Northeastern University

Robot Sensing and Navigation - EECE5554
LAB 4 Analysis Report

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Introduction

In this lab, the idea of combining GPS and IMU sensors is introduced. Its benefits and limitations are examined, and a navigation stack is created by utilizing the two sensors.

Questions and Answers

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

   At the Ruggles station circle, the nuance car was used to gather the data. Five rounds of the circular driving loop were completed by the vehicle. Fig. 1 showed that even though the path taken was circular, some of the data points tended to stray from it, suggesting the existence of noise. Magnetometer results are unreliable when hard and soft iron distortions are present.

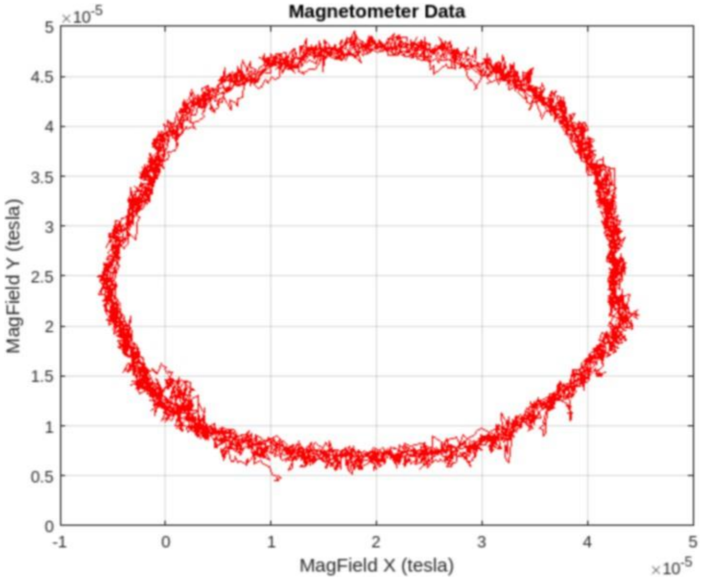

Fig. 1 Raw magnetometer data.

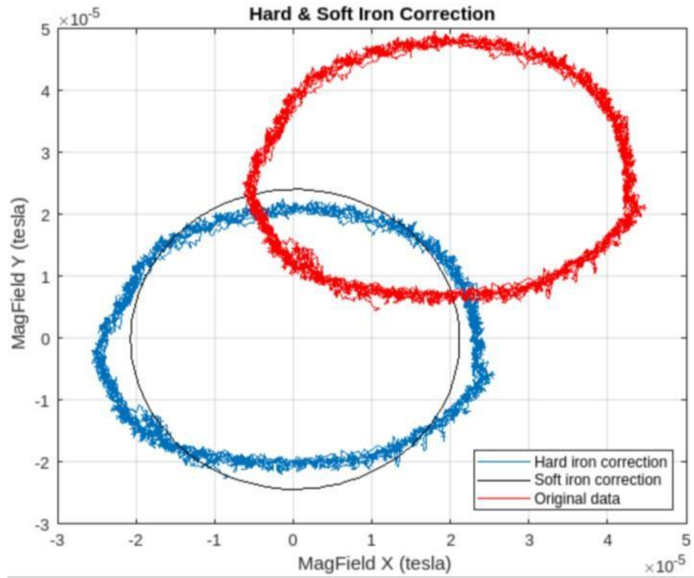

Fig. 2 Hard and soft iron calibration.

   An object that produces a magnetic field that causes disruptions is known as hard iron distortion. The existence of permanent or magnetised materials may be the cause of this. When an object (such as iron or nickel) modifies the magnetic field lines surrounding it instead of producing a magnetic field, this is known as soft iron distortion. Hard iron distortions cause the circle's centre to move away from the origin in two dimensions. On the other hand, the circle's shape is warped in mild iron distortions. The distortions of soft and hard iron have been adjusted in Fig. 2.

   Plot is fitted and adjusted to the origin. The mean value of the magnetometer measurements is subtracted from the raw data to account for hard iron aberrations. The raw magnetometer data is fitted using an ellipsoid to adjust for soft iron aberrations, and the calibration parameters are computed. The transformation matrix, bias offset, and scaling factor are among the parameters. To remove soft iron distortions, the transformation matrix is applied to the normalized magnetometer data.

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?**

   Complementary filters combine information from several sensors to generate precise yaw estimates. The filter produces the estimated yaw by combining weighted measurements from the magnetometer and gyroscope.
   First, using arctan(-y/x), the yaw is calculated using the corrected magnetic parameters. The low-pass filter receives the corrected magnetic yaw at a sampling rate of 40 Hz. We put in place a high-pass and low-pass filter with cutoff frequencies of 0.98 Hz and 0.02 Hz, respectively. This was achieved by repeatedly fine-tuning the filter to approximate an exact yaw. After integration, the angular velocity gyro z is passed via a high pass filter. The complementary filter receives the total of the low pass and high pass filters after they are acquired.

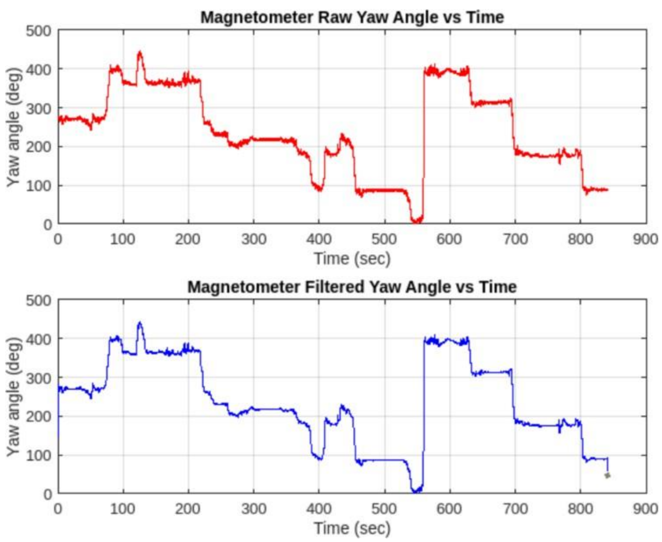

Fig. 3 Magnetometer yaw estimates before and after correction.

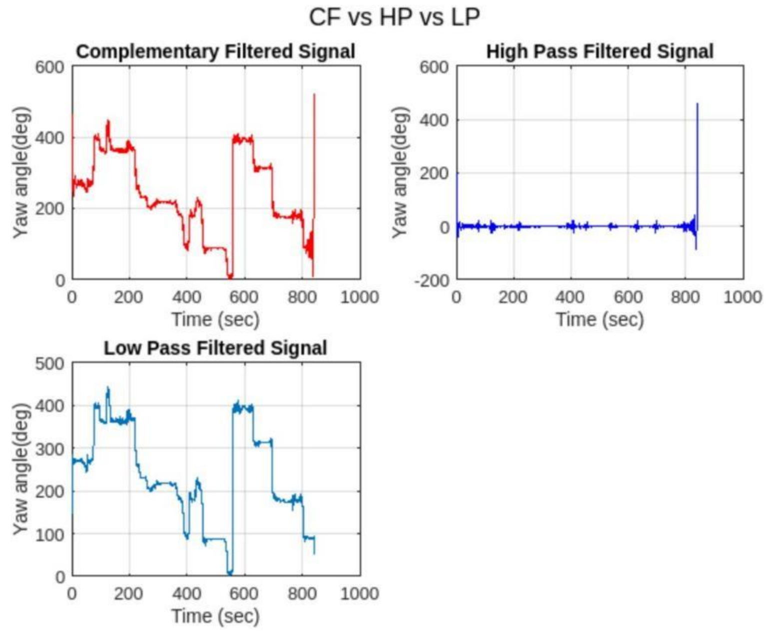

Fig. 4 Complementary Filter, Low Pass & High Pass Filter

3. **Which estimate or estimates for yaw would you trust for navigation? Why?**
   Since complementary filters integrate the input from two or more sensors, their estimations of yaw are more precise. Every approach has advantages and disadvantages of its own. For example, gyroscope noise is lower than accelerometer noise during short time intervals, but, in contrast to accelerometers, it accumulates measurement bias over longer time intervals. The long-term stability of the accelerometer angle estimates, and the short-term precision of the gyro angle estimates are what the complementary filter seeks.
   Furthermore, a gyroscope experiences drifts over time, whereas a magnetometer is impacted by both internal and external magnetic fields. Similar to this, GPS gives an exact heading but frequently encounters multipath reflections and signal loss. In order to reduce the limitations of individual sensors and predict yaw accurately for navigation, it is therefore best to fuse information from many sensors.

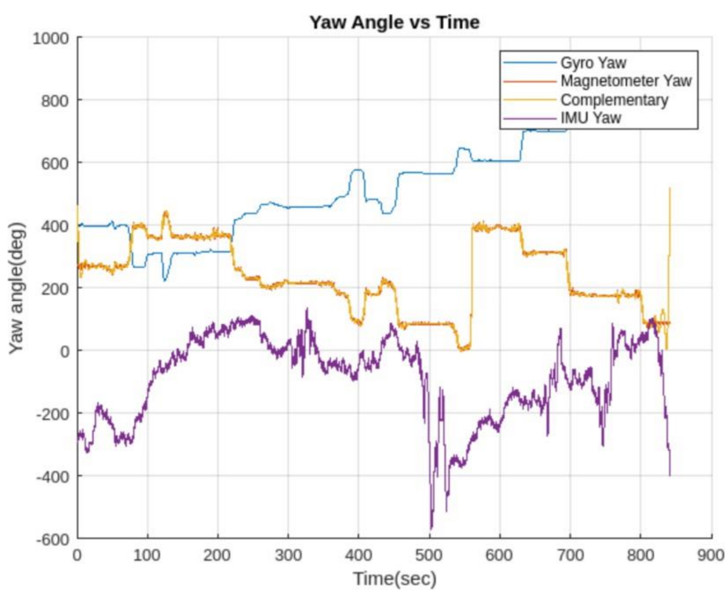

Fig. 5 Yaw angle plots between four methods.

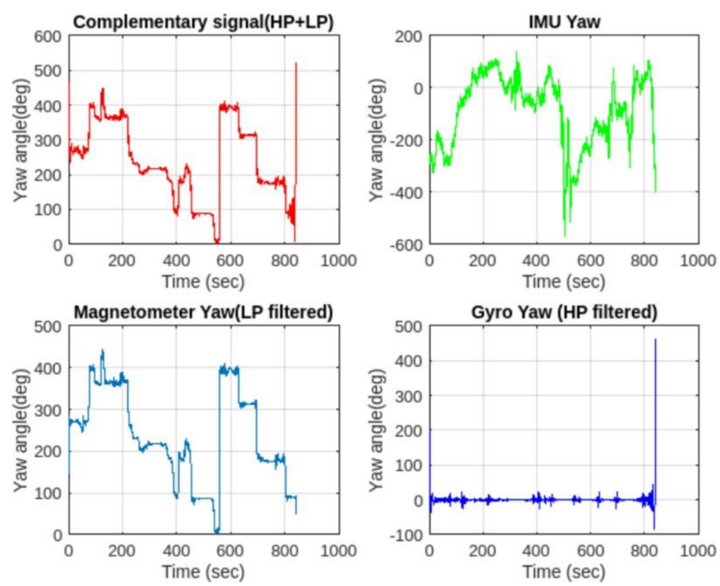

Fig. 6 Yaw estimates from different filters.

4. **What adjustments did you make to the forward velocity estimate, and why?**
After reducing bias from the accelerometer values, forward velocity was determined. The accelerometer records the acceleration caused by gravity, the vehicle's stationary location, and the front accelerometer. The forward velocity was calculated by subtracting these acceleration data points from the measured acceleration. To estimate the forward velocity, the forward acceleration along the x-axis was integrated after removal. This modification enhanced the estimate of forward velocity while lowering bias.

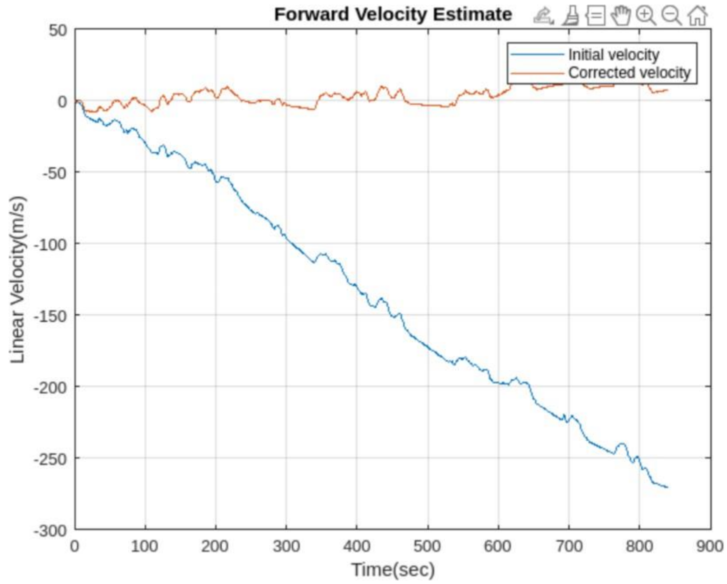

Fig. 7 Forward velocity estimate before and after correction.

5. **What discrepancies are present in the velocity estimate between accel and GPS. Why?**
Velocity estimates based on accelerometers and GPS are not the same. Because the vehicle causes vibrations and shocks when measuring acceleration, accelerometer data is prone to inaccuracies. Because of the quick changes in angular velocity and acceleration during turns, as well as the tendency for data to drift over time, measurement mistakes also happen during these situations. On the other hand, GPS data is not affected by the noise and vibrations of the vehicle because it depends on the movement of the GPS receiver. However, errors in the data can be caused by sounds resulting from atmospheric factors, signal inference and obstruction, multi-path effects, etc. Hence, there are differences in the velocity estimation between the two data sources.

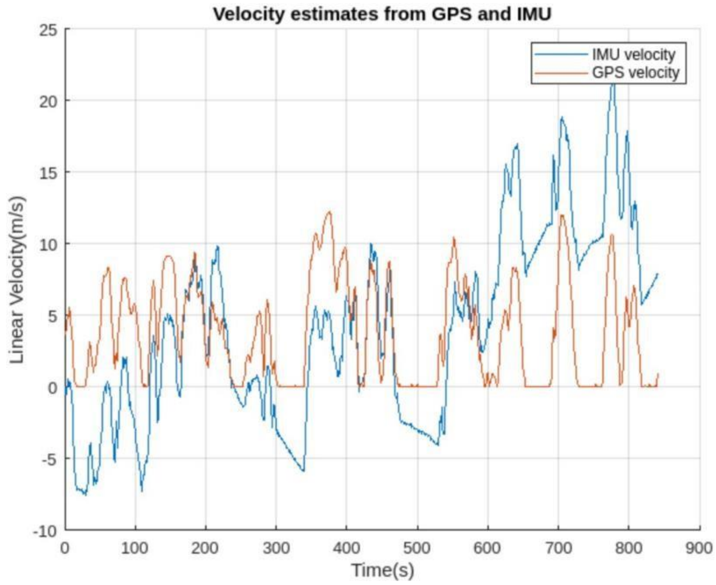

Fig. 8 Velocity estimates from GPS and IMU.

6. **Compute $\omega\dot{X}$ and compare it to $\ddot{y}_{obs}$. How well do they agree? If there is a difference, what is it due to?**
Fig. displays the charts for computed $\omega\dot{X}$ and $\ddot{y}$obs. 9. Despite having modest differences, the graphs are nearly identical since they come from various measurement sources.t. The gyroscope measures angular acceleration along the z direction, whereas the accelerometer measures linear acceleration in the x axis.n. As a result, the accelerometer and gyroscope become more sensitive to linear motion and angular motion, respectively.n. Moreover, noise in jobs is larger than in errors because errors connected with data integration are integrated into the data, leading to more noAdditionally, the gyroscope with drift over time and the vehicle's external vibrations have an impact on the accelerometer.moment.

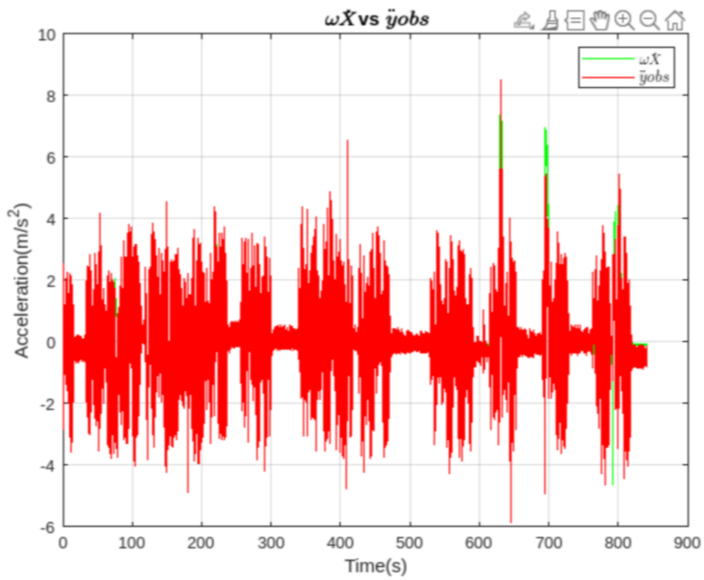

Fig. 9 $\omega\dot{X}$ vs $\ddot{y}_{obs}$

7. **Estimate the trajectory of the vehicle (x_e, x_n) from inertial data and compare it with GPS. (adjust heading so that the first straight line from both is oriented in the same direction). Report any scaling factor used for comparing the tracks.**
By combining the velocity estimations from GPS and IMU data, the vehicle's trajectories (xe, xn) are determined. The projected trajectory of the vehicle from inertial data was matched with the GPS track using a scaling factor of 0.4. Through trial and error, the best fit between the two trajectories was used to establish this particular value.

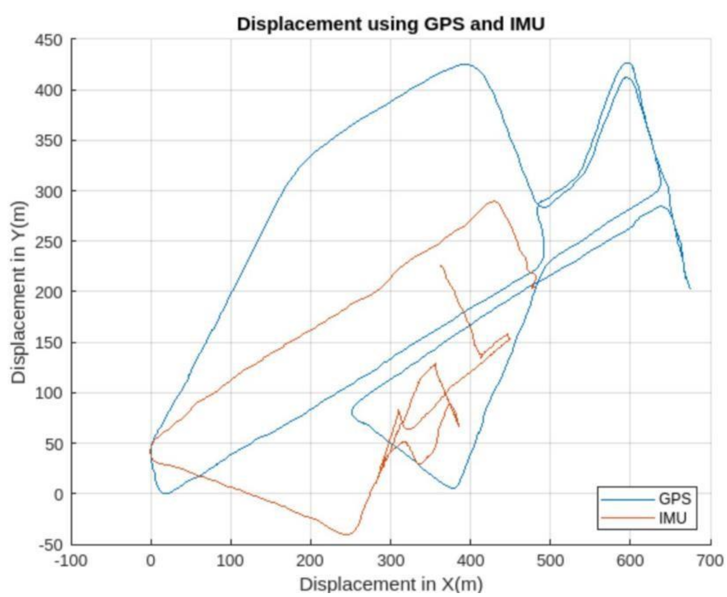

Fig. 10 Estimated vehicle trajectory.

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?**
The VectorNav specifications state that the IMU can travel for approximately ten minutes without a location fix. It updates its position at a 400 Hz rate. Position estimates align closer when travelling in a straight line as opposed to when making bends and curves. Just the first few seconds of the close battle were watched. The precision of the navigation is comparable to GPS data during this time, but it then diverges. When comparing the declared dead reckoning performance to the measured results, it was not very good. The actual path travelled and the path traced at specific locations match, albeit with a large displacement. Numerous elements, such as drift, bias, sensor noise, external vehicle vibrations, etc., can have affected the performance.

9. **Estimate x_c and explain your calculations.**
X_c can be estimated with the following equations,

$$v^U_{sensor} = v^U_{car} + \omega \times \rho^R_{sensor}$$

$$a^U_{sensor} = a^U_{car} + \dot{\omega} \times \rho^R_{sensor} + \omega \times (\omega \times \rho^R_{sensor})$$

$${}^R_T R^T a^R_{sensor} = a^U_{car} + \dot{\omega} \times \rho^R_{sensor} + \omega \times (\omega \times \rho^R_{sensor})$$

$${}^R_T R^T \begin{bmatrix} a_{imux} \\ a_{imuy} \\ 0 \end{bmatrix} = \begin{bmatrix} a_{utmx} \\ a_{utmy} \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \dot{\omega} \end{bmatrix} \times \begin{bmatrix} x_c \\ 0 \\ 0 \end{bmatrix}^R + \begin{bmatrix} 0 \\ 0 \\ \omega \end{bmatrix} \times (\begin{bmatrix} 0 \\ 0 \\ \omega \end{bmatrix} \times \begin{bmatrix} x_c \\ 0 \\ 0 \end{bmatrix}^R)$$

$$\begin{bmatrix} a_{imux} \\ a_{imuy} \\ 0 \end{bmatrix}^R = {}^R_U R \begin{bmatrix} a_{utmx} \\ a_{utmy} \\ 0 \end{bmatrix}^U + \begin{bmatrix} 0 \\ \dot{\omega} x_c \\ 0 \end{bmatrix}^R + \begin{bmatrix} -\omega^2 x_c \\ 0 \\ 0 \end{bmatrix}^R$$

$$A = \begin{bmatrix} a_{imux} \\ a_{imuy} \\ 0 \end{bmatrix}^R - {}^R_U R \begin{bmatrix} a_{utmx} \\ a_{utmy} \\ 0 \end{bmatrix}^U, B = \begin{bmatrix} -\omega^2 \\ \dot{\omega} \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} a_{imux} \\ a_{imuy} \\ 0 \end{bmatrix}^R - {}^R_U R \begin{bmatrix} a_{utmx} \\ a_{utmy} \\ 0 \end{bmatrix}^U = \begin{bmatrix} -\omega^2 \\ \dot{\omega} \\ 0 \end{bmatrix}^R x_c$$

X_c is estimated to be approximately 0.17m.