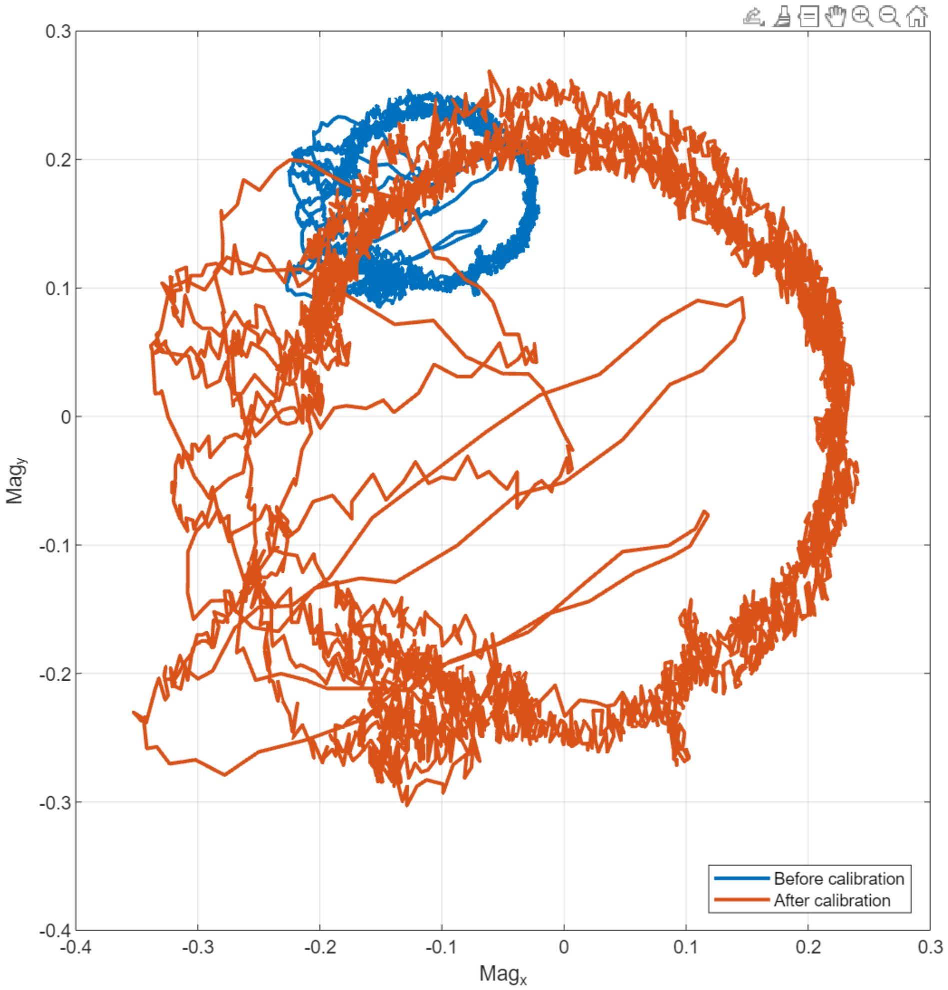
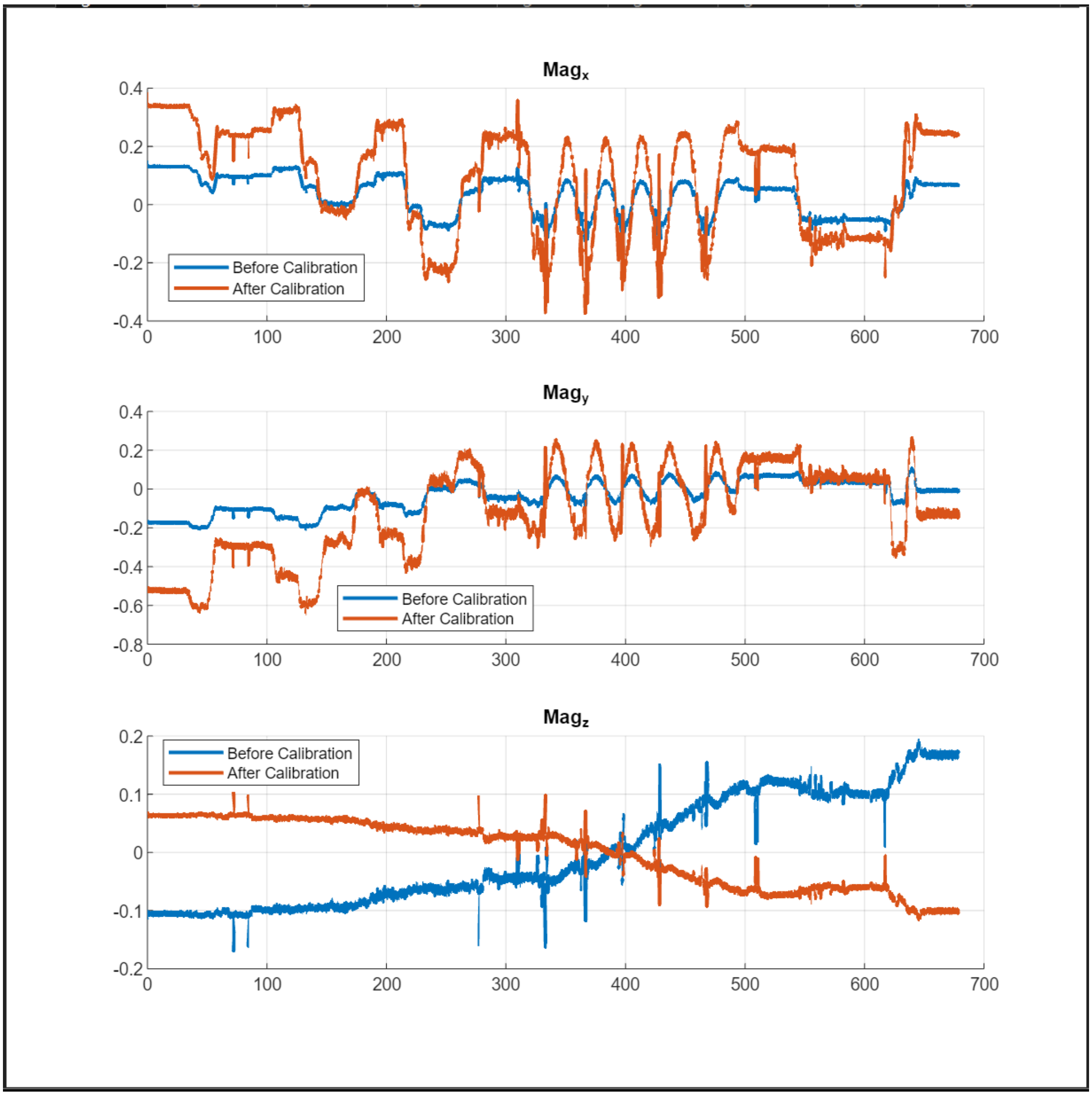
Report

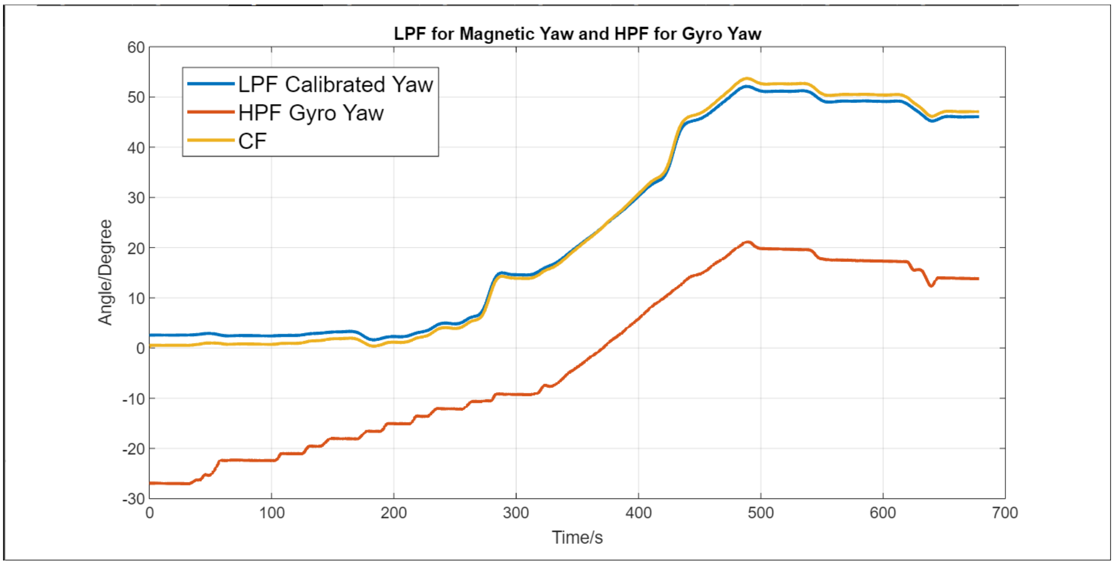
The magnetometer X-Y plot and soft iron calibration:



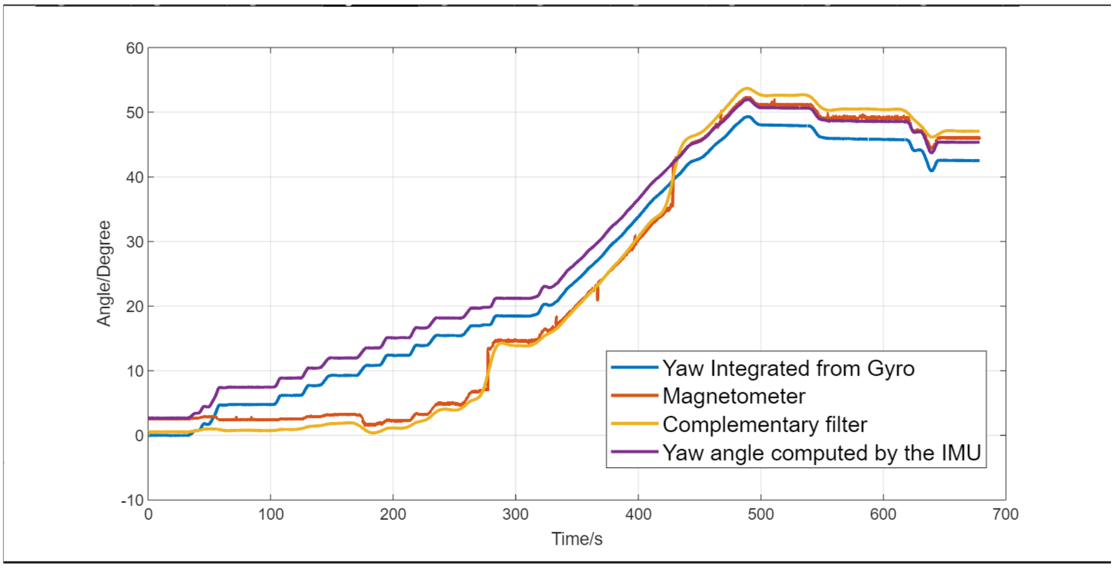
The time series magnetometer data changing before and after:



LPF for magnetic yaw and HPF for gyro yaw

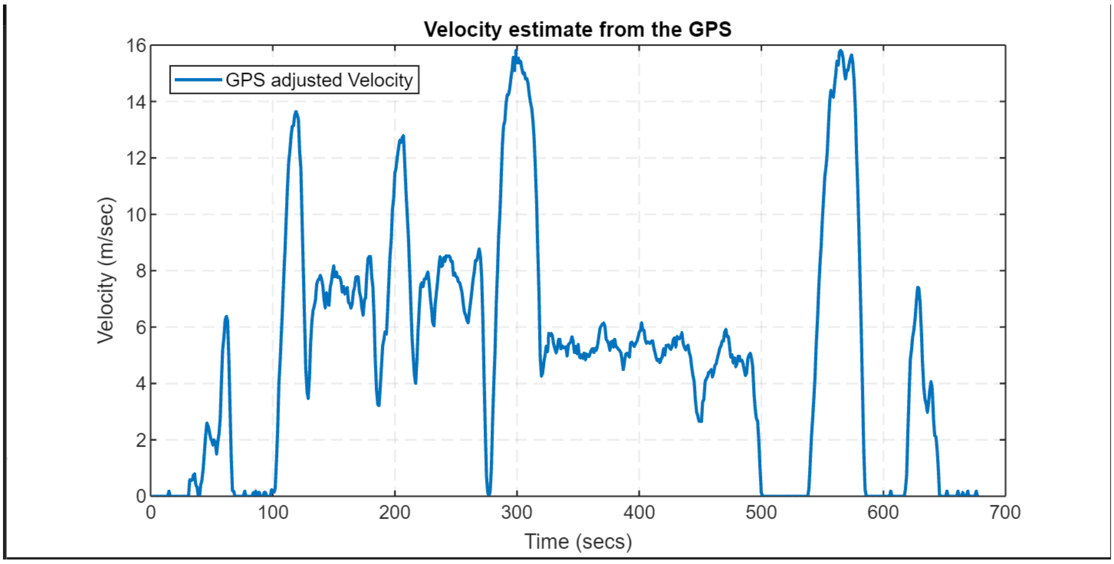


yaw angle using four methods

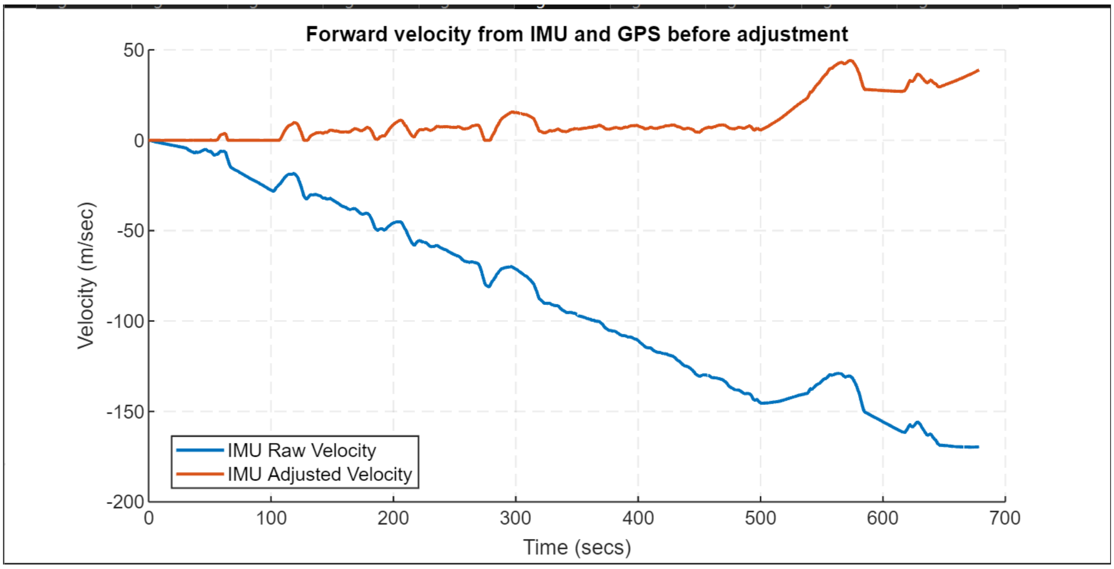


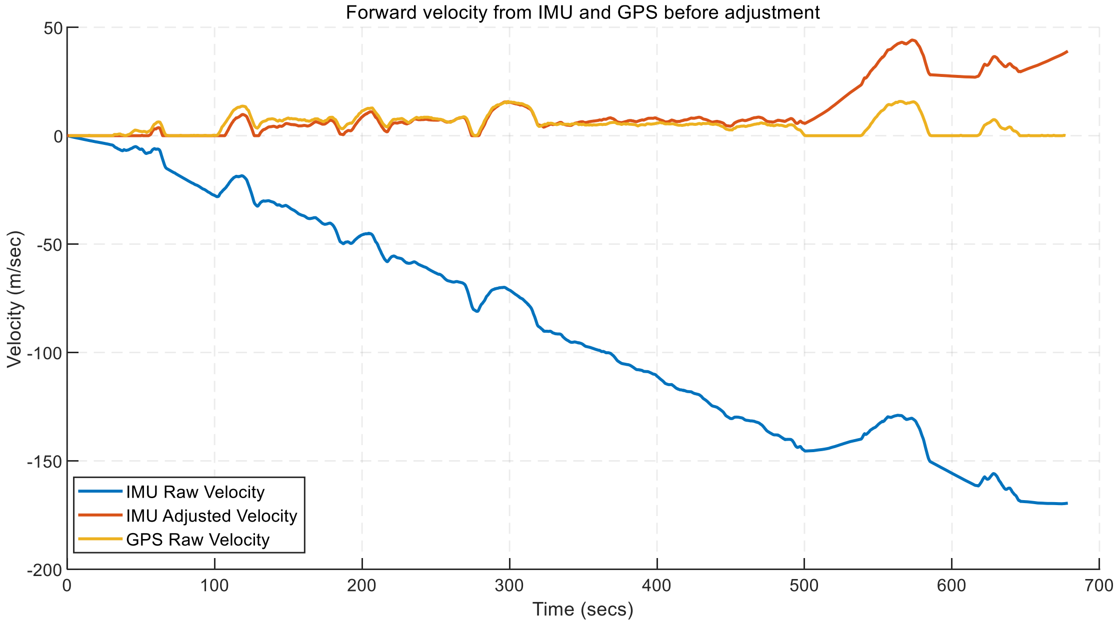
2 . Estimate the forward velocity.

GPS estimate velocity



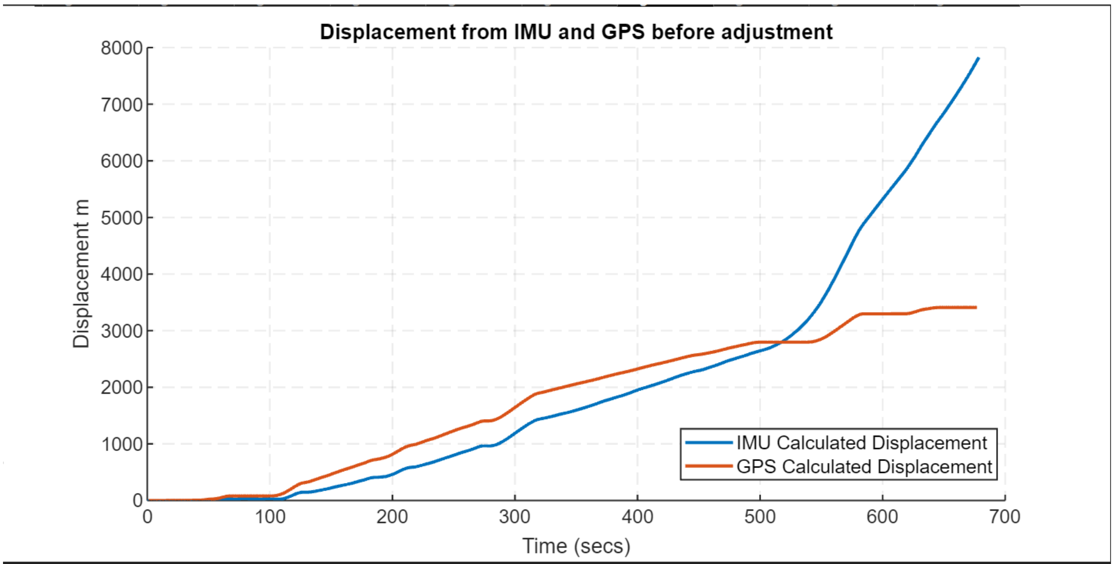
IMU and GPS before adjustment forward velocity



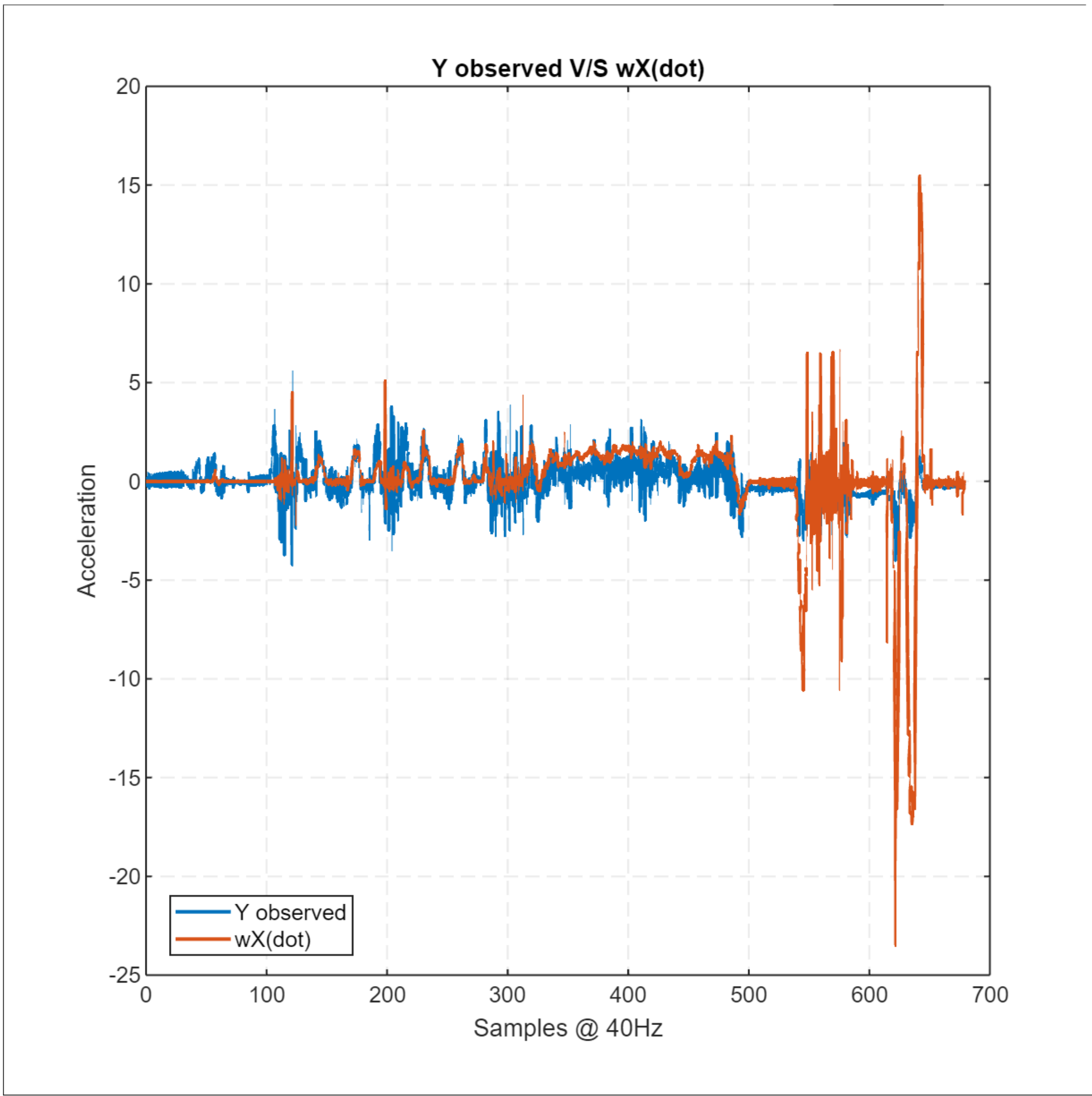


3. Dead Reckoning with IMU

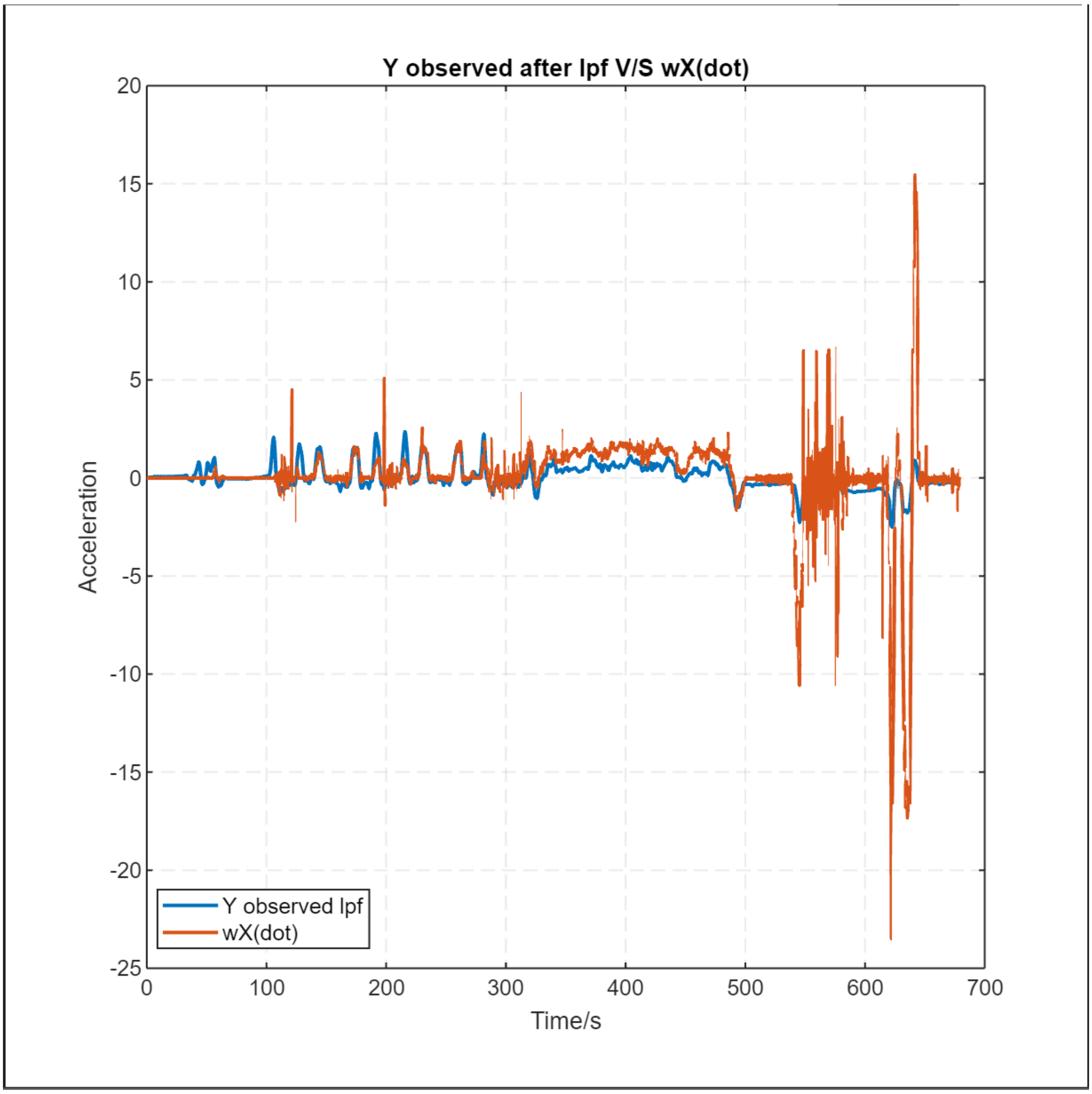
GPS displacement and integrated forward velocity obtain displacement.



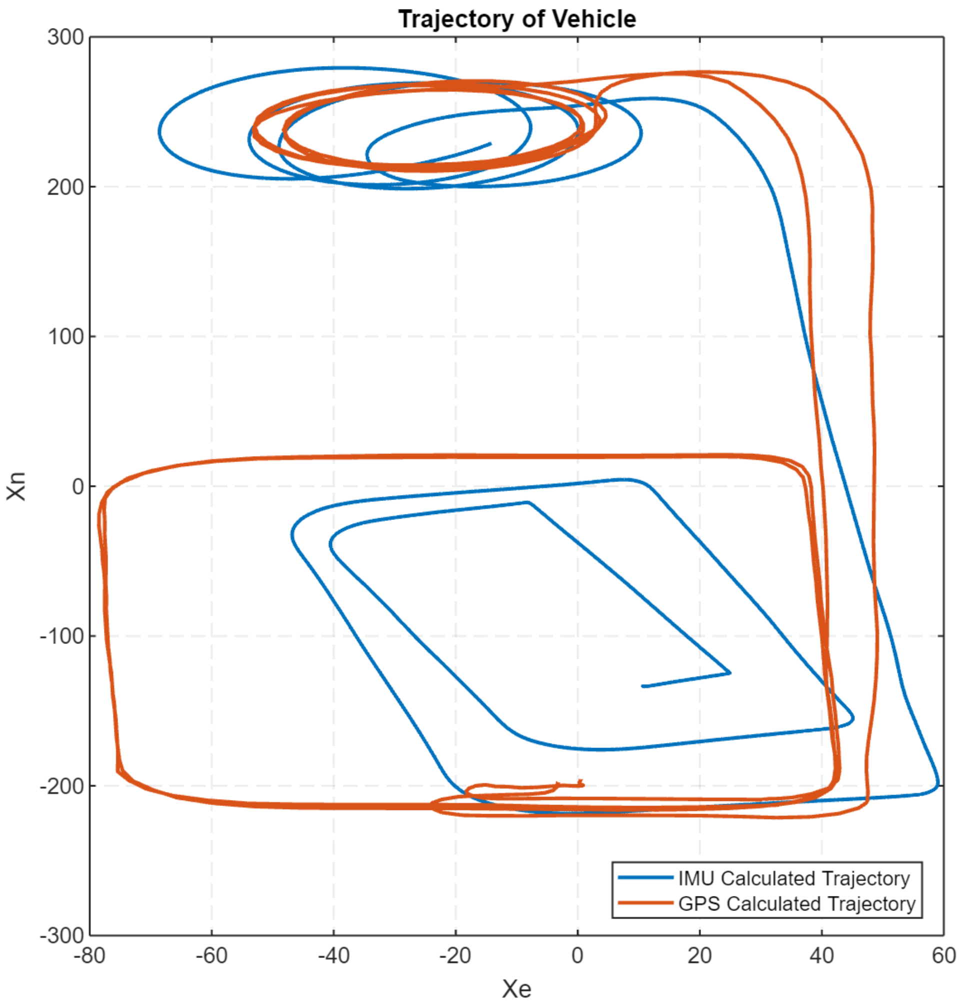
Compare $\omega\dot{X}$ and $\ddot{y}_{obs}$



IMU adjusted velocity calculated the $\omega\dot{X}$, so they agree well. Perform lpf to the $\ddot{y}_{obs}$, the consistency was improved.



Trajectory from the GPS and IMU



Questions to answer.

1. To calibrate the magnetometer readings, the data obtained during circling was utilized. The calibration process involved several steps. Firstly, the average for each axis was computed. Next, the radius of the circle was determined for each sample, followed by calculating the maximum radius and scale factors for each axis. Subsequently, a rotation matrix was computed using the scale factors and average values for each axis. Finally, the magnetometer readings were corrected using the rotation matrix.
   Magnetometer readings can suffer from two types of distortions: hard-iron distortion and soft-iron distortion. Hard-iron distortion is caused by the presence of ferromagnetic materials near the sensor, resulting in a constant offset in the magnetometer readings. On the other hand, soft-iron distortion is caused by the presence of other magnetic fields that can be influenced by nearby magnetic materials or structures, causing the magnetometer readings to be stretched or compressed.
2. To implement a complementary filter, a weighted averaging technique was employed, combining low-pass filtered data and high-pass filtered data. The low-pass filter had a cutoff frequency of 0.1 Hz, while the high-pass filter had a cutoff frequency of 0.00001 Hz.
3. The yaw was determined by utilizing the angular velocity, as it provided the closest match to

the yaw value provided by the IMU itself.

4. To obtain accurate data for estimating the orientation of the car, it is essential to maintain a constant speed during the circling data collection process. This is necessary to ensure that the mean acceleration remains zero. To achieve this, the mean value of the collected acceleration data is used as an offset and is subtracted from all readings. Furthermore, the initial speed of the car is adjusted to remain constant during the entire data collection process. These steps are crucial in obtaining precise data and ensuring that the estimated orientation of the car is reliable.
5. Typically, the GPS-derived speed and the speed calculated by the IMU show a high degree of agreement. Nevertheless, beyond 500 seconds, a substantial disparity emerges between the calculated speeds, potentially due to the IMU's drift that accumulates over time.
6. There is a strong correlation between $\omega\dot{X}$ and $\ddot{y}_{obs}$. The consistency between these two variables was further enhanced after applying a low pass filter.
7. The IMU trajectory exhibits a reversed heading in both directions. To correct for this, scaling factors of 0.5192 and 0.7042 were applied in the x and y directions, respectively.

   According to the findings, the device can operate without a position fix for roughly 500 seconds. The circling phase yields the highest degree of concurrence between the two trajectories. Did the stated performance for dead reckoning match actual measurements? Why or why not? :

   No, because the IMU sensor has a big noise and it might need to be fixed. So the result we get has a significant change in z axis during circling. And that is the reason the trajectory obtained using dead reckoning has poor accuracy.