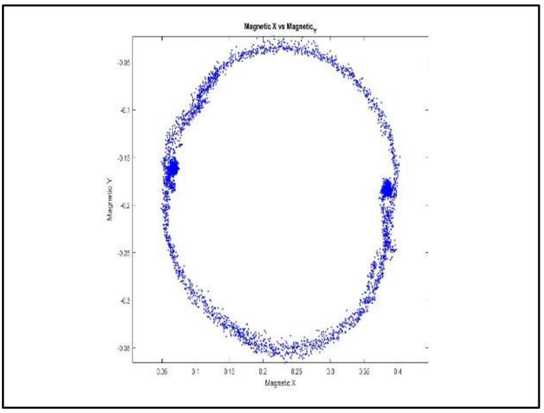
EECE 5554 - Robotics Sensing and Navigation

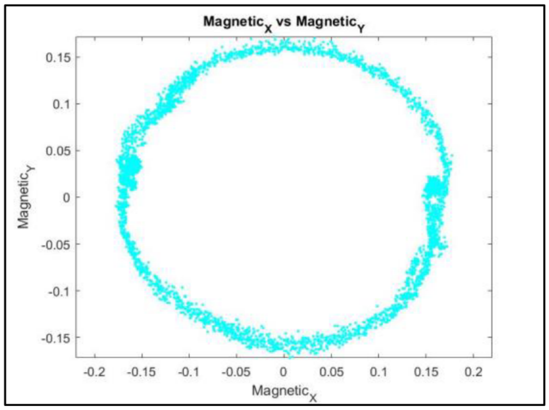
Lab 3: IMU Accelerometer, Gyroscope, Magnetometer and Allan Deviation Analysis

Task 1: Estimate the heading (yaw):

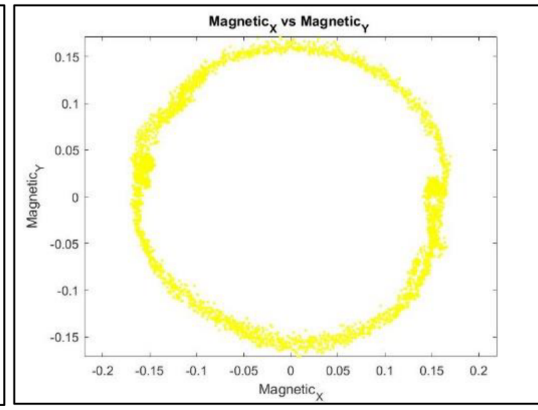
A: Calibration of Magnetometer



BEFORE CORRECTION MagX vs MagY

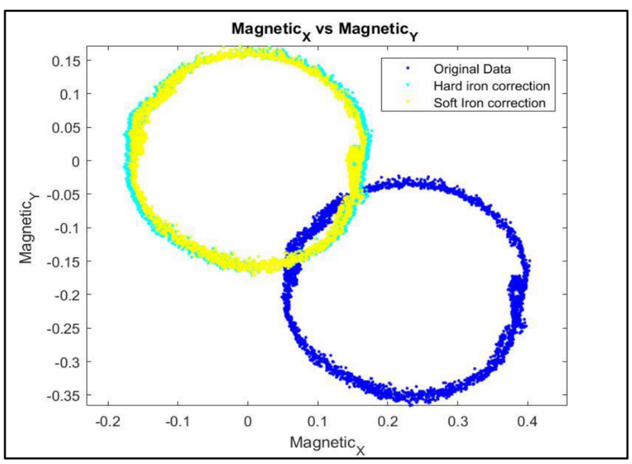


After hard iron CORRECTION



After soft iron CORRECTION

Comparison of original data and correct magnetometer readings for "hard-iron" and "soft-iron" effects using the data collected when going around in circles.



Comparison before and after the calibration

The magnetometer will be affected by hard and soft iron effects. To calibrate the magnetometer, we need to plot the magnetometer data on X-Y plane. If there’s no error, the data plot will be a nearly perfect circle. But it’s almost an ellipse with offsets. To do that the first thing we need to do is to calculate the center of the ellipse and remove the hard iron effects. Then we need to find the axis of the ellipse and get its angle. Then rotate the whole data sets to make the axis align with x-axis. After that we apply scale factor to the ellipse and make it look like a circle. Finally, we rotate it back, and that’s how we remove the soft iron effect from magnetometer reading

Hard Iron Correction:

The hard iron distortions were removed by removing the offsets in the origin of the ellipse by averaging the maximum and minimum x,y values and then subtracting those values from the data.

$$(X\_max + X\_min) / 2$$
$$(Y\_max + Y\_min) / 2$$

After adjusting the offset values as you can see from the above figure that the hard-iron corrected data w is centered at (0,0) and the offset values found are X-offset value = 0.193890000000000 Gauss Y-offset value = - -0.188450000000000 Gauss.

Soft Iron Correction:

The soft iron distortion was removed by finding the major and minor axes and then applying rotations and scaling based on the angle calculated between the offset axes and the true axes and rotating the circle back to the original position. However, from the scaling factor value i.e., 1.161964963168740 we can say that soft-iron effect is very less as scaling factor indicates that it is almost a circle

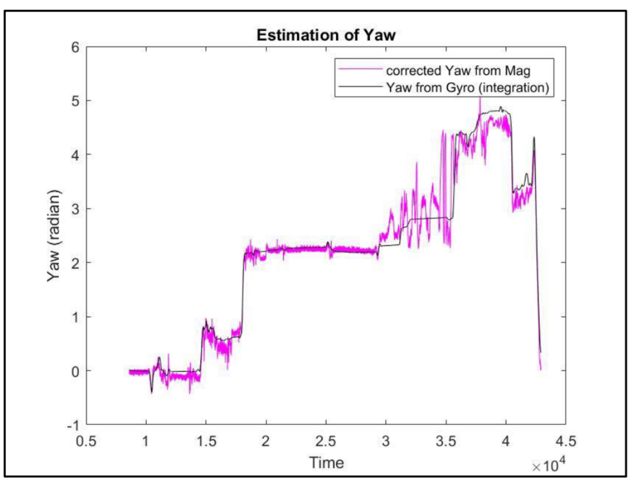
Thus, magnetometer is now calibrated and both hard-iron and soft-iron effects are removed. Above is a good estimate and is a factor in future heading calculations.

B: Yaw angle calculation

For this subset of data related to the magnetometer and IMU, yaw angle plots were generated. From the magnetometer, the yaw angle was calculated using:

arctan2(magnetometer_y_values, magnetometer_x_values)

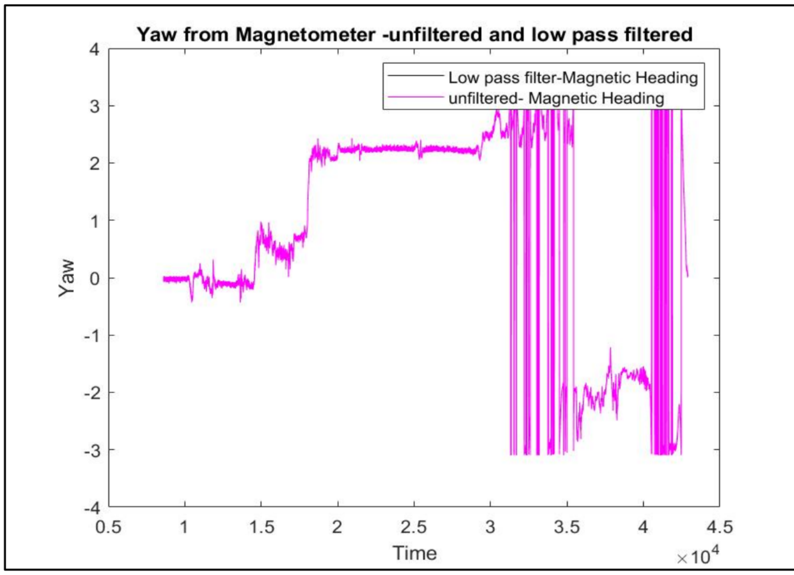
For the gyroscope data, the yaw angle was calculated by integrating the angular velocity in the Z direction according to our corresponding timestep. The two data sets are as shown below wrapped to between -pi and pi radians.

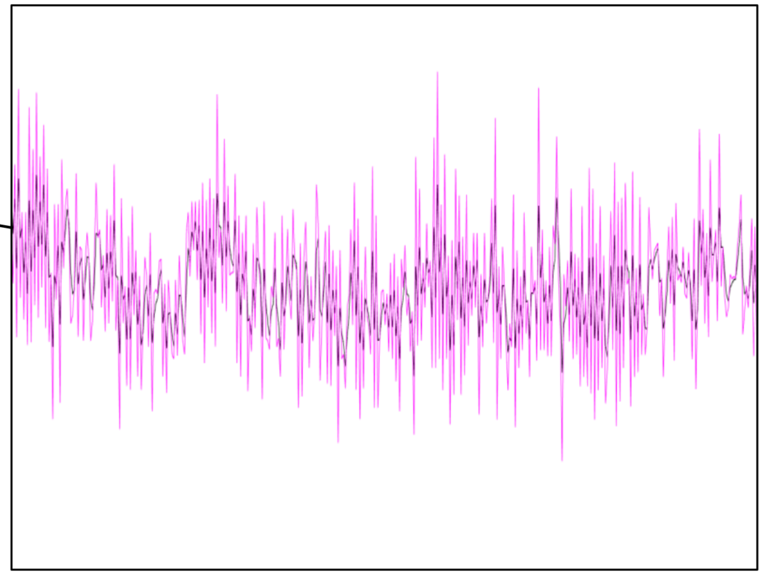


From the above figure, we can notice that the overall yaw angle trend calculated from the above two methods are consistent. However, the yaw angle from corrected magnetometer readings (magenta) is still very noisy. There is much high-frequency component noise during the whole data. It is also seen that heading from magnetometer has more fluctuations compared to gyro's heading which shows that magnetometer data is more prone to error which is expected as well. We can see that the yaw from magnetometer readings gives a good indicator of orientation in the static conditions and almost no noises.

In comparison, the yaw angle from integrated gyroscope measurement (black) is smoother and provides a good indicator of yaw angle in dynamic conditions.

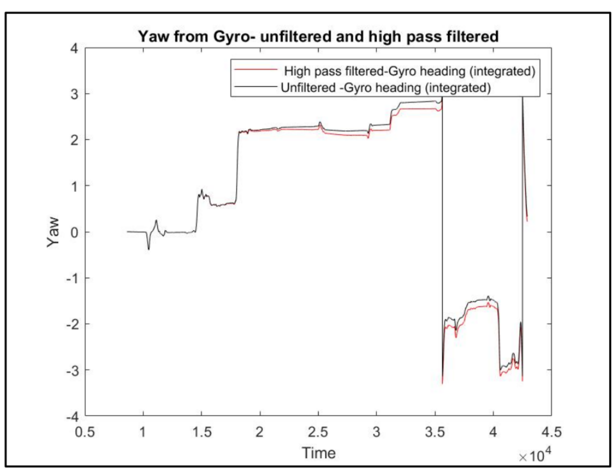
Low pass filter: Filtering Magnetometer heading- an LPF is filter which permits the low-frequency and blocks high-frequency for flowing through it.





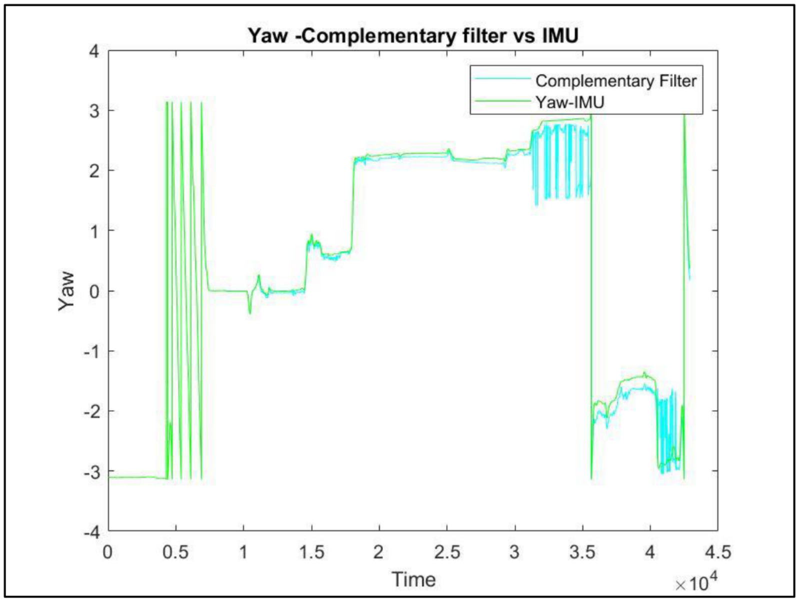
Above figure is the heading angle calculated from magnetometer. By convention, magnetic declination is positive when magnetic north is east of true north, and negative when it is to the west. Magnetometer data contains high-frequency noise; **thus, we used a low pass filter to get rid of that.** The filtered reading (black) is not visible because both the filtered and unfiltered data follow the same trend perfectly. In a Zoomed view (right side), you can see that the low-pass filter is working and reducing high frequency noise as expected.

High pass filter: Filtering Gyro heading- An HPF is a filter which permits high frequency and blocks low frequency for flowing through it. In the same way.



We can see from the above graph that unfiltered Gyro heading data does not contain too many high frequency components. But still for the given data, high pass filter is working as expected as it follows the ups and downs in data.

Complementary filter: Complementary filter is used to combine filtered magnetometer and gyro headings.



The yaw rate from the gyroscope matches quite closely to the more accurate magnetometer readings. However, the magnetometer data is noisier with several ripples. Hence a complementary filter is implemented to obtain a better estimate of the heading since I want to keep the sharp high frequency changes from the gyroscope but also the low frequency content from the magnetometer.

As the Magnetometer data is more prone to error, so less weightage is given to it and more weightage is given to Gyro data.

Final heading can be estimated as follows:

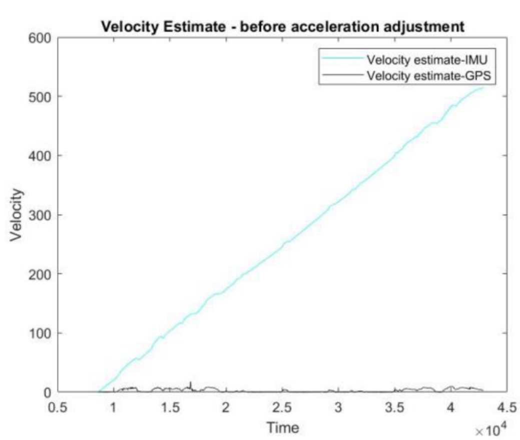
*Final heading = alpha*filter magnetometer heading + (1-alpha) *filter gyro heading*

We can see from the figure that heading from complimentary filter follows almost the same trend and values as that of Yaw computed by IMU for most of the time.

2: Estimating the Forward Velocity

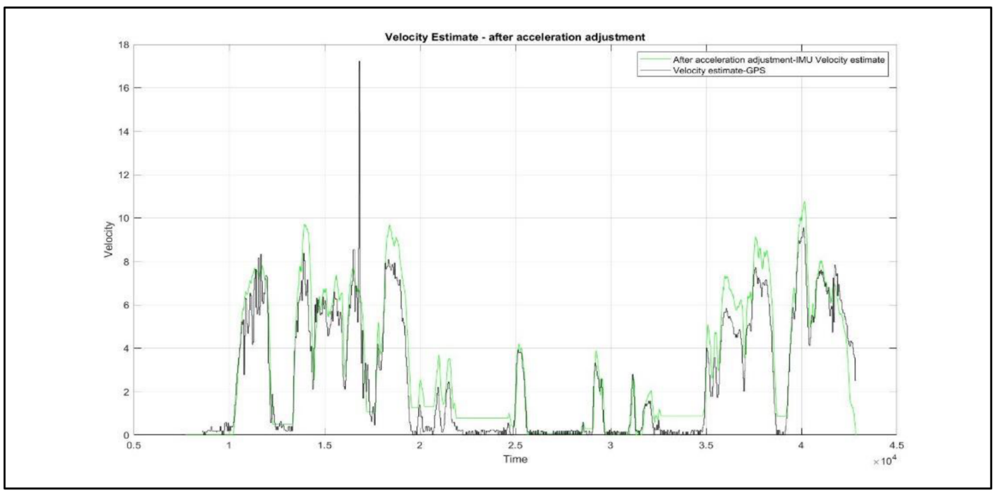
Integrating the forward acceleration to estimate the forward velocity.

The acceleration in the z direction was integrated using cumtrapz to obtain the velocity. The GPS data used as a comparison was calculated by taking the consecutive difference in the easting and northing values and then taking the magnitude of both the sets of data points. The resulting comparison did not match up very well as shown below:



As you can see, while the areas of acceleration and deceleration match up with the GPS estimate, there was a lot of bias and noise in the acceleration data that caused drift in the integrated velocity values. The duration for which the timestamp when vehicle is stationary is noted the acceleration should be zero, but it was not so in the actual data, and it contained some bias as well. To correct for this**, mean of the data for this time duration was subtracted from the whole data set**. This reduced the drift and improved the velocity estimate. A further tweak in the bias calculated in the above case by infinitesimal value improved the velocity estimate a lot. Set acceleration to zero for the time duration when car is static. If for a time duration of 10 seconds, acceleration is less than 0.5 m/s2, it is assumed that car is static. And for this duration, acceleration is force set to zero. This 10 second check is run from starting of data set (after moving car into circles for calibration) till the end and the results look comparable to GPS velocity estimate. If calculated velocity from IMU turns out to be negative (as it might become negative for very few data points and that too, very little value (<0.25 m/s) for very less time), make it zero as the car did not move backwards. For the duration when GPS velocity is zero, there is still some bias as there is further scope for acceleration data adjustment.

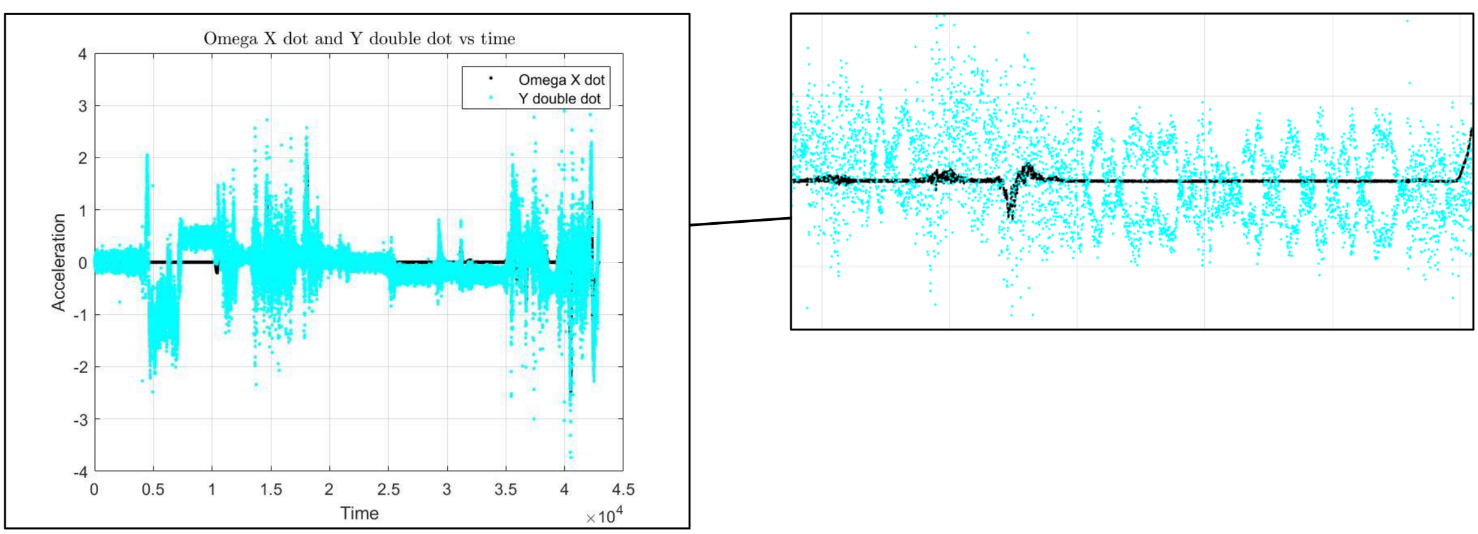
Hence, the final velocities after all these corrections are shown below:



3: Dead Reckoning with IMU

1. **Compute $\omega \dot{X}$ and compare it to $\ddot{y}obs$.**

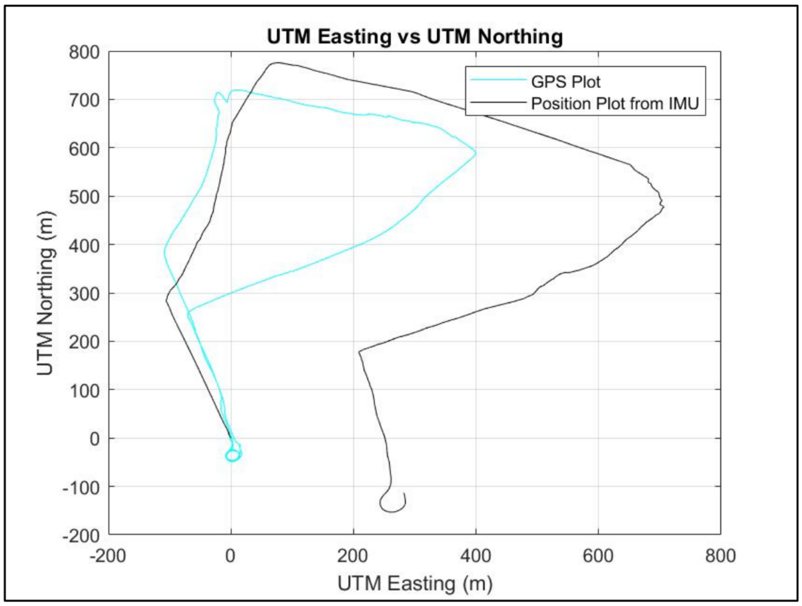
If the vehicle has no velocity component in the y direction and that the IMU offset from the car frame is 0, ωX' is compared to Y double dot''. The figure is shown below:



From the above figure we can observed that both $\omega \dot{X}$ and Y double dot follow the same trend. We can see when one graph is going up and down, other is also doing the same. But $\ddot{y}obs$ values are very noisy with high frequency components and there is some bias as well because we have ignored the offset by setting value of xc is zero. Noise can be attributed to the fact that $\ddot{y}obs$ is nothing, but the linear acceleration observed by the sensor in its Y-direction and even when the car was stationary, sensor recorded some value close to zero which can happen due to car's vibration while being powered ON.

2.Compare IMU and GPS trajectory:

The figure shown below is plot by using heading from magnetometer and integrated distance i.e., by integrating velocity and data from GPS is used to plot the above graph. A scaling factor of 1/0.9 is used to make the IMU position plot comparable to that of the GPS. You can see from the graph that both the plots follow the same trend. However, IMU plot does not matches with GPS data perfectly because of some errors present in acceleration or velocity or magnetometer heading data obtained from IMU.



3.Estimate Xc: Using the equation provided in the lab instructions:

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

$$\ddot{y}_{obs} = \ddot{Y} + \omega\dot{X} + \dot{\omega} x_c$$

Using the equation $\ddot{y}obs = \ddot{Y} + \omega\dot{X} + \dot{\omega}xc$, we assumed that the car is not skidding sideways. So, the value $\dot{Y} = 0$ and the equation reduces to $\ddot{y}obs = \omega\dot{X} + \dot{\omega}xc$. $\boldsymbol{xc = y\ddot{obs} - \omega\dot{X} / \dot{\omega}}$ As $\boldsymbol{xc}$ is inversely proportional to $\boldsymbol{\dot{\omega}}$, for some values of $\boldsymbol{\dot{\omega} = 0}$, $\boldsymbol{xc} \rightarrow \infty$. Therefore, while solving the above equation, $\boldsymbol{\dot{\omega} = 0}$ values are not considered.

mean $\boldsymbol{xc}$ is obtain as -0.1867 m or -18.67 cm.

Data was collected in a personal car and sensor was placed in the front on the top of dashboard in the middle near driver's seat and sensor's x was pointing forward and z downwards. A negative $\boldsymbol{xc}$ value suggests that the car's center of mass is behind the sensor by 18.67 cm which is roughly near the gear change stick in between the two seats at the front. Maybe it is also nearly the COM of the vehicle because four people were seated in the car with different weights. Hence, calculated $xc\ is\ reasonable$

References:

1.https://sites.google.com/site/myimuestimationexperience/filters/complementary-filter, http://web.archive.org/web/20091121085323/http://www.mikroquad.com/bin/view/Research/Complementar yFilter

2.Compensating for Tilt, Hard-Iron, and Soft-Iron Effects | Fierce Electronics

3.https://github.com/rlrosa/uquad/blob/master/doc_externa/Calibracion_sensores/MTD-0801_1_0_Calculating_Heading_Elevation_Bank_Angle.pdf

4.https://kionixfs.kionix.com/en/document/AN005-Tilt-Sensing-with-Kionix-MEMS-Accelerometers.pdf

Conclusion:

In this lab, we build a navigation stack using two different sensors – GPS and IMU and understand their relative strengths and drawbacks.