# Lab 4: Dead Reckoning

## Abstract

In this lab, an inertial measurement unit (IMU) and a Global Positioning System (GPS) puck were used to collect two datasets from a moving vehicle. This data was used to calibrate the magnetometer readings, obtain forward velocity plots and finally plot a dead reckoning of the path followed using the IMU data.

## Methodology

IMUs output linear accelerations(accelerometer), angular velocities (gyrometer), orientations and magnetic field strength (magnetometer) in all three axes. From the GPS we obtain positions in terms of latitudes and longitudes, which we then convert to UTM coordinates for easier analysis.

Magnetometers suffer from hard iron and soft iron errors. Hard iron errors are caused by permanent magnetic fields. Soft iron errors are caused by ferromagnetic materials. We calibrate by transforming and translating the data as outlined in the discussions section after observations.

We integrate the linear accelerations to get velocity which on further integration gives position. Similarly, we integrate angular velocity to get angles.

With a complementary filter, we utilize sensor fusion to combine the high frequencies of the gyroscope with the low frequencies of the angle from the magnetometer to get a yaw of minimum noise.

Finally, with the forward velocities and yaw calculated we estimate the path followed by the vehicle and compare our estimated path with the more accurate GPS data.

## Procedure

### 1. Data Collection

A GNSS puck and a VN-100 IMU were used for Lab 4. The two datasets recorded were:

- The first dataset was collected while driving around the roundabout in front of Ruggles station and behind Egan Research centre. The circular path was repeated five times. This dataset is for the calibration of the magnetometer data.
- The second dataset was collected while driving on a random path around the Northeastern campus, with stops at traffic lights and multiple accelerations and decelerations. This dataset was initiated and ended at the same location after traversing a path of 2km.

In both cases, data recording was initiated only after the car was started. This was done to ensure the absence of variations in data from the vibrations of the vehicle.

## 2. Calibration of Magnetometer Yaw

Ideally, we should have a circular plot with the centre at the origin. Hard iron errors can be seen on our plot of yaw as a shift in origin while soft iron errors can be seen as a distortion of the circular plot.

- Using the gathered magnetometer data, a plot was plotted between the X and Y components of the magnetic field. This is seen in Fig 1.1. The plot is slightly distorted, rotated and certainly shifted from the origin. This is due to the hard and soft iron errors.
- To rectify the hard iron errors, the entire plot was simply shifted back to the origin by subtracting the offset x and y coordinates.
- To remove the soft iron errors, the magnetometer values were first rotated about the Z-axis using a rotation matrix.
- The resultant values were scaled by pre-multiplying them with the following matrix:

$$\begin{bmatrix} \sigma & 0 \\ 0 & 1 \end{bmatrix}$$

  where $\sigma$ = major axis/minor axis. This converted the elliptical shape of the output back to a circle. The magnetometer data after calibration is shown in Fig 1.2.

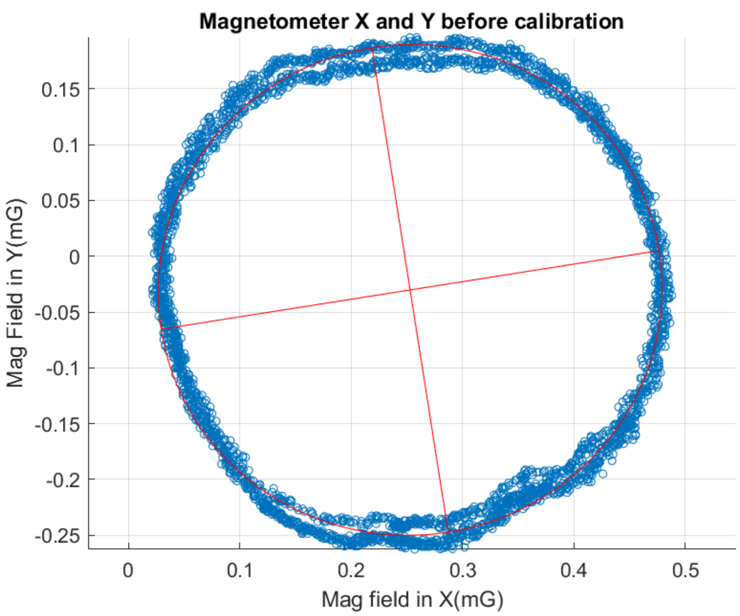


Fig 1.1 Plot of X vs Y from magnetometer before calibration

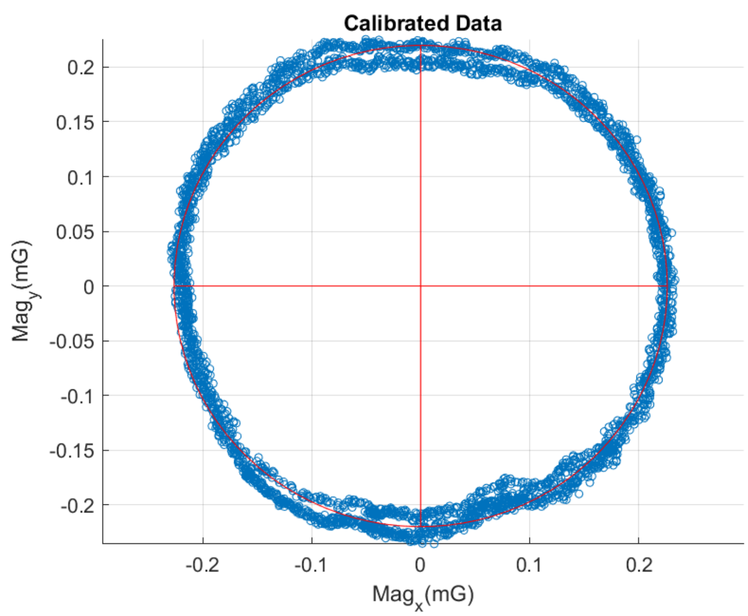


Fig 1.2 Calibrated Magnetometer

- With the calibration values, we calibrate the magnetometer in the second dataset. The calibrated yaw angle was obtained as atan2(Y, X). These values were then unwrapped using the ‘unwrap’ function. The comparison of raw yaw and calibrated yaw is seen in Fig 1.3.
- The RMSE for raw yaw was 1.2323 while that for calibrated yaw was 3.4958. The average RMSE between these two readings is 0.0173.

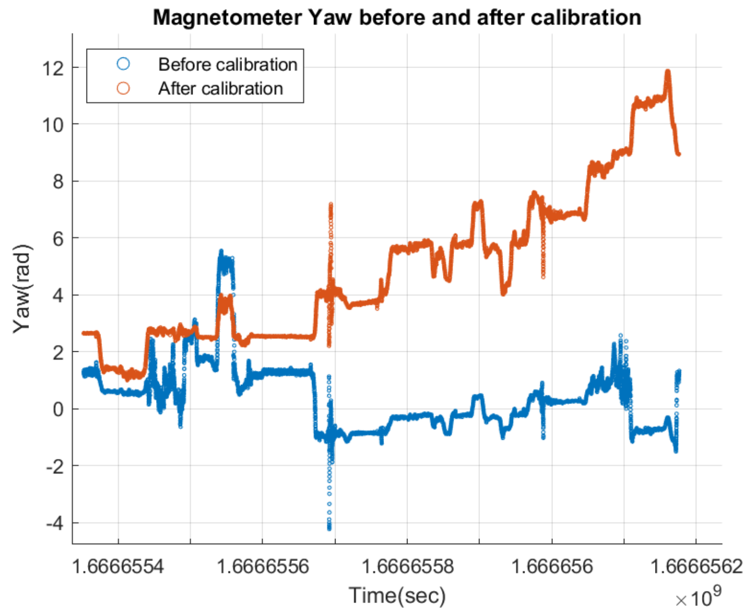


Fig 1.3 Yaw plot before and after calibration

3. Calibration of Magnetometer Yaw

- The angular velocity around the z-axis obtained from the gyroscope was integrated with respect to time and then unwrapped. This gives us the yaw angle (rotation around the z-axis). This is then compared with the yaw obtained from the calibrated magnetometer shown in Fig1.4.

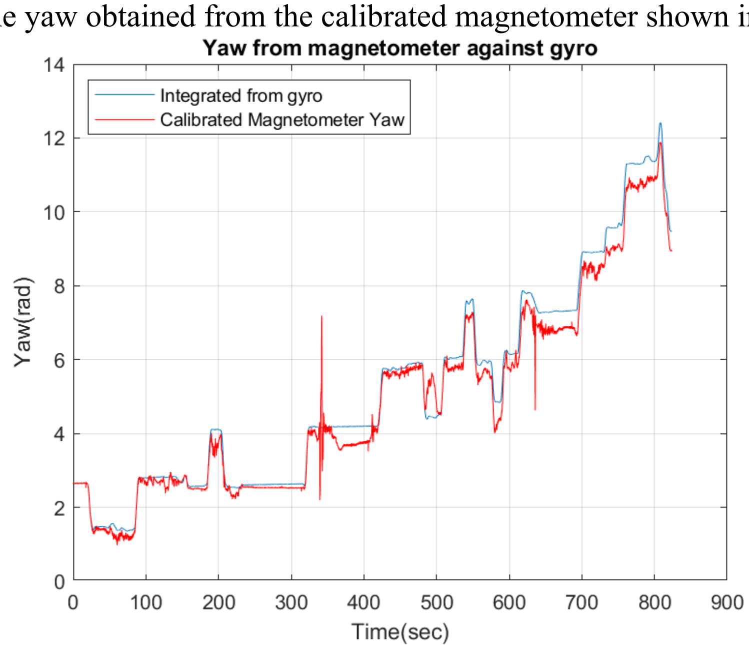


Fig 1.4 Yaw from two calculations

- The RMSE for gyroscope yaw is 3.7748 while that for magnetometer is 3.4958. The average RMSE between these two was found to be 0.0016.
- These two yaws are then passed into a complementary filter. The magnetometer yaw suffers noise at higher frequencies, while the gyroscope data suffer drift over long periods of time.
- A complementary filter is a computationally inexpensive sensor fusion technique that consists of a low pass and a high pass filter. It then sums the outputs of these filters to generate the final output. The graph of the low pass filter, high pass filter and complementary filter can be seen in Fig1.5 whereas the comparison between IMU yaw (obtained from quaternions) and the yaw obtained from the complementary filter is shown in Fig 1.6.

- The values for the low pass and high pass filters were chosen to be 0.002 and 0.0002 which were chosen empirically. The complementary filter gives a result that matches the yaw angle from the IMU sensor as can be seen in Fig 1.6.

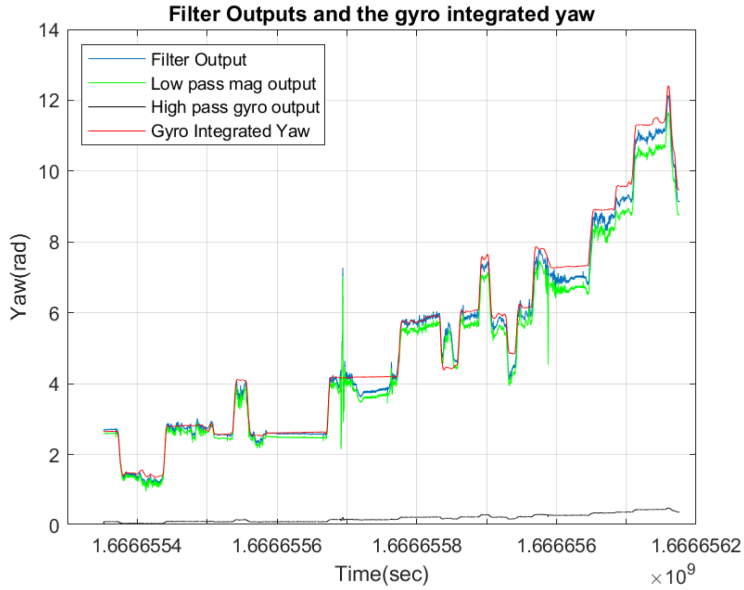


Fig 1.5 Plot of Complementary filter estimate

## 4. Estimating Forward Velocity

- Integrate the acceleration in the x-axis direction (forward direction) to get forward velocity. We assume no lateral shift, so acceleration in the y-axis direction is taken at zero (engine vibrations cause minor disturbances).
- However, we can observe that even when the vehicle was stopped or at constant velocities, acceleration was not completely zero. This implies that there are varying biases at different points in time. Also, velocity cannot be completely negative as observed from the graph as that would mean the vehicle is travelling in reverse only.
- To remedy this, the dataset has been segmented into smaller parts and their means have been computed, which are then subtracted from the corresponding datasets. These subtracted means are also scaled by a factor that is varied to best match our acceleration to a non-biased value (could've been implemented using a least squares method). Fig. 1.7 shows the result of this removal.

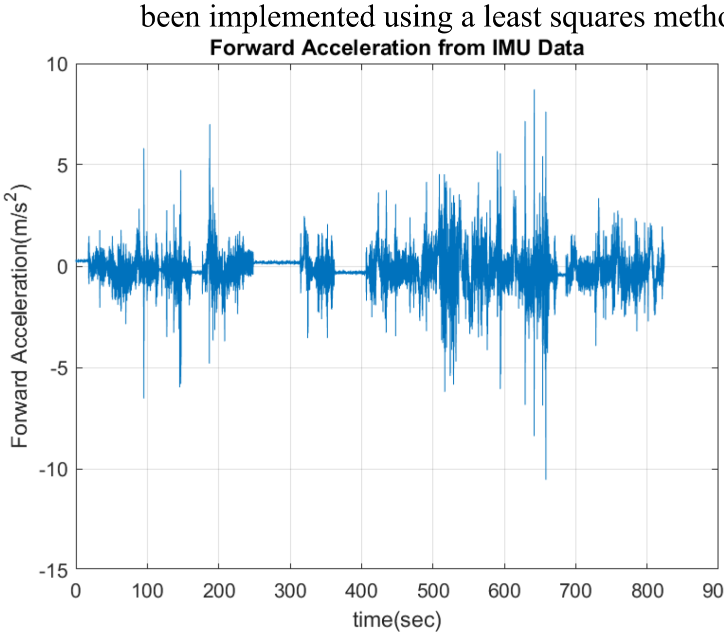


Fig 1.6 Plot of acceleration before bias removal

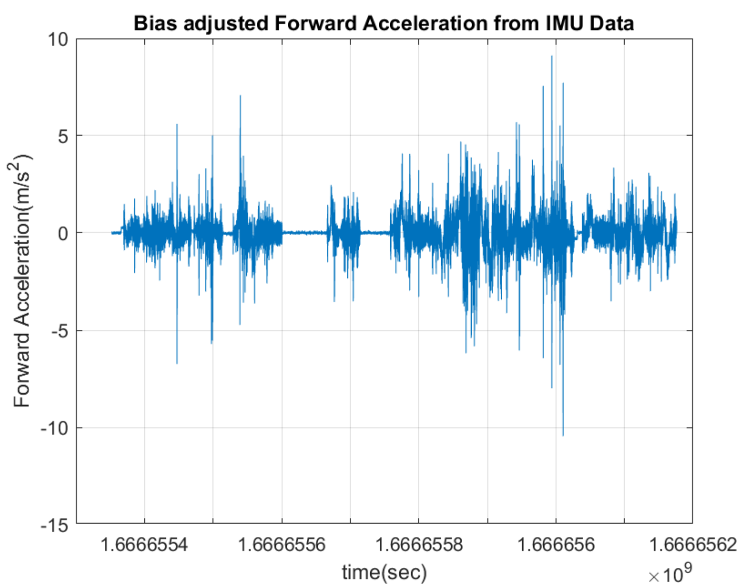


Fig 1.7 Acceleration after adjustment

- This result is then once again integrated to get the forward velocity once again. A comparison of the velocities from imu before and after bias removal has been shown against differentiated GPS data in Fig.1.8and Fig.1.9.

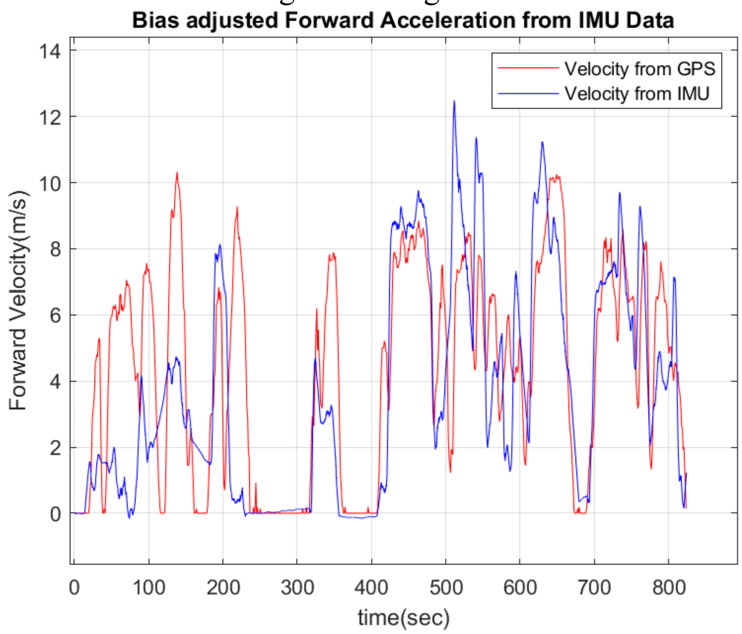


Fig 1.8 Velocity after adjusting acceleration biases

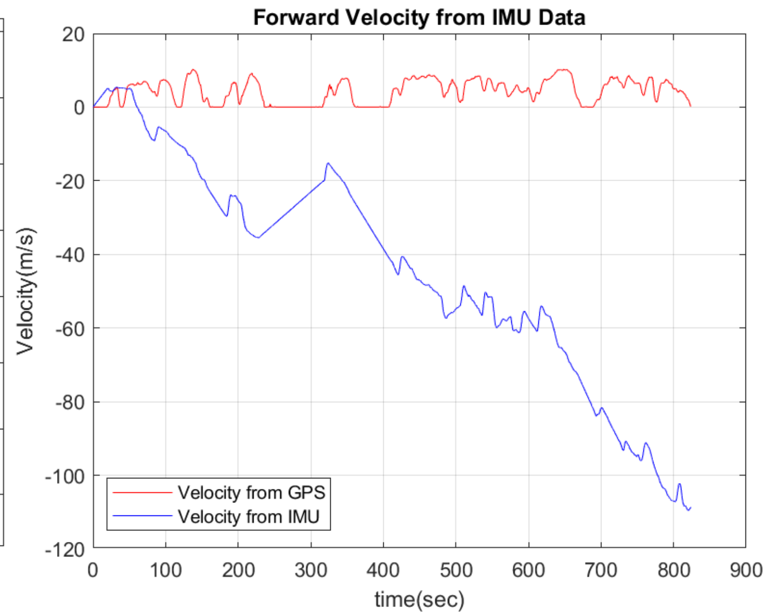


Fig 1.9 Velocity before adjustment

5. Dead reckoning using the above-obtained data

- $\ddot{y}_{obs}$ is the velocity observed along the y_axis. A comparison of $\omega X$ and $\ddot{y}_{obs}$ is shown in Fig 1.10. The difference is because of the presence of lateral acceleration which was assumed zero in our calculations. A reason for this disparity could be the presence of engine vibrations and a component of the acceleration due to gravity that presents itself when the vehicle is tilted due to a slope of uneven ground. Also, the roads are not perfectly flat and hence it can be assumed that there is always a component of gravity acting in that direction.

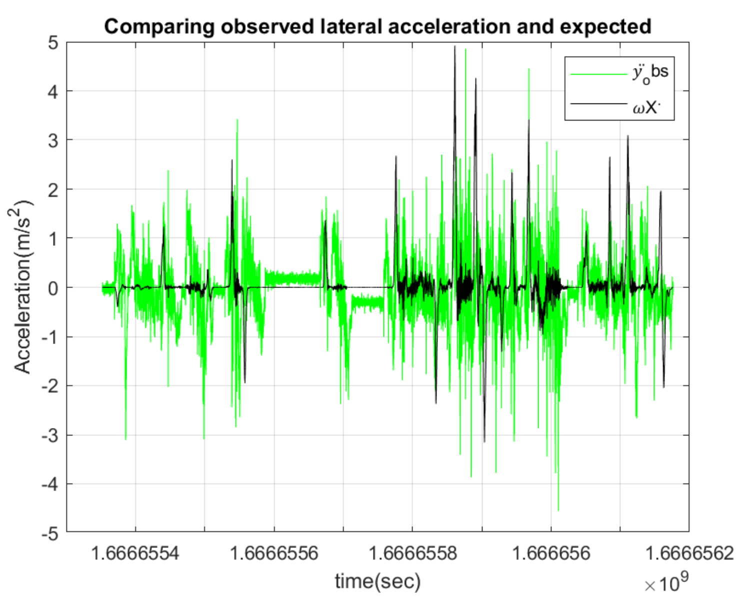


Fig 1.10 Comparing observed and expected lateral velocities

- Using the equation,

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

- We obtain a dead reckoning result or an estimated trajectory of our vehicle from the IMU data. We integrate our acceleration to get position and we multiply our forward velocity with the sine and cos components of our calculated yaw to get the required trajectory points. These displacements are plotted together with the UTM Easting and UTM Northing values from the GPS to compare them.

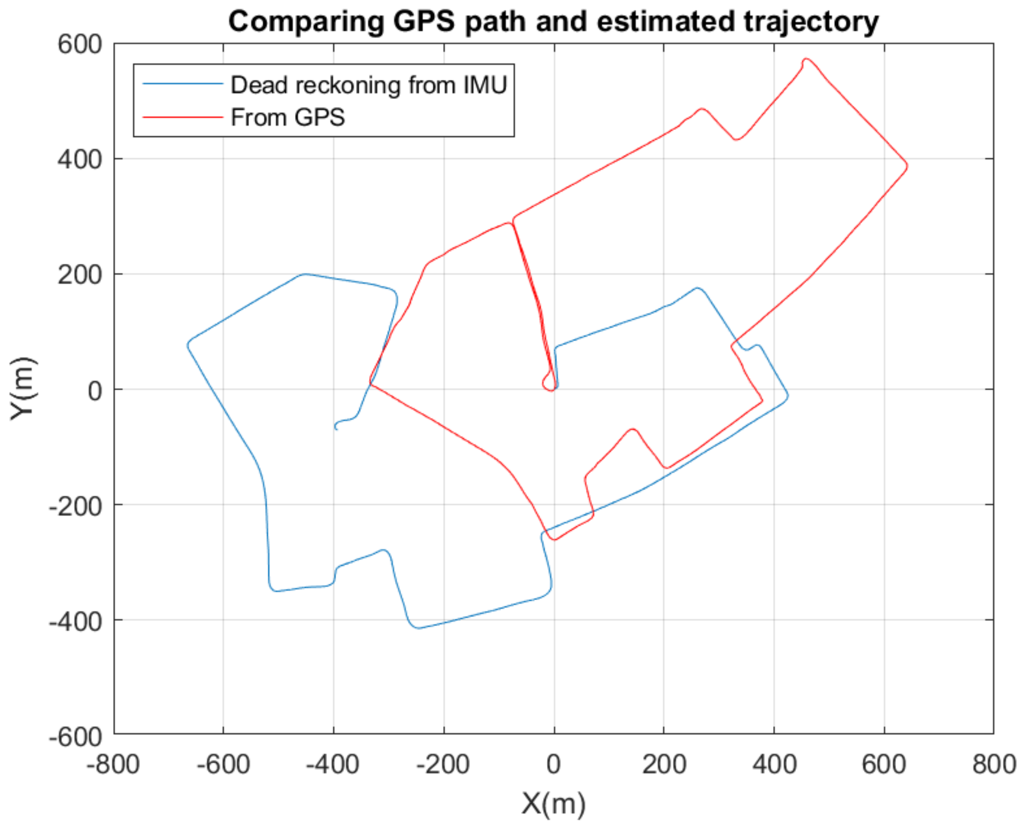

Fig 1.11 Paths generated by IMU against that of GPS

- It can be observed from the comparison that, our dead reckoning result does somewhat resemble the actual path portrayed by the GPS result. However, it still falls short, because of the errors accumulated from different random walks and biases summed up during integrations.
- While a bias removal was carried out, it was not perfect as can be seen from our velocity comparison. It can be expected to be accurate up to distances of less than 10m or up to the first turn.

## Discussions

Answers to the required questions are:

1. The two types of errors present were hard iron errors and soft iron errors. Hard iron errors can be seen as a shift of centre from the origin. These are caused by the presence of permanent magnetic fields in the vicinity like phones and speakers.

Whereas, soft iron errors present themselves as a distortion of the shape of the plot into an ellipse. These are caused by the presence of temporary magnetisable ferromagnetic objects in the vicinity.

To calibrate this, we first shift the centre of the plot to the origin and then we fit an ellipse to it. We figure out the deviation of true north from sensor north and we correct it by multiplying a rotation matrix with this inclination. We then use the major and minor axis to transform it into a circle by equating.

2. We employ a low pass and a high pass filter to implement a complementary filter.

   We integrate the angular velocity around z to get rotation or yaw angle. We then compute the same yaw angle from the calibrated magnetometer(X and Y component) using atan2(Y, X). Finally, the yaw from the gyroscope was passed through a high pass filter with a normalized passband frequency of 0.002 and that of the magnetometer was passed through a low pass filter with a passband frequency of 0.0002.
3. The magnetometer yaw suffers noise at higher frequencies while giving values with little drift over time. The gyroscope data suffer drift over long periods of time but excels at measuring fine changes in angles.

   Hence, a gyroscope overall is pretty stable whereas a magnetometer can suffer sudden drastic changes due to any external magnetic disturbances. This susceptibility of the magnetometer makes it less reliable. To get a better result, we plug both these values into a complementary filter as mentioned above to get a better result.

   So, I would generally prefer a gyroscope to measure angles, but given the chance, I would utilize both in a filter.
4. On integrating acceleration in a forward direction, it was observed that acceleration was not zero even when the velocity was constant (zero or constant). This implies the presence of uneven biases, as zero was observed at different values throughout the plot.

   To remedy this, the dataset has been segmented into smaller parts and their means have been computed, which are then subtracted from the corresponding datasets. These subtracted means are also scaled by a factor that is varied to best match our acceleration to a non-biased value (could’ve been implemented using a least squares method).

   Changes are made to correct acceleration because integrating erroneous acceleration gives us more flawed velocities.
5. The forward velocity from the differentiation of the GPS coordinates is always positive or zero. However, the velocity calculated from the IMU also goes negative. This is not natural and is an effect of biased and error-ridden acceleration integration.

   The process of bias removal carried out here is not perfect and hence gives a result that is not completely accurate. Hence, our forward velocities will differ from each other.

   Furthermore, our GPS operates at a sampling rate of 1 Hz, while our erroneous acceleration values are at 40Hz, hence more variations in lesser time(due to gravity and vehicular vibrations.)
6. $\ddot{y}_{obs}$ is the velocity observed along the y_axis. A comparison of $\omega X$ and $\ddot{y}_{obs}$ is shown in Fig.---. This shows that the observed lateral acceleration has higher values than the computed result. A reason for this disparity could be the presence of engine vibrations and a component of the acceleration due to gravity that presents itself when the vehicle is tilted due to a slope of uneven ground. Also, the roads are not perfectly flat and hence it can be assumed that there is always a component of gravity acting in that direction.

7. The dead reckoning result has been reported above. No scaling factors were used to match the initial heading and starting point.
8. It can be observed from the comparison that, our dead reckoning result does somewhat resemble the actual path portrayed by the GPS result. However, it still falls short, because of the errors accumulated from different random walks and biases summed up during integrations. While a bias removal was carried out, it was not perfect as can be seen from our velocity comparison. It can be expected to be accurate up to distances of less than 10m or up to the first turn.

# Conclusions

An IMU and GPS puck was used to record two data bags. One was used to successfully calibrate the magnetometer values. With a complimentary filter, we obtained a more accurate yaw value. Forward velocities were obtained from the GPS and IMU data and bias removal was done on the accelerometer data. Finally, dead reckoning was used to estimate a trajectory followed in the second data bag and compared to the more accurate GPS-provided path.

# References

[1] Pengfei Guo, Haitao Qiu, Yunchun Yang and Zhang Ren, "The soft iron and hard iron calibration method using extended kalman filter for attitude and heading reference system," *2008 IEEE/ION Position, Location and Navigation Symposium*, 2008, pp. 1167-1174, doi: 10.1109/PLANS.2008.4570003.

[2]C. S. Raveena, R. S. Sravya, R. V. Kumar and A. Chavan, "Sensor Fusion Module Using IMU and GPS Sensors For Autonomous Car," *2020 IEEE International Conference for Innovation in Technology (INOCON)*, 2020, pp. 1-6, doi: 10.1109/INOCON50539.2020.9298316.

[3] https://d1.amobbs.com/bbs_upload782111/files_44/ourdev_665531S2JZG6.pdf

[4] https://sites.google.com/site/myimuestimationexperience/filters/complementary-filter

[5] https://arxiv.org/pdf/1904.06064v1.pdf

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**** Gitlab Username of a team member whose driver program was used: zadbuke.a ****

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