GPS and IMU Localization

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Abstract

When it comes to solving positioning challenges in transient environments, a selection of multiple types of devices can be used. Each of these devices has their own set of advantages and drawbacks. In this study, we used the VN-100 Inertial Measurement Unit (IMU) device to collect accelerometer, gyroscope, and magnetometer data, and a BU-353S4 GPS Receiver to record positioning data. We then completed steps to correct and manipulate this data to obtain each device's projected trajectory of a drive around Boston. We were finally able to draw conclusions about the effectiveness of both the IMU and GPS devices in establishing precise positioning data.

Test Setup and Data Collection

In this study, drove around Boston collected data from both an IMU and GPS device. The placement of these devices was important to the data collection process as they had to be in certain orientations in order to ensure accurate datasets. The IMU device was placed on the dashboard of the car and was secured at a zero degree angle with the x-axis pointing directly forward. This setup was important because we made the initial assumption that we were working in a 2D plane and that the x-direction was always pointing in the direction of the trajectory of the vehicle. Next, we placed the GPS on top and in line with the IMU device to ensure that there were limited barriers between the communication of the GPS and surrounding satellites and that the GPS and IMU datasets were as accurate as possible.

I wrote two device drivers that collected, parsed through, and published data from each sensor to a ROS topic. We recorded these two topics to a ROS bag to be analyzed.

Data Analysis

Through analyzing the data from our ROS topics, we were able to isolate and correct important parameters that explained the motion of our vehicle. Plots of the data can be seen in the below sections:

Heading Correction

We corrected the heading, or yaw angle, of our vehicle by taking into account the hard-iron and soft-iron distortions of the magnetometer data. Hard iron distortions are due to alterations of the magnetic field data associated with the sensor location. This can be physically seen as a permanent bias from the true zero of the magnetometer data. Soft iron effects are seen as distortions in the existing magnetic field, and are seen as stretching or warping of the magnetic field. Both of these effects can be visually displayed and corrected through plotting the magnetometer data. The raw magnetometer data, along with the hard iron and soft iron corrected data, is shown below in *Figure 1*:

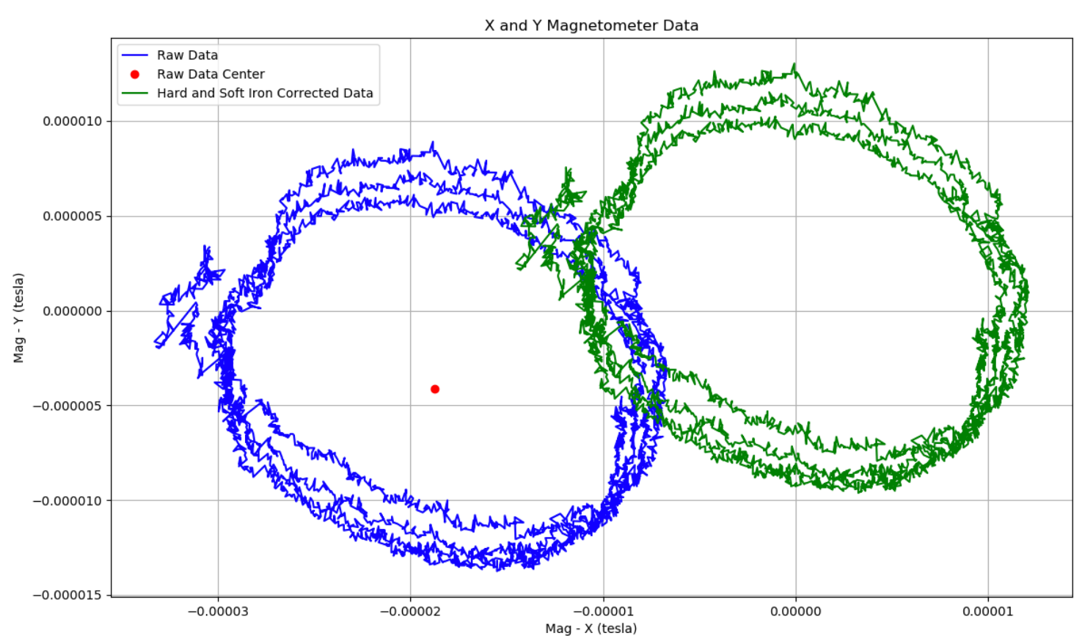

Figure 1: Raw and Corrected Magnetometer Data

Using the corrected magnetometer data, I was able to calculate an estimated yaw angle for each Magnetic Field X and Y set using the following equation:

$$yaw = arctan2(M_x / M_y) \qquad \text{(Eq. 1)}$$

I was able to calculate another yaw estimation by integrating the angular velocity around the Z-axis from the IMU device. The integral of angular velocity yields the angle, and the rotation around the Z-axis defines the yaw angle based on the orientation of our IMU device during data collection. Finally, I applied a complementary filter to both of these yaw calculations using the following equation:

$$filter = 0.9 * (integrated\ yaw) + 0.1 * (magnetometer\ yaw) \qquad \text{(Eq. 2)}$$

Plots of all three yaw calculations are seen below:

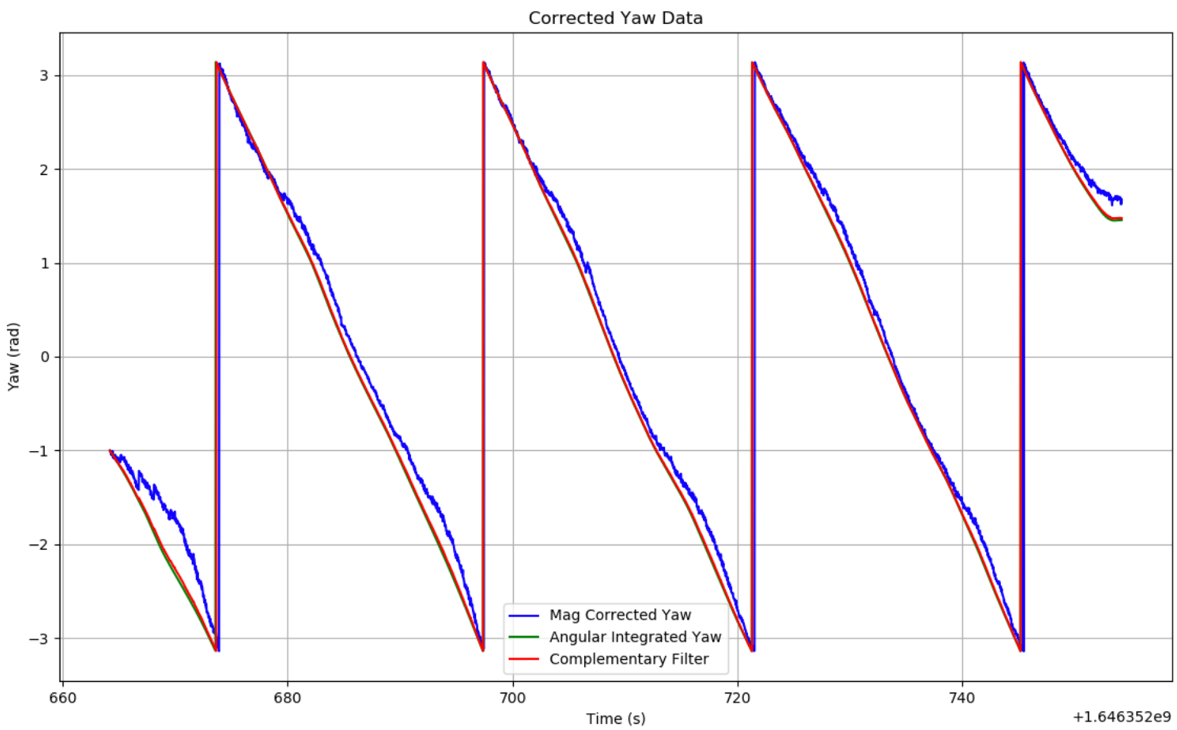

Figure 2: Yaw Calculations

As one can see from *Figure 2* above, the yaw found by the corrected magnetometer calculation has more noise than that of the integrated angular rate. This is mainly due to the magnetometer being more susceptible to external influences during data collection that will affect the output. The integrated angular rate calculation shows a much more smooth and accurate representation of the yaw angle, however it is likely to slowly drift over time due to the integration aspect. The main reason we calculate the complementary filter is to use the advantages of both the integrated angular rate calculation and corrected magnetometer data calculation to obtain the most accurate final result. For the reasons stated above, we apply a high pass filter to the integrated angular rate calculation and a low pass filter to the magnetometer calculation and combine the two for an accurate estimation of yaw angle throughout our data collection. As seen below in *Figure 3*, our complementary filter yaw calculation agrees almost exactly with the yaw calculated directly from the IMU, with slight variations due to external effects that contributed to noise in the magnetometer calculations.

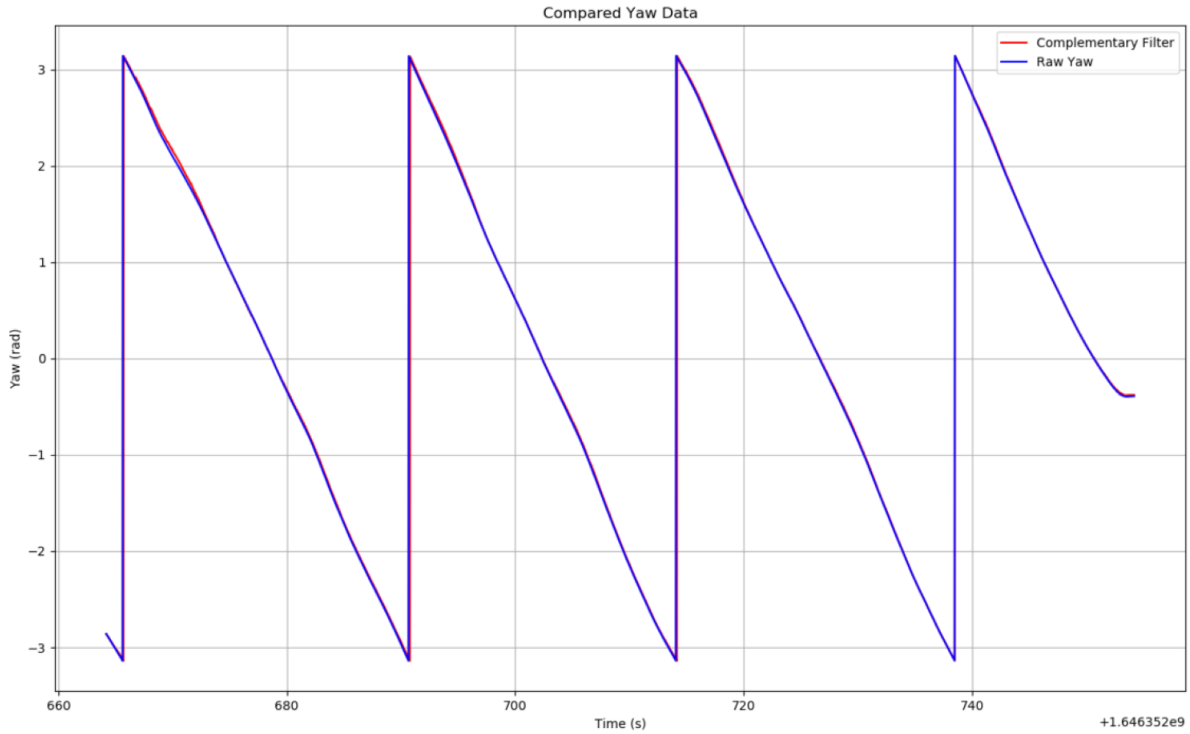

Figure 3: Raw Yaw from IMU and Complementary Filter Yaw

Estimating Velocity

Now that we have an accurate estimate of the vehicle's orientation, we need an estimate of the vehicle's velocity at each time stamp. We did this multiple ways using both the IMU and GPS devices. The plots are shown below in *Figure 4*:

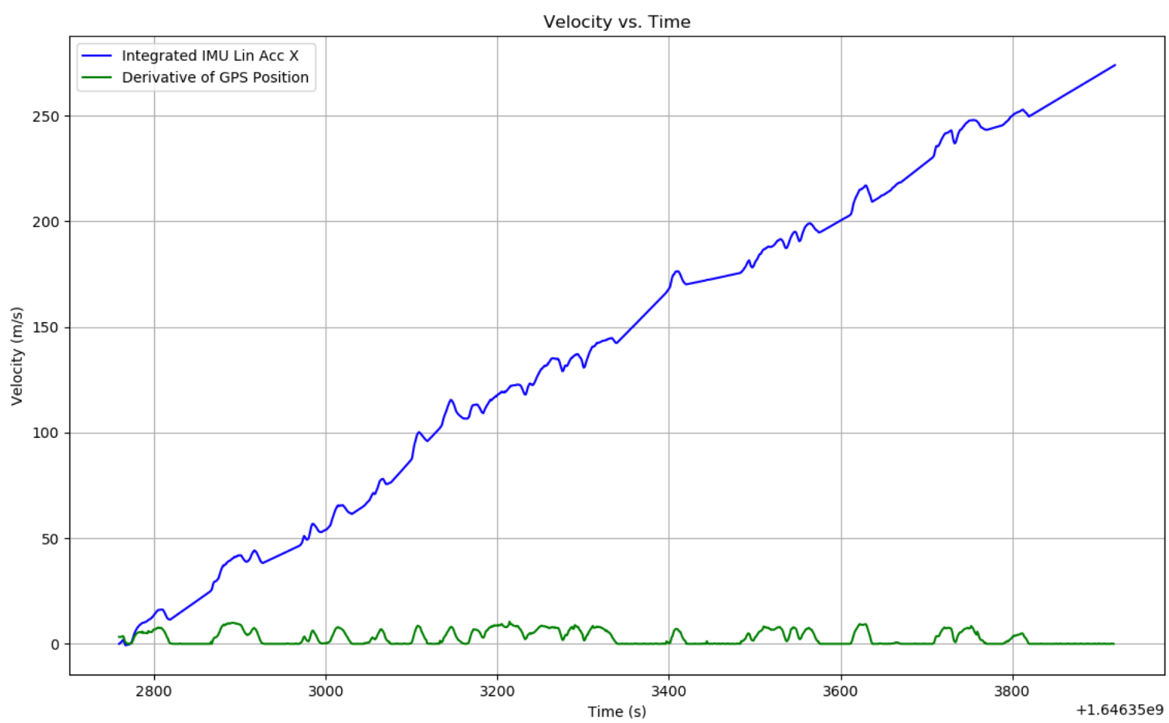

Figure 4: Velocity Estimates from the IMU and GPS

As one can see in *Figure 4*, the velocity plots appear as if they do not agree. The GPS position derivative estimation initially looks like a more reasonable estimation, remaining roughly below 12 m/s and constantly returning to around 0 m/s, representing times of zero velocity at red lights, stop signs, traffic jams, etc. However the integrated IMU acceleration estimation shows a constant drift in velocity. This direct velocity estimation is not correct as I was, in fact, not driving 250 m/s at any point in my drive. This is due to a few factors. First, there is bias in the accelerometer reading. The acceleration due to gravity is felt by the accelerometer, and since our IMU device was not perfectly level throughout the entire drive, that acceleration was added to the X direction acceleration throughout the data collection. Second, there is sensor noise that needs to be silenced. The accelerometer does not remain perfectly balanced when not moving due to its sensitivity.

To limit these factors, and create a more accurate representation of the IMU acceleration, I began by subtracting the mean bias from the stationary data taken at the beginning of the route from the X direction acceleration values. After plotting, I realized that there is a constant drift in the integrated IMU data that correlates directly to the derived GPS position data. I created a new zero to base the integrated values off of, shown below in *Figure 5* in red, and calculated the integrated values based off of that new zero. Finally, I set values below zero velocity, equal to 0, as we never moved in reverse. The results I obtained after making these adjustments, as well as the original IMU and GPS velocity calculations, are shown below in *Figure 5*.

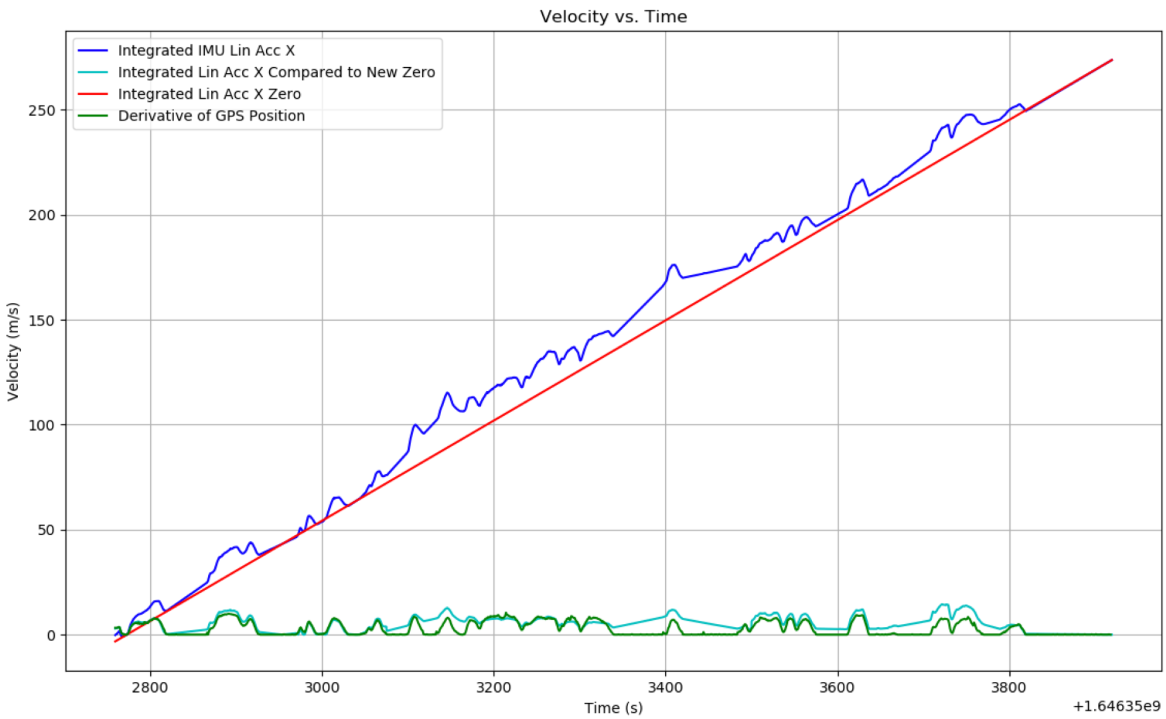

Figure 5: Adjusted IMU Velocity Estimate

Estimating Vehicle Trajectory

Now that we have accurate estimates of both the vehicle's orientation and velocity throughout our drive, we can estimate its trajectory. We first want to compare theoretically correct values to visualize where some errors may be and what they might be due to. First we compare the connection between the linear acceleration in the Y direction (Y double dot), yaw rate about the Z axis (Wz), and the velocity in the X direction (X dot) all experienced by the IMU. The connection between these parameters can be described by the equation:

$$Y_{double\ dot} = W_Z * X_{dot} \qquad \text{(Eq. 3)}$$

The plots for this relationship are shown below in *Figure 6* and *Figure 7*:

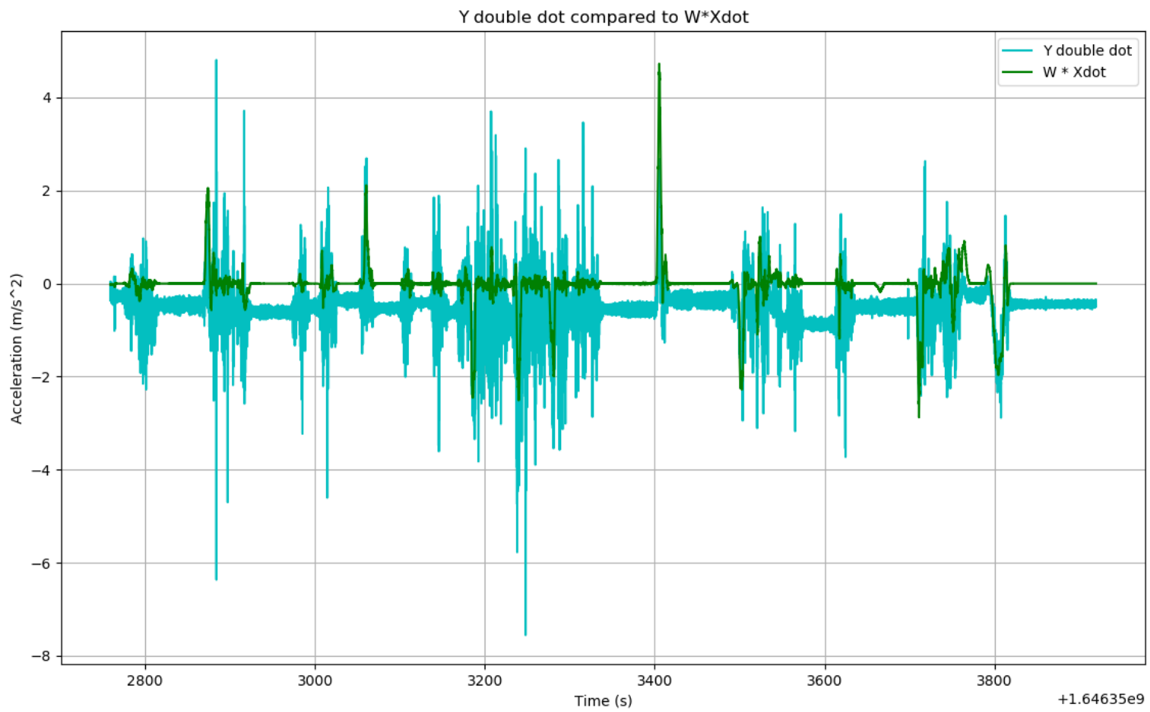

Figure 6: Comparison Between Y Lin Acc, Yaw Rate Z, and X Velocity After Adjustments

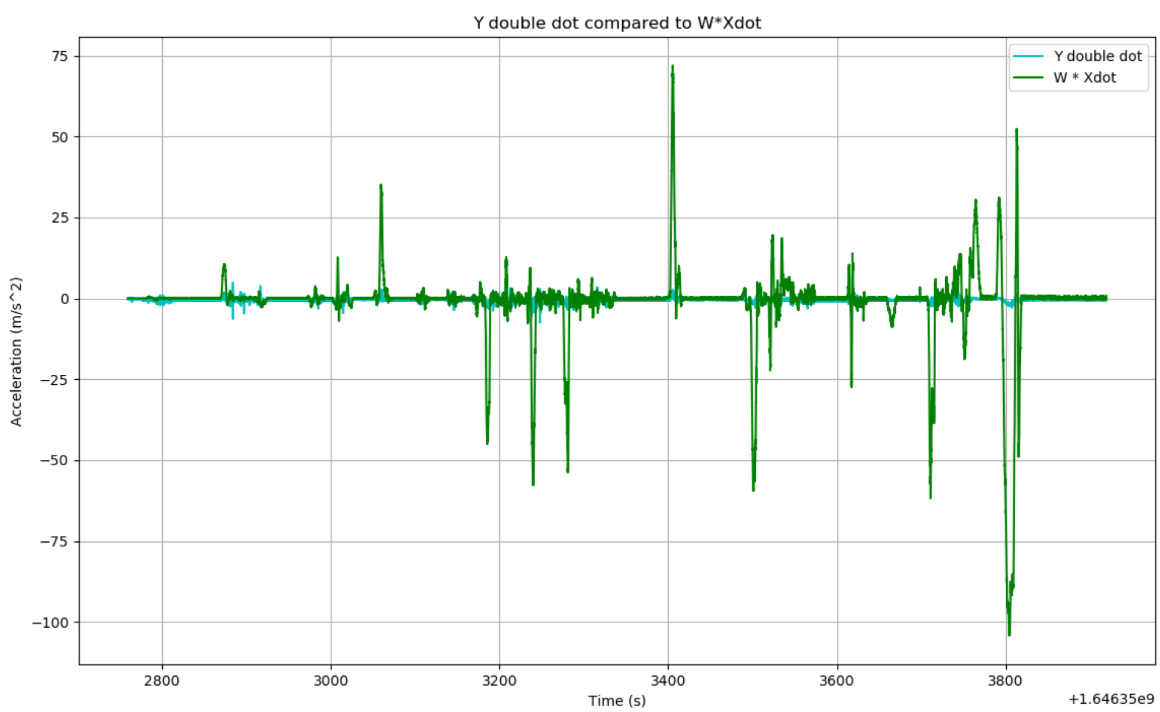

Figure 7: Comparison Between Y Lin Acc, Yaw Rate Z, and X Velocity Before Adjustments

As seen in *Figure 6* above, the graphs have some similar and differing qualities. The graphs are similar in that they follow the same general shape. When there are spikes in the observed linear acceleration in the Y direction by the IMU, there are similar spikes in the angular rate Z and X velocity graph. This shows the relationship between the parameters and *Eq. 3*. The clear differences are due to similar reasons listed above. There is a clear bias offset in the observed IMU Y acceleration. This is mostly due to the effect of the linear acceleration due to gravity having a component in the Y direction throughout the drive. Another reason they do not match is that the integrated acceleration in the X direction, or Xdot, has been cleaned of the previously mentioned gravitational bias, and altered to more closely match that of the GPS readings. Since the Xdot readings used in this calculation have been adjusted to subtract the bias and reduce the presence of noise, there is less error present in the measurements than that observed directly by the IMU device, therefore leading to less noise in *Figure 6*.

Figure 7 shows a plot where the Xdot used has not been adjusted for the stationary bias or to clean up any noise. A more direct relationship can clearly be seen, showing the bias effect between Figures 6 and 7, although there is still error between the two calculations. These errors are mostly due to the noise effects of the integrated X direction linear acceleration. Due to the bias, many of the values when we were not accelerating oscillate and display an incorrect value. The angular rate multiplied by Xdot also typically has a greater magnitude because by combining the two parameters, there is more room for error compared to the linear acceleration in the Y direction. This acceleration should theoretically be equal to zero as we were not moving in the horizontal direction relative to the trajectory of the car.

In order to obtain the estimated trajectory of the vehicle, I split each X-direction velocity reading in to 2 components, an East and a North, similar to that read by the GPS device, using the following equations:

$$Vel_E = |V| * cos(yaw) \qquad \text{(Eq. 4)}$$

$$Vel_N = |V| * sin(yaw) \qquad \text{(Eq. 5)}$$

In equations 4 and 5, “|V|” is the estimated X direction, or forward pointing, velocity of the vehicle at every point in its drive. These are displayed above in *Figure 5*. The “yaw” values are the estimated orientation of the vehicle at every point in its drive. The various methods to calculate these yaw values are displayed above in *Figure 2*. Once we have broken the velocity into East and North components, I simply integrated those with respect to time to obtain an easting and northing position at each time stamp.

I plotted two variations of the projected trajectory of the vehicle below. In *Figure 7*, I used the yaw values calculated by the corrected magnetometer data, and in *Figure 8* I used yaw values calculated using a complementary filter:

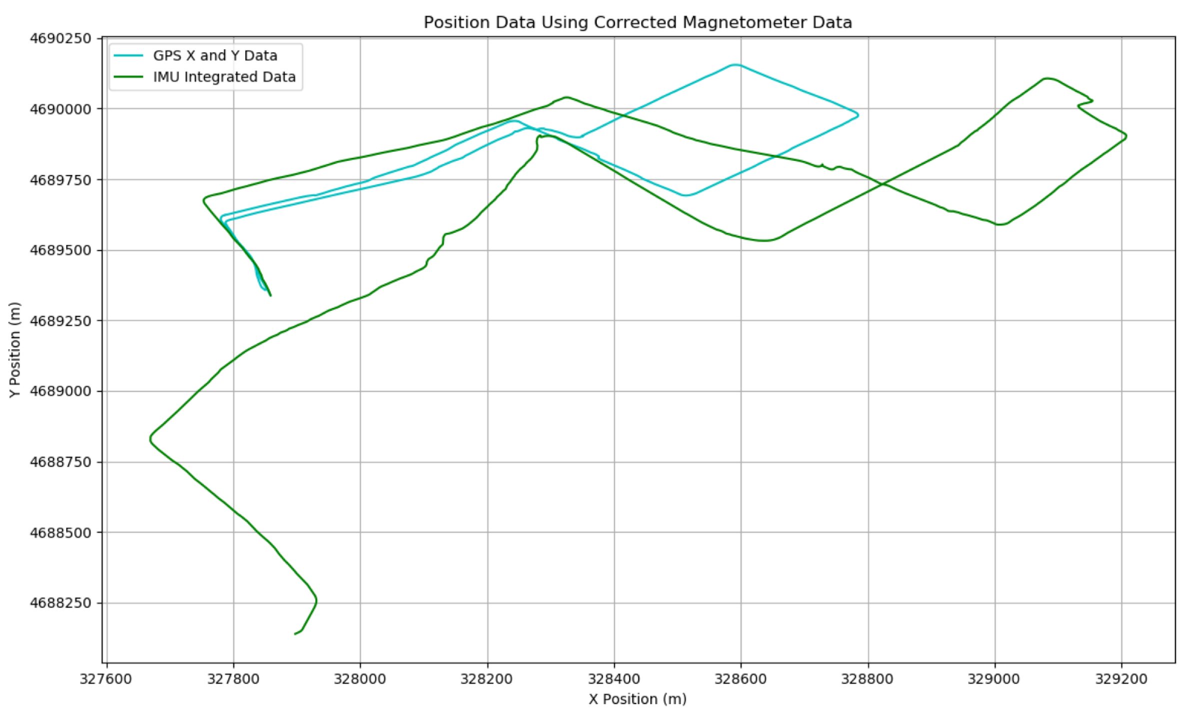

Figure 8: Estimated Trajectory using Corrected Magnetometer Data, Flipped and Rotated 195 Degrees

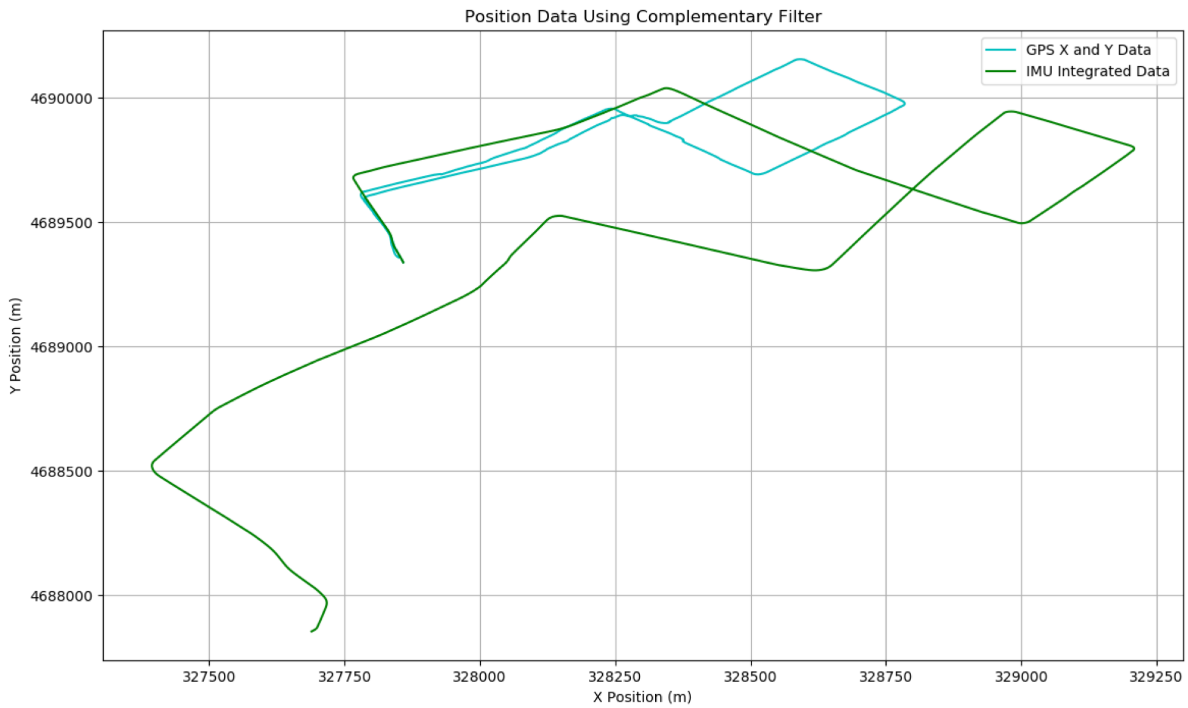

Figure 9: Estimated Trajectory using a Complementary Filter, Flipped and Rotated 105 Degrees

As seen above, the estimated trajectory using a complementary filter shown in *Figure 9* is a better representation of the true trajectory of the vehicle. This is due to the factors discussed above in the section under *Figure 2*.

A few of the major advantages and disadvantages to using IMU devices in navigation are present in *Figure 9*. First, it is clear that at many of the turns in the route, the estimated trajectory by the IMU device tends to overshoot that of the GPS route. This is mainly due to the differences observed above in *Figure 5*. The beginning of the route tends to follow the GPS route relatively closely, however as differences begin to build between our projected velocity calculations, the error begins to grow between the IMU and GPS estimated trajectories. However, the shape of both graphs is generally very similar. This shows that the yaw calculations calculated by the complementary filter are very accurate.

The calculations shown above in *Figure 6* are under the assumption that the center of mass of the vehicle is coincident with the vehicle frame. When that assumption is not made, *Eq. 3* is expanded to:

$$A_{X,IMU} = A_{X,CoM} - W_Z * V_{Y,CoM} - W_Z^{\,2} * x_c \qquad \text{(Eq. 6)}$$

$$A_{Y,IMU} = A_{Y,CoM} + W_Z * V_{X,CoM} + W^{dot}_{\ \ Z} * x_c \qquad \text{(Eq. 7)}$$

Assuming that we were not sliding horizontally in the Y direction, and therefore setting any accelerations and velocities in the Y direction equal to zero, *Eq. 7* can be rearranged and solved to obtain an estimation for the location of the IMU device relative to the vehicle frame:

$$x_c = 0.342\ m$$

Conclusion

Both IMU and GPS devices are extremely powerful and useful pieces of technology when it comes to positioning, however both have their advantages and disadvantages in different use cases. From this study, it is evident that GPS devices are, in no surprise, superior in positioning over longer distances and periods of time than using data from IMU devices. However, IMU devices have proven to be extremely efficient in accurately detecting small changes in vehicle orientation, even throughout a longer period of time. Understanding these advantages, as well as the effect that noise, gravity, and other external factors have on raw data readings, is crucial to effectively using these devices for positioning. When used together correctly, they provide the necessary technology to accurately describe the positioning and orientation of many robotic applications.