EECE5554 – Robotics Sensing and Navigation

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Lab4 Report

The data collection for this lab was performed using NUANCE - NEU's autonomous car. We have taken the data for orientation, angular velocity, linear acceleration and magnetic field for this experiment using the Vectornav VN-100 IMU Sensor (Inertial Measurement Unit). We have also collected data for UTM Easting and Northing from the GPS Puck. The IMU was mounted on the vehicle as close to the horizontal as possible with electrical tape, such that the X-axis was pointing forward. The X-axis is in line with the path of the vehicle in the plane. The GPS Puck was mounted on the roof of the vehicle so that we could avoid interference. It was aligned with IMU.

Part-1: Estimate the Heading (Yaw)

Magnetometer Calibration:

The car was stationary for 10s at the start. At the beginning of the ride, we took 3-4 circular turns so that we could calibrate the magnetometer data.

Ideally, the plot of the Magnetic Field in the Y-axis vs X-axis should be circular. Hard-iron distortions cause an offset in this plot from the origin. Soft-Iron distortions change the shape of the circle by stretching or shrinking it to an ellipse. We have corrected the hard-iron distortions first, and then the soft-iron distortions to get a plot where the shape is almost circular. This can be seen from the following two figures which represent the raw as well as the calibrated data plots:

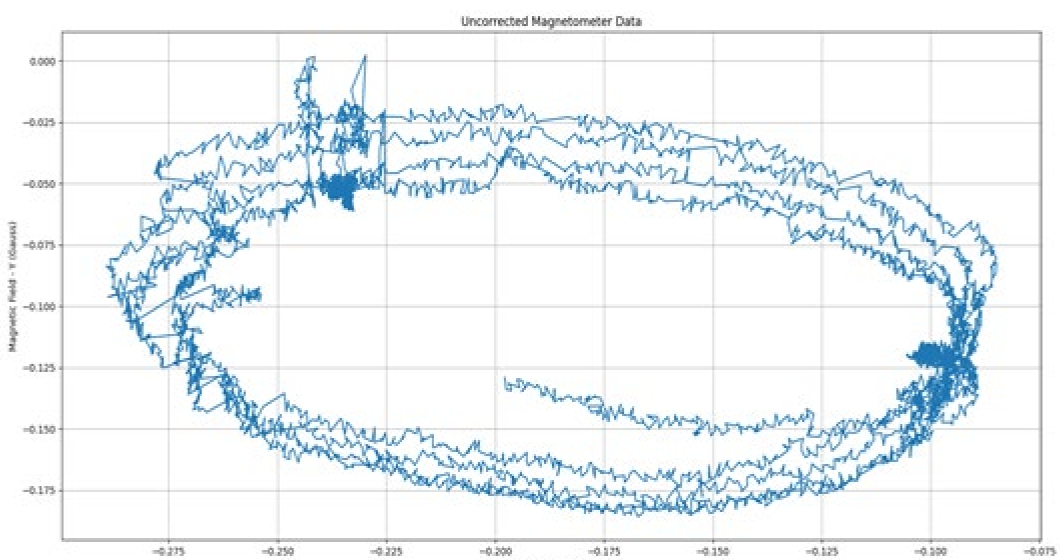

Figure 1: Magnetometer data (not calibrated)

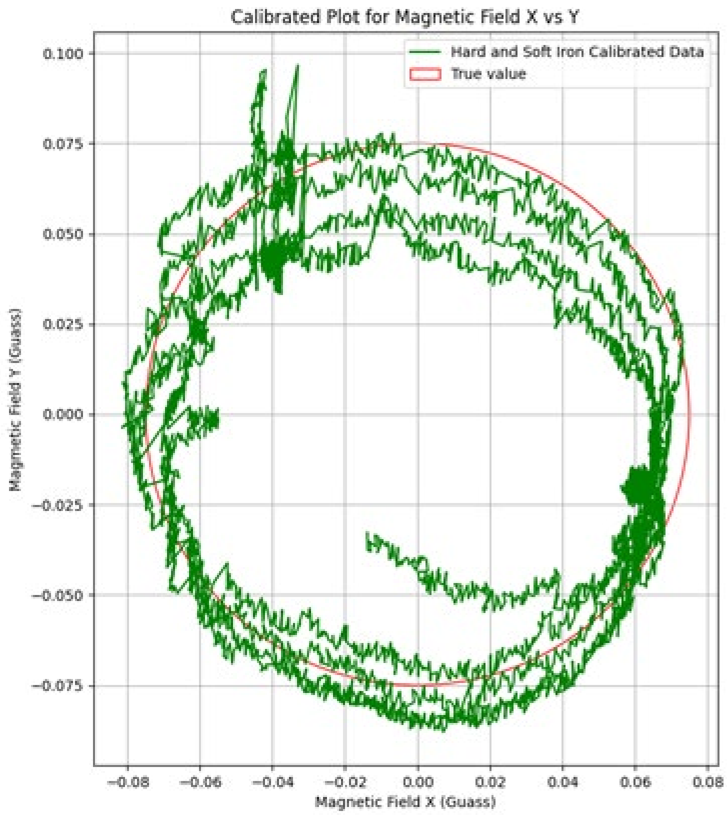

Figure 2: Calibrated magnetometer data

Yaw Estimation:

We can calculate Yaw using multiple methods:

1. **From Magnetometer** – Using the calibrated magnetometer data from before, we can calculate Yaw by taking the inverse tan of the ratio of Magnetic Fields in the Y and X axes.

2. **From Gyroscope** – We can integrate the angular velocity in the Z-axis from the gyroscope to get the Yaw. While calculating using this method, we need to subtract the bias from the angular velocity readings.

The data from the above two methods is plotted in Figure 3. From the figure below, we can see that the Yaw angle calculated from both methods is almost the same, with some noise in the magnetometer data. The curves track each other most of the time, and the differences which arise are mainly due to driving errors like uneven acceleration, not driving in an exact circle or some stops along the way. The differences are also caused by the properties of the magnetometer and gyroscope. Magnetometer is not suitable for dynamic measurements, whereas, there is a drift in the Gyroscope data over time.

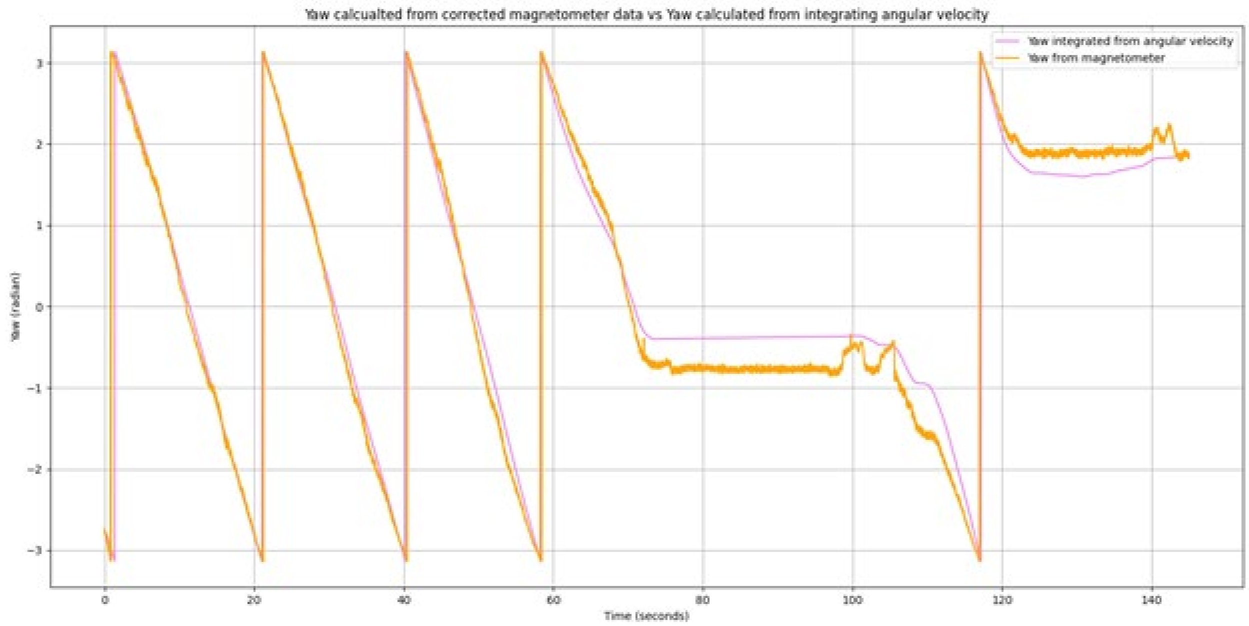

Figure 3: Yaw from Magnetometer vs Gyroscope

Because of the differences in Yaw readings, we have implemented a complementary filter on both datasets. A high pass filter is applied to the gyroscope data to retain the high-frequency points while removing the bias due to low-frequency drift. A low pass filter is applied to the magnetometer data to retain the steady-state drift while filtering out high-frequency noise. In below figure 4, we have compared the complementary filter data with Yaw orientation readings from the IMU sensor.

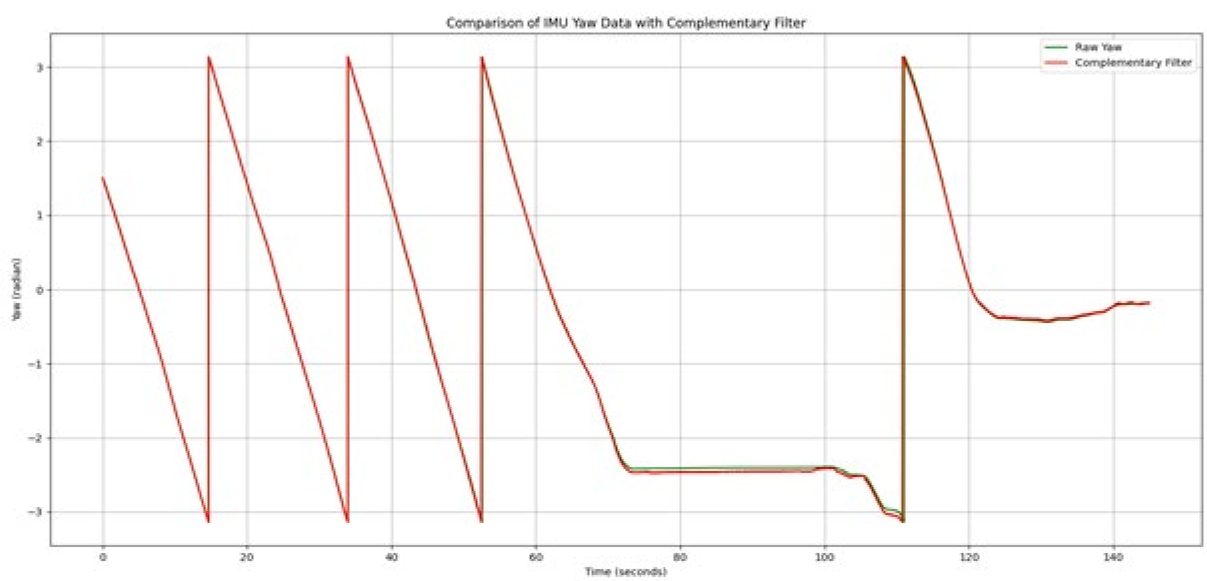

Figure 4: Complementary Filter Output vs IMU Yaw Data

As we can see in the above figure, the complementary filter gives us the best estimate of the Yaw Data. The filter output is tracking the IMU Yaw readings with a high level of accuracy with minor differences here and there which might be caused because of noise.

Part-2: Estimate the Forward Velocity

The velocity of the car was calculated from IMU as well as GPS sensors. Linear acceleration in the X-axis is obtained from the accelerometer which can then be integrated to obtain velocity in the X-axis. We have not used the acceleration on the Y-axis as we are moving forward on the X-axis and the car is not skidding in a sideways direction.

Velocity from GPS is calculated from the distance obtained by the length of the hypotenuse of X (utm easting) and Y (utm northing) components of the GPS Position data. Velocity is then calculated by taking the gradient w.r.t. time. Figure 5 below shows the plots:

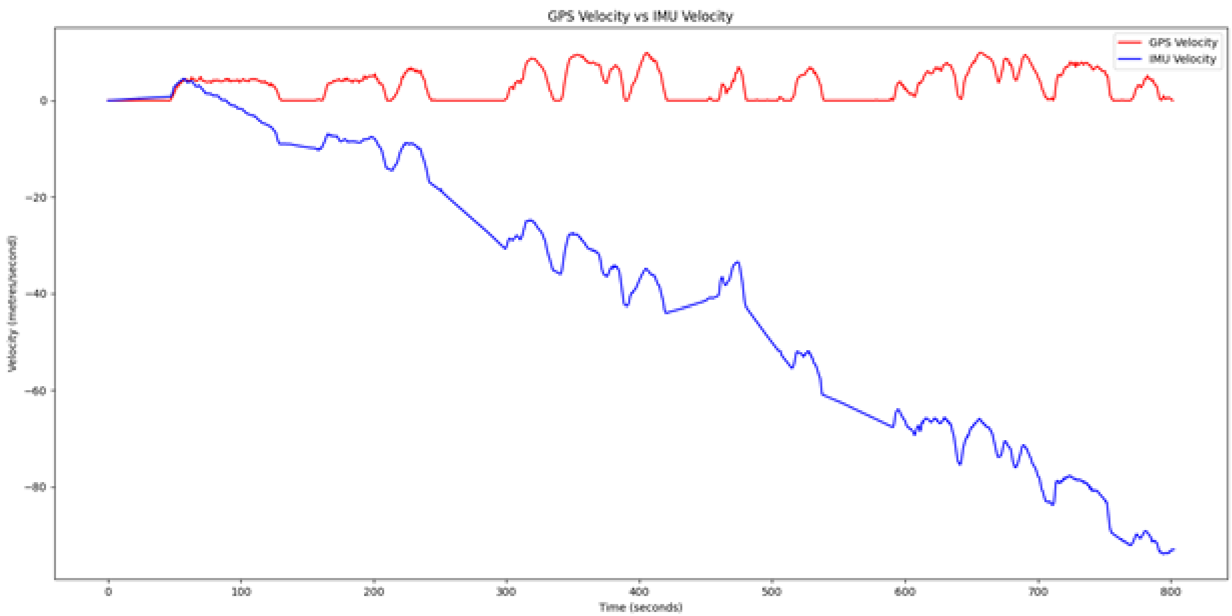

Figure 5: GPS Velocity and Velocity from IMU

We can see from the above plot that the IMU velocity is increasing in the starting 10s. However, velocity should be zero since the car is stationary. This is because there is a bias in the accelerometer readings due to its high sensitivity.

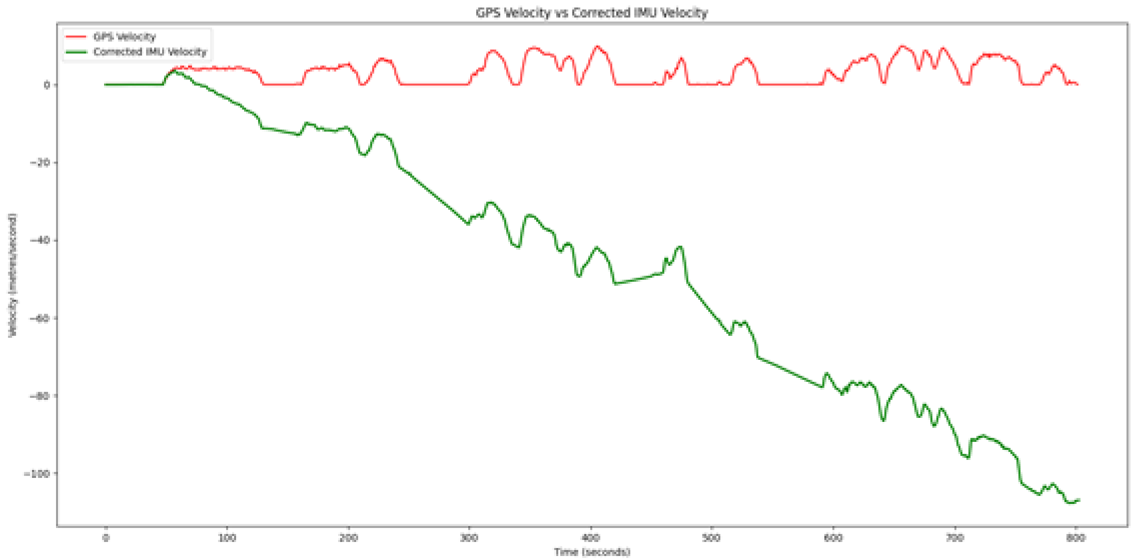

Figure 6: GPS Velocity and Corrected Velocity from IMU

In the adjusted velocity plot above, we have subtracted the mean from the integrated acceleration from the IMU which was causing a stationary bias. Now, the curves are perfectly tracking each other in the initial 10 seconds. The data is jagged and noisy as the car stopped many times during the experiment in a crowded area.

Part-3: Dead Reckoning

We will calculate the Linear Acceleration in the Y-axis by multiplying the angular velocity about the Z-axis with the forward velocity we obtained earlier in the X-direction. We will compare this with the Linear acceleration from the IMU in the following figure:

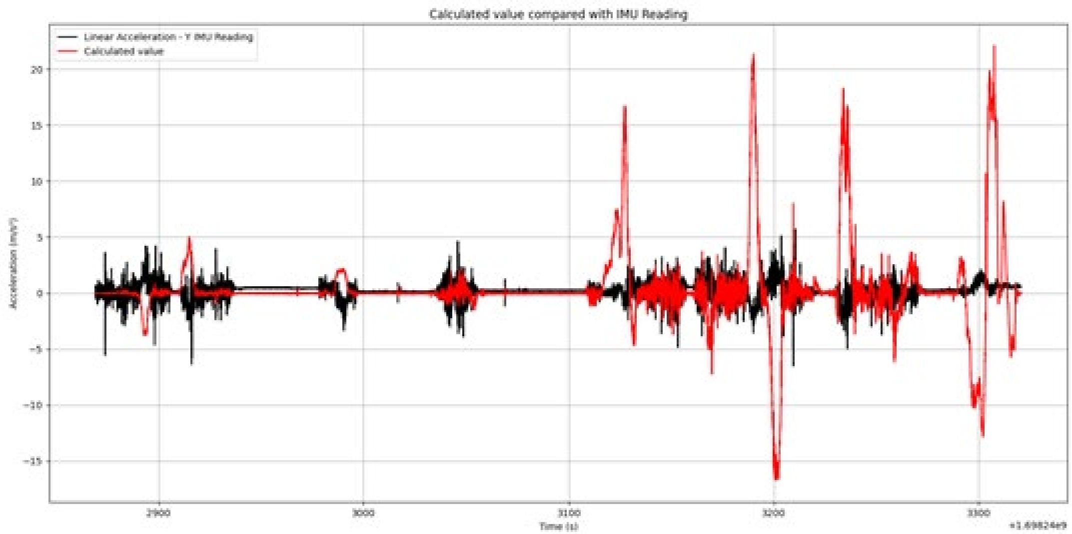

Figure 7: Comparison of actual and calculated linear acceleration

The curves are mostly similar in shape as predicted by the equation governing these variables. There is more noise in the calculated value as compared to the IMU readings as the forward velocity in the X-direction was obtained by integrating the linear acceleration. This is evident from the spikes in the curve. There is bias in the IMU readings since gravitational acceleration has a component in the Y-direction.

We will now estimate the trajectory of the vehicle from all the previously calculated parameters and compare it with the trajectory obtained by plotting UTM Easting and UTM Northing from GPS Data. We have used a complementary filter to plot the estimated trajectory.

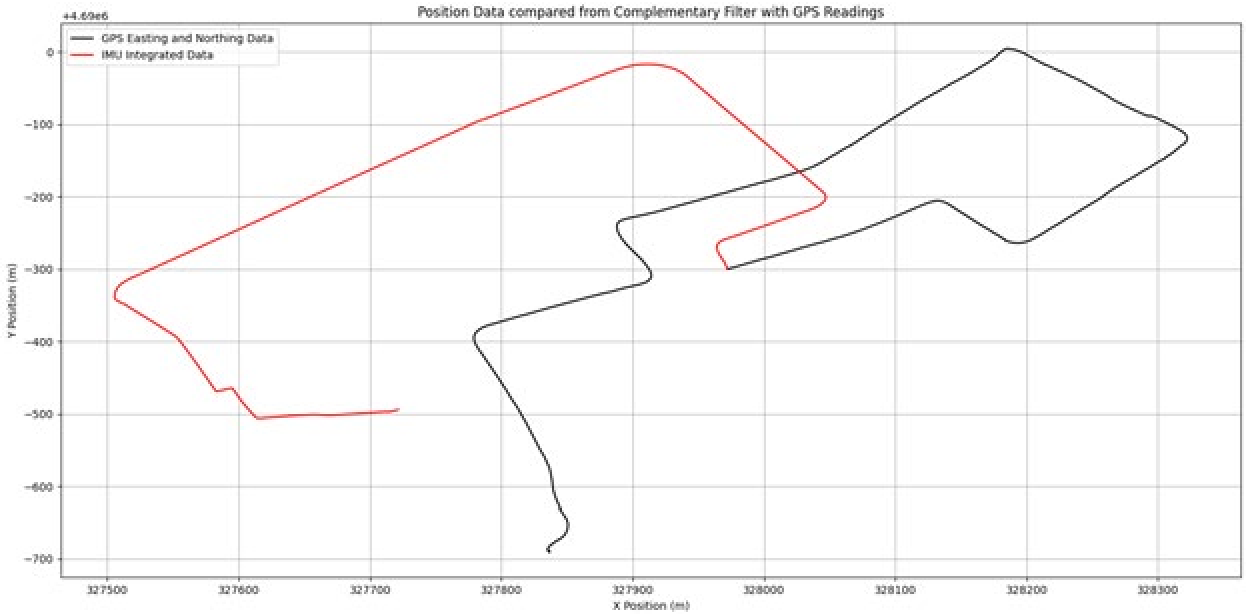

Figure 8: Comparison of Estimated and GPS Trajectories

The shape of the trajectories is the same as the Yaw estimation from the Complementary Filter was precise. Initially, the trajectories are aligned in the same direction. However, after a certain point, the directions of the trajectories change completely. This might arise due to errors in forward velocity estimation.

The center-of-mass (CM) of the vehicle is denoted by R for position and V for velocity. The inertial sensor is situated at a fixed distance from the Centre of Mass (Xc), described by the vector r = (Xc, 0, 0). The displacement only occurs along the x-axis in the vehicle frame. The velocity of the inertial sensor is calculated as follows: $v = V + \omega \times r$, where ω represents the z-axis angular velocity obtained from the gyroscope, and r is given by (Xc, 0, 0). Here, V is the actual linear velocity, while v represents the measured linear velocity.

Correspondingly, the acceleration can be determined using the equation: $\ddot{x} = \dot{v} + \omega \times v = \ddot{X} + \dot{\omega} \times r + \omega \times \dot{X} + \omega \times (\omega \times r)$. To identify a range of possible Xc values, the equation $Xc = (V - v)/\omega$ is applied. We can see that Xc and ω exhibit an inverse relationship. This implies that smaller values of ω will result in larger values of Xc, and vice versa. This approach allows for the isolation of the radius of rotation when the vehicle is executing a turn. Furthermore, when the car is moving in a straight line at a constant speed, V is set as the minimum velocity, yielding a more reasonable range of estimates.

The centre of mass (Xc) as calculated from the above equations is given by:

Xc = 0.833474 meters