EECE5554 Robotic Sensing & Navigation

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**Lab 4: Dead Reckoning Navigation with IMU and Magnetometer**

**Part I: Heading Estimate / Magnetometer Calibration**

Before the magnetometer data can be used, the data must be corrected for hard-iron and soft-iron effects. A specific data set is collected for calibration purposes by driving a car in a circle for 5-6 laps. The recorded data is run through the magnetometer compensation model, shown by the matrix equation below.

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Figure 1: Magnetometer compensation model**

The 3x3 matrix, or the circularizing matrix, is the soft iron distortion matrix, which is largely used to correct the distortions along the principal axes. The bh variables, or hard-iron biases, are tuned to center the data back to the origin. These variables are tuned to correct the raw magnetometer data, with the idealized reference circle, shown in the graph below.

**A graph of colored circles

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Figure 2: Corrected and Raw Magnetometer data**

While the corrected data appears more circular and centered when compared to the original raw data, the IMU experienced severe drift during the recording process, which was not accounted for, which will cause issues further on.

Converting the raw magnetometer data from gauss to degrees involved taking the inverse tangent of the x and y axes magnetometer data and converting the result from radians to degrees. This was done to the both the raw data and the corrected data. While the raw data conversion result was fairly clean with occasional spikes to zero or NAN values, the inverse tangent of the calibrated data resulted in volatile numerical values, which was cleaned using a low-pass filter to produce the result shown in Figure 3 below.

**A graph of a graph showing a number of magnetometers

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Figure 3: Filtered Corrected Magnetometer Data vs Raw Data**

The yaw complimentary filter uses a combination of the filtered magnetometer yaw data, and a high-pass filtered gyroscopic yaw data set. The data is combined as a weighted sum between the two data sets, shown in the equation below. The weight is experimentally determined as the alpha value shown in the equation. Here, a higher alpha value weights the filter more heavily to the gyroscopic data. An alpha value of 0.7 is selected, as the magnetometer data contains drift, which is less reliable.

The magnetometer and gyro integrated yaw data is plotted on the same graph to visualize any difference in data. While both data sets follow the same overall trend, the disparity between the two sensors is apparent. This plot is shown in Figure 4.

**A graph of a graph showing a blue and pink line

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Figure 4: Magnetometer vs yaw integrated from gyro**

After applying the complimentary filter equation, the resulting data from the complimentary filter is plotted on the same graph. It is indicated by the black line in Figure 5 below. Moving forward, this complimentary filter will be taken as the main Yaw data.

**A graph of different colored lines

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Figure 5: Yaw data comparison between gyro, magnetometer, and complimentary filter data**

The dataset in Figure 5 is also plotted against the original yaw data, or the Euler angle from the IMU. The Euler angle, represented by the blue line shown in Figure 6, was unwrapped, converted to degrees, and passed through a high-pass filter to show the proper trend.

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Figure 6: Yaw data comparison between gyro, magnetometer, complimentary filter data, and Euler angle**

While the magnetometer yaw data set suffers from severe drift, this may not be representative of the expected reliability of the magnetometer sensor. However, as this incident points out, the most trustworthy yaw estimates stem from a combination of the gyroscopic yaw and the magnetometer yaw, as significant deviations in one source can be reduced or mitigated with another. Thus, the complementary filter yaw is most trustworthy for navigation.

**Part II: Forward Velocity Estimate**

The forward velocity from the GPS is estimated by using the northing and easting positional data and dividing the displacement between time intervals given by the utc time stamps to determine velocity. The velocity estimate from the GPS data is recorded in the graph below.

**A graph of a graph showing a number of points

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Figure 7: Estimated velocity from GPS over time**

The forward velocity from the IMU is estimated as the integral of the recorded acceleration in the x direction. Immediately, it becomes apparent that adjustments have to be made for the velocity calculation, as the non-adjusted data trends upwards rapidly. This is likely due to the acceleration data being offset, translated where the resting state would record a positive acceleration rather than 0. This causes the graph to rarely dip below acceleration = 0, thus causing the integral to primarily increase. This behavior is shown in Figure 8 below.

**A graph of a graph showing the growth of a stock market

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Figure 8: Adjusted vs non-adjusted IMU velocity estimate**

The velocity estimate is adjusted by eliminating the offset in the acceleration data and applying a high-pass filter to smooth the outlier data points. This velocity estimate is graphed in conjunction with the GPS velocity estimate, shown in Figure 9 below.

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Figure 9: GPS vs IMU velocity estimates**

While the trends in both GPS and IMU velocity estimates are similar, the IMU velocity data drifts around the y=0 line, occasionally presenting a negative velocity. This could imply backwards driving; however, the car was never put in reverse during recording. More likely, this is due to the visible drifting in data, seen in the calibration plot in Part I.

**Part III: Dead Reckoning with IMU**

In computing , calculated from the product of the complementary yaw derivative and the estimated velocity from the IMU, the result is compared to the accelerometer data, . The trends are very similar, as shown in Figure 10 below. However, most amplitudes are not nearly as large in the data, and the data is suspiciously trending below zero throughout the dataset.

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Figure 10: vs accelerometer data**

This difference may be in part to the complementary yaw data used throughout the calculation, or a minor hitch in the IMU, similar to the drift experienced in the calibration data.

The trajectories of both the IMU and GPS data are plotted in the following graph, with easting along the x-axis and northing along the y-axis. While the general shape of the trajectories is somewhat similar, and the major turns are present in both trajectories, the IMU data differs greatly from the GPS trajectory. These lines are plotted in Figure 11 below.

**A map of a person's body

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Figure 11: IMU & GPS trajectories in easting and northing**

With each layer of smoothing and adjustment for each data set, the IMU trajectory appears almost too smooth compared to the GPS data. The initial heading in the trajectory is not visible in the IMU data any longer.