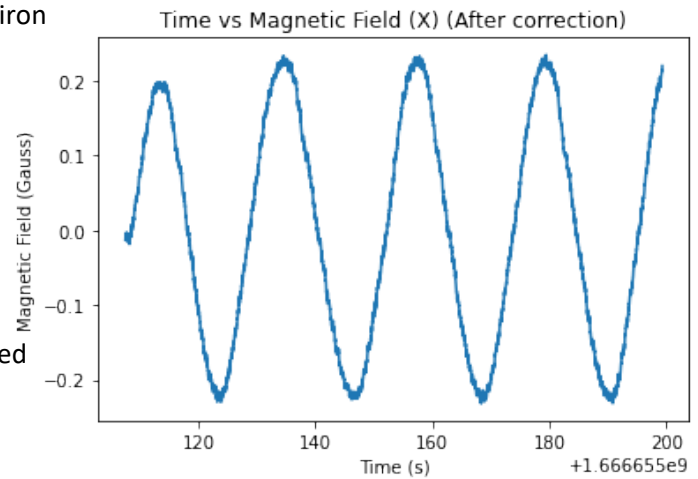


Fig 1.6

2) Driving data

A) Estimating the Heading/Yaw

Fig 2.1 shows the magnetometer yaw calculated from The X & Y axis, and gyroscope yaw integrated over a time Series.

We can see that most of the time the yaw calculated from both the magnetometer and the gyroscope remain consistent. the 'red' portion marked on the graph indicates that the car had stopped for that portion of time ,which turns out to be a good reading given out by the magnetometer. But when the car is moving, We can detect some amount of noise and fluctuations from the magnetometer (as seen from the 'purple' box).

Whereas, the gyroscope readings are pretty smooth in moving conditions and give An good estimate of the yaw angle. Therefore, I would trust gyroscope yaw.

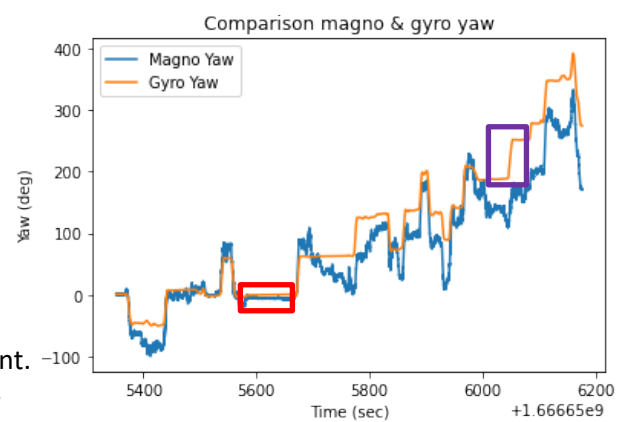


Fig 2.1

• Complementary filter

It takes the slow moving signals from the magnetometer and fast moving signals from gyroscop and combines them to give a better output. Components are high pass filter
low pass filter

The equation for a low pass filter of a magnetometer is :

$$y_n = (1 - \alpha)x_n + \alpha y_{n-1}$$

Where x_n is the yaw from magnetometer

The equation for a high pass filter of a magnetometer is:

$$y_n = (1 - \alpha)y_{n-1} + (1 - \alpha)(x_n - x_{n-1})$$

Where x_n is the yaw from gyroscope.

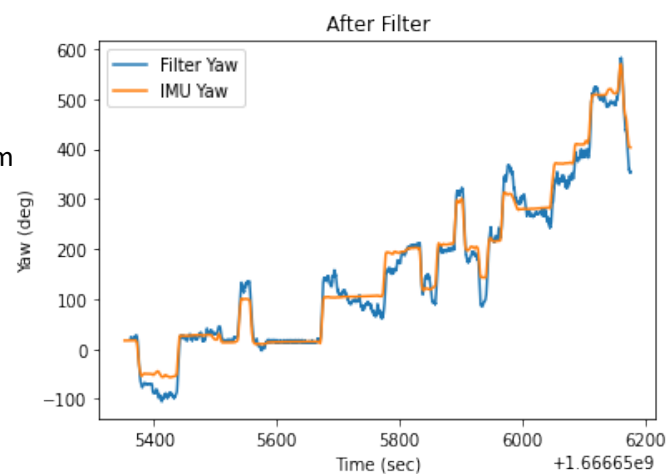


Fig 2.2

The α value chosen for the filter was 0.9596 ,which helped in negating the high frequency noise.

Fig 2.2 shows the implemented complementary filter using the equations above. We can clearly see from the graph that the original IMU yaw and the filtered magnetometer yaw matches quite well except for a few regions. Thus, the filtered yaw is not as noisy like the magnetometer one (as seen in the previous graphs) and drifting has also been greatly reduced.

3) Estimating the Forward Velocity

Fig 3.1 shows the velocity vs. time graph after directly integrating acceleration (without any corrections). As expected the graph comes out to be a straight line. But , the problem is due to the increase in bias over Time due to the accelerometer component ,which Results in high values of velocity (which are impractical).

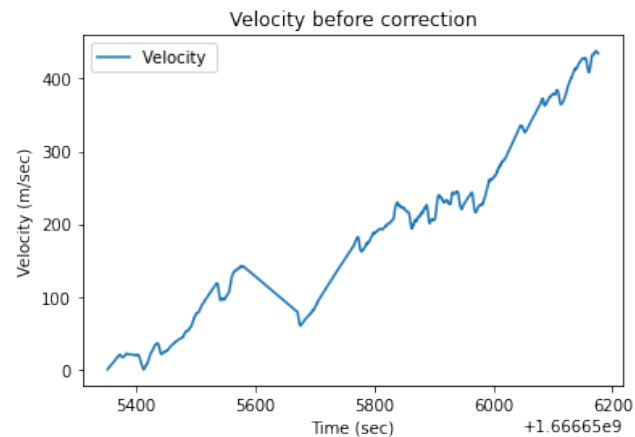


Fig 3.1

Fig 3.2 shows the GPS velocity against time. This graph is practical based as it shows the velocity with good accuracy when compared with that of the speedometer. The 'red' box shows the time period when the car was at rest. The velocity has remained almost constant throughout the time.

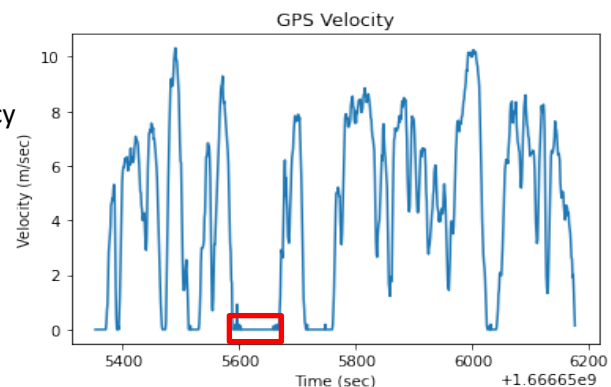


Fig 3.2

From Fig 3.3 we can observe that there is a huge error which has been accumulated over time between the estimated velocity obtained directly after integration and the true velocity obtained from GPS. An assumption which was made was that velocity will always be positive as we are always going forward.

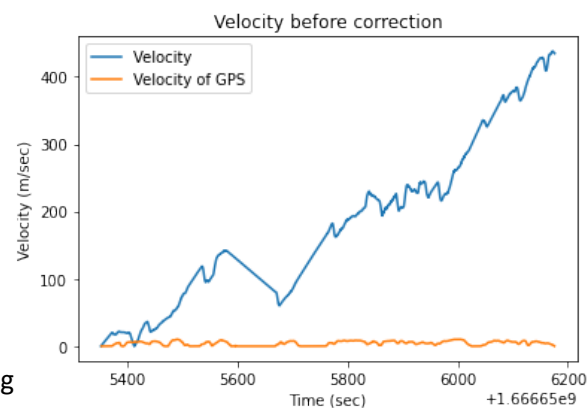


Fig 3.3

- **Correcting Acceleration Bias**

To get an accurate estimate of velocity, we have to first reduce/remove the bias from the Acceleration component. Due to many high frequency components, a low pass filter is applied. This smoothens out the lines to an extent. But there is presence of constant horizontal lines where the velocity and acceleration should have been zero after comparing it with GPS, but is not. This maybe due to the unevenness of the surface of the road, which often leads the accelerometer to give readings even when the car is at a rest. To remove these drifts, for every time period where they occurred, they were subtracted from the following measurements. Normalizing was also done for some regions to get a mean of 0. By doing this process, a rough estimate of velocity was obtained and compared with that of the GPS as seen in Fig 3.4. The velocity obtained from acceleration after correction still lacks finer details but follows a similar trend when compared to the GPS ('red' box) but performs well in some cases ('purple' box).

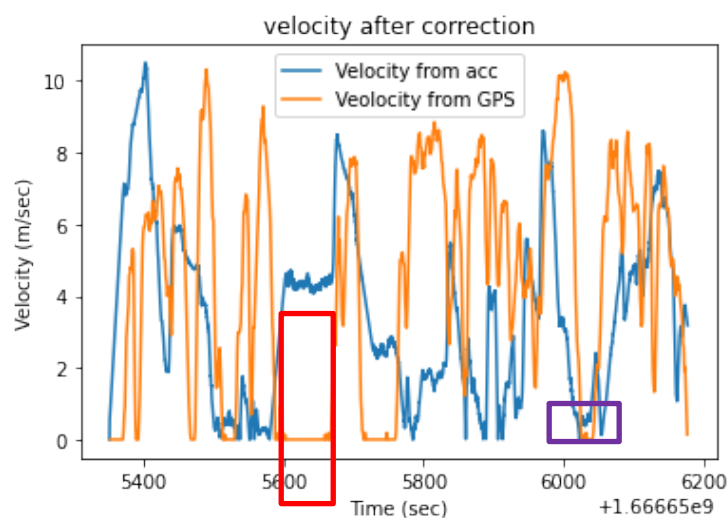


Fig 3.4

4) Dead Reckoning

Dead reckoning is the process of calculating current position of moving object (here ,car) by using previously estimated position , speed,direction,course over elapsed time.

Fig 4.1 shows the position estimated by integrating the corrected Velocity obtained from acceleration. But as seen from the 'red' box, there is still some bias present, which is causing the line to curve and not be straight.

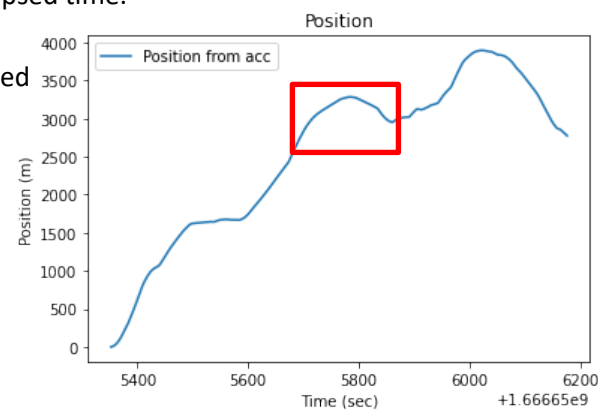


Fig 4.1

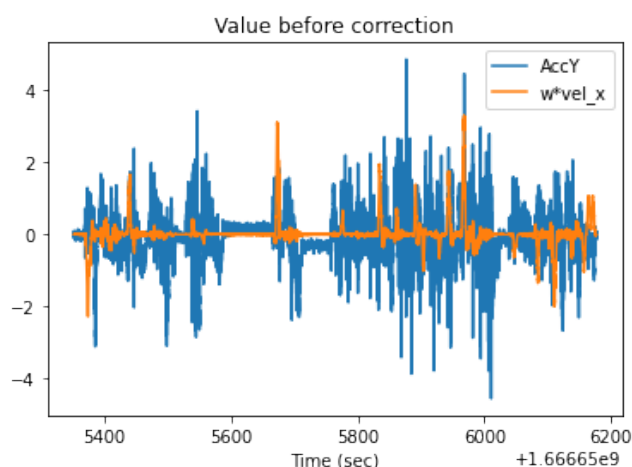


Fig 4.2

Fig 4.2 shows the trend between Acceleration in Y axis and $w \cdot \text{vel_x}$ where vel_x is the estimated velocity as Seen from the above graph and w is the Angular velocity in the Z direction. It is evident that the Acceleration in Y axis is pretty noisy and many high frequency components are present. There are also many drifts in the data values. This is maybe due to the low frequency noise will give a random walk while integrating and this will keep on increasing with time. To remove these errors, a low pass filter can be used to remove the specific low-frequency noises.

Fig 4.3 shows the output Acceleration in Y axis and $w \cdot \text{vel_x}$, where vel_x is the estimated velocity as Seen from the above graph and w is the Angular velocity in the Z direction. This was done after applying a low pass filter. Now both the values almost match after removing the noises.

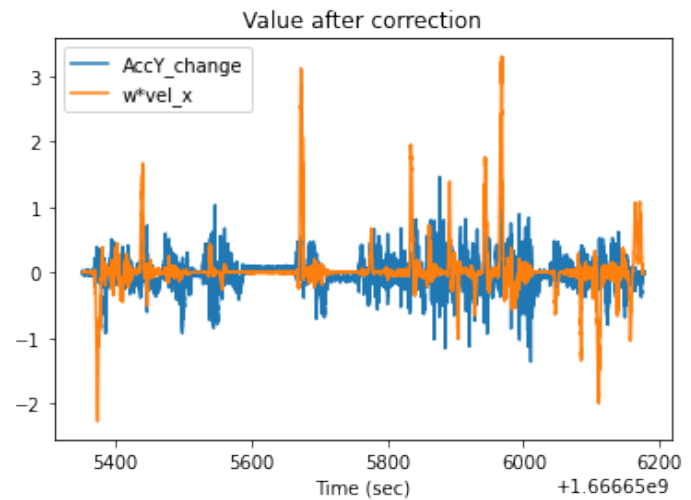


Fig 4.3

Fig 4.4 shows the area where the car drove as tracked by The GPS.

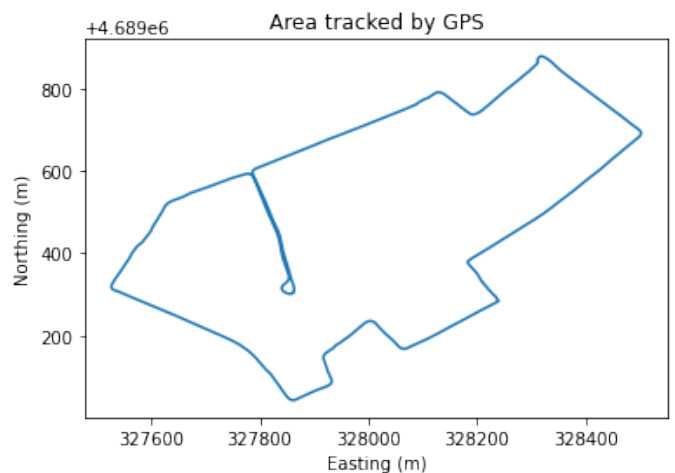


Fig 4.4

Fig 4.5 shows the estimated position of the car .

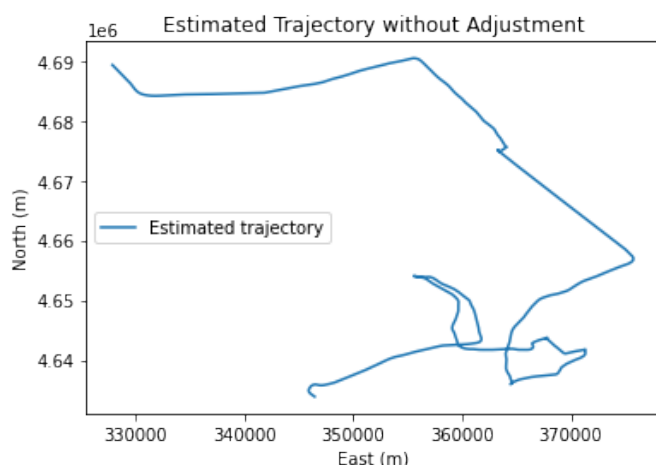


Fig 4.5

By comparing Fig 4.4 & Fig 4.5 , we get to know the many errors and difficulties faced while dead reckoning. These estimation errors increase with the distance to the known initial position as error are cumulative in nature. To obtain a better trajectory , the IMU should be moved at a uniform speed and a flat road having less roughness. Also, frequent updates within a fixed position are necessary.

The position of IMU and GPS matched at the first time i.e. the position where we started from around time =0

- Determining X_c

$$\ddot{x} = \dot{v} + \omega \times v = \dot{X} + \dot{\omega} \times r + \omega \times \dot{X} + \omega \times (\omega \times r)$$

From the above equations , replace ' r ' by $\begin{matrix} x_c & 0 \\ 0 & 0 \end{matrix}$, ' w ' by $\begin{matrix} 0 \\ \omega \end{matrix}$

\ddot{x} = imu acc x and y components ; \ddot{X} = gps acc x & y components putting these in the above equation we will be able to arrive at some equation of the form $Y = Zx_c$, from this $x_c = Z(\text{transpose})Y$

Euler form to rotation matrix will be needed. The value maybe near the center of mass of vehicle

- References

- 1) <https://www.vectornav.com/resources/inertial-navigation-primer/specifications--and--error-budgets/specs-hsicalibration>