EECE: 5554 Robot Sensing and Navigation

Lab 4: Navigation with IMU and Magnetometer

Introduction:

Navigation using IMU (Inertial Measurement Unit), and GPS (Global Positioning System) is called Dead Reckoning. The IMU provides information on acceleration and orientation. The GPS provides information on the absolute position.

The initial step in dead reckoning starts from the initial estimate of the vehicle's position, obtained from GPS. The acceleration and orientation received from the IMU are integrated over time to get the velocity and position of the car. These estimates are subjected to errors over time which significantly leads to drift in the estimated position of the vehicle.

Questions:

- 1. How did you calibrate the magnetometer from the data you collected? What were the sources of distortion present, and how do you know?
 - Hard Iron Calibration The cause of hard iron distortion is due to the presence of a permanent magnet or ferromagnetic material near the sensor which causes magnetic interference in magnetic field sensors such as magnetometers. This interference causes an offset from the origin of our reference frames. The calibration process is simply to remove the offset. An ellipse is drawn on top of the magnetic field and plotted on the X and Y axes aligning with the origin. The centre point of the ellipse denotes the offset, and this offset is discarded by subtracting all the values. Fig.1 shows the hard iron calibration.
 - Soft Iron Calibration Soft iron distortion is caused by ferromagnetic materials, which means they are not magnetic in nature but become magnetized in the presence of a magnetic field. The correction is again done by fitting and plotting an ellipse onto the magnetic field data, and it is rotated until it syncs with the reference frame. A scaling matrix is used to obtain the required circle and again the data is rotated back to its original position. We calculate the rotation matrix from the angle formed between the major axis and the reference frame. To bring it back to its original position we rotate it using a negative angle of the rotation matrix calculated at the start. Fig.1 shows the soft iron calibration.

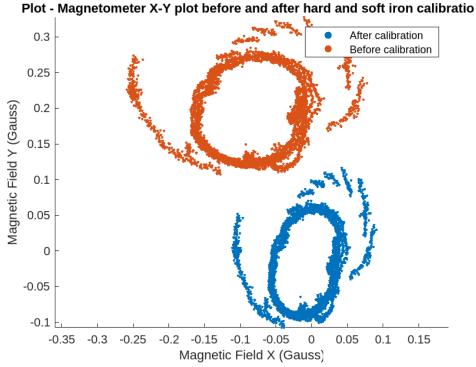


Fig.1 Hard and Soft Iron calibration before and after.

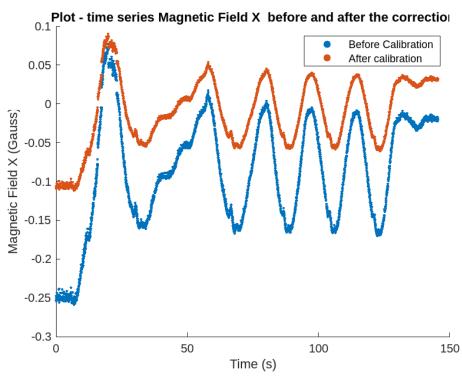


Fig.2 Time series plot of magnetometer data along the X-axis before and after correction.

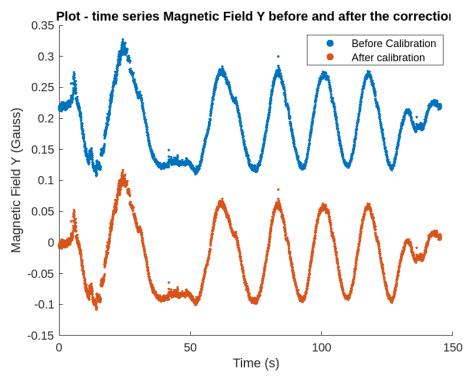


Fig.3 Time series plot of magnetometer data along the Y-axis before and after correction.

2. 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?

- Basically, the magnetometer provides good measurements during static conditions and the gyroscope provides good measurements during tilting or dynamic conditions. We combine the data of these sensors using a complimentary filter.
- We use both high pass and low pass filters in the complementary filter. The low pass filter filters the high frequency signals caused due to vibration in the magnetometer. The high pass filter filters low frequencies caused by gyroscope drift.
- The cutoff frequencies used in the low pass filter:
- The cutoff frequencies used in the high pass filter:
- The alpha of the complementary filter is 0.3.

Plots after filtering:

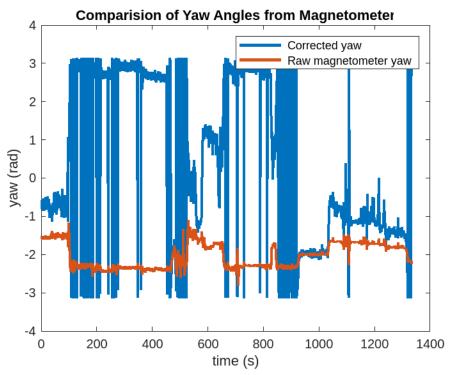


Fig.4 Comparison plot between the raw magnetometer yaw and corrected yaw.

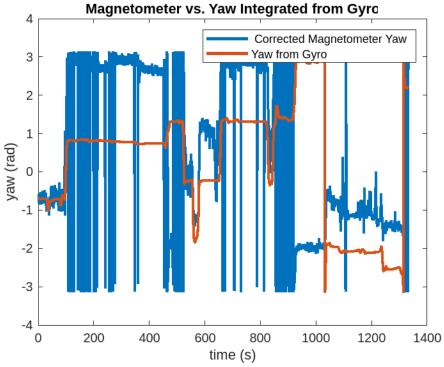


Fig.5 Comparison plot between yaw angles from the magnetometer and yaw integrated from Gyro.

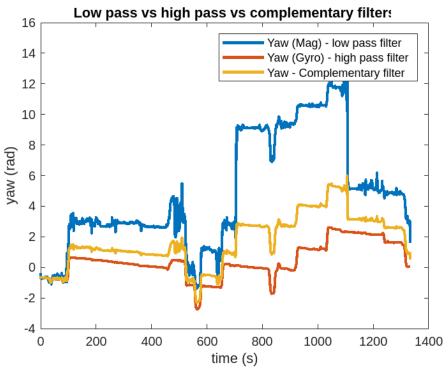
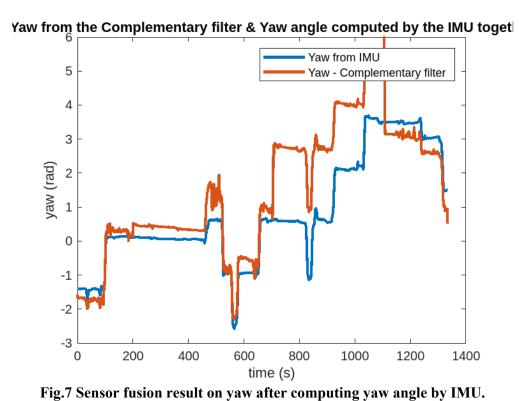


Fig.6 Results of low pass filter on magnetometer data and high pass filter on gyroscope data and the complementary filter.



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

• The magnetometer produced good measurements of orientation during stationary conditions. Gyroscope produced good measurements of tilt during dynamic conditions. The best estimate for use would be after applying the low pass filter on the magnetometer data and the high pass filter on the gyro. The combination of these two filters is present in the complementary filter so the output of the complementary filter is best for navigation.

Forward Velocity Estimation plots:

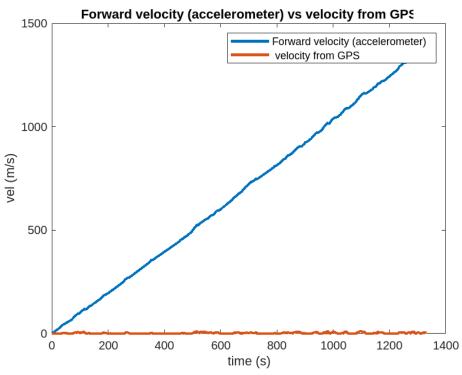


Fig.8 Estimation of velocity from both GPS and Accelerometer before correction.

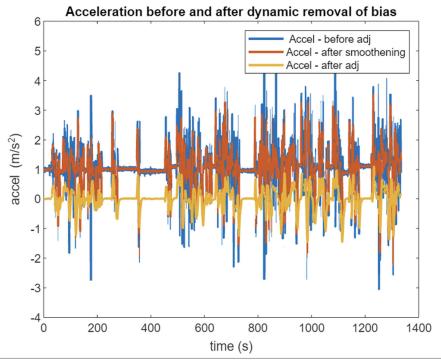


Fig.9 This plot show acceleration before correction, after smoothening and acceleration after correction.

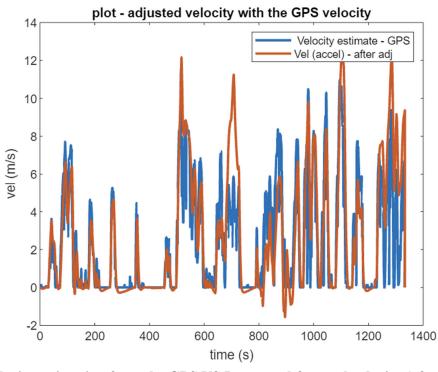


Fig.10 Velocity estimation from the GPS VS Integrated forward velocity (after acceleration correction).

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

- Stopping in traffic showed zero velocity in GPS as there was no movement. The
 easting and northing value remained the same. But there was a reading for acceleration
 during those stationary time periods. As we integrated acceleration, the velocity values
 were too high, and the acceleration reading was noisy. Calculating the right time
 intervals for this randomness solved the issue and the bias was also corrected.
- The noise from the accelerometer reading was removed using a moving average filter. The noise was caused by vibrations. Time intervals where the velocity was zero were calculated. The range of acceleration values was calculated along with that the bias was also calculated by taking the mean of the values in the time interval. The acceleration values were subtracted with the bias. Then the forward velocity is calculated from the corrected acceleration. Fig.10 shows the corrected acceleration.

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

- As we collected GPS data at 1 Hz and IMU data at 40 Hz. This rate causes a high peak in the GPS velocity plot and there is an abrupt change in the northing and easting could also be another reason for the plot to be this sharp.
- In the plot it is clearly visible that there are certain regions where the acceleration didn't adjust velocity well. Any other method other than using the mean of the values would have helped us adjust the bias.

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

• There is a high consistent difference between $\omega \dot{X}$ and y_{obs} . The inconsistency is majorly seen with y_{obs} . It shows high frequency almost all throughout the plot. This can be neglected using low pass filter and this high frequency occurs due to accumulation of errors.

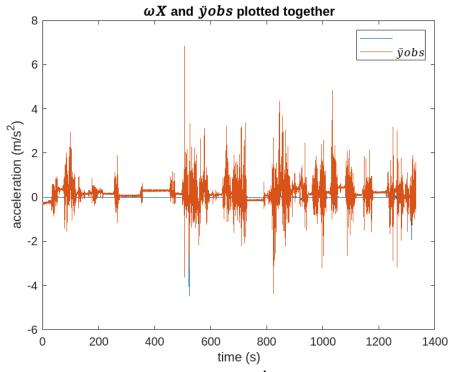


Fig.11 Plot between $\omega \dot{X}$ and $y_{obs}^{"}$.

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 are oriented in the same direction). Report any scaling factor used for comparing the tracks.

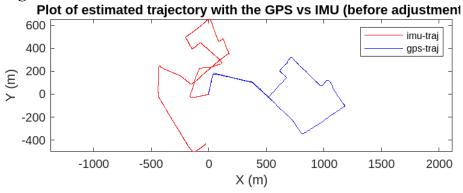
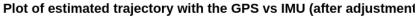


Fig. 12 Trajectory before correction.



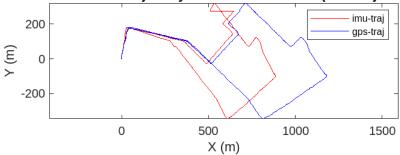


Fig.13 Trajectory after correction.

- In this plot it is clearly see after adjusting the heading and the first straight line there is a deviation with the final locations and the IMU trajectory.
- 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 of time 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?
 - We are able to see the differences in the above fig.11 & 12 in the trajectory of the GPS and IMU even if the straight line and the heading match.
 - As the error gradually build up, this causes the deviation in the turns and eventually the
 whole trajectory between the GPS and IMU is mismatched. Thus, without a position fix
 it is not possible to navigate.
 - The GPS and IMU estimates match closely within the first 200 seconds approximately.
 - Yes, the stated performance within the 2m range match because the error is not that high as seen after this part.

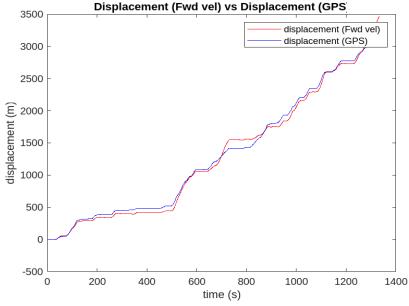


Fig. 14 Comparison plot of displacement by integrating forward velocity VS GPS displacement.