EECE5554 Lab4 Report ChenghaoWang

1. Part A
   a. Data description

      Based on the instruction, our team collected the dead-reckoning data using NU autonomous car. Three parts of data were collected separately to reduce the matlab load time, where the first part was collected at the circular route near Ruggles, the second part was stationary data, and the third part was semi-rectangular data near the campus. For ROS driver, we have used previous ROS driver to publish two topics (IMU topic publish, GPS topic publish) simultaneously.

Figure 1 NU Autonomous car

2. Part B
   a. Heading estimation
      i. Magnetometer Calibration

         For GPS there are "hard-iron" and "soft-iron" effects, where hard iron distortions will only shift the center of the circle away from the origin, they will not distort the shape of the circle in any way. Soft iron distortions, on the other hand, distort and warp the existing magnetic fields. When plotting the magnetic output, soft iron distortions are easy to recognize as they will distort the circular output into an elliptical shape. So, before we start processing our GPS data, we need to remove "hard-iron" and "soft-iron" effects first.

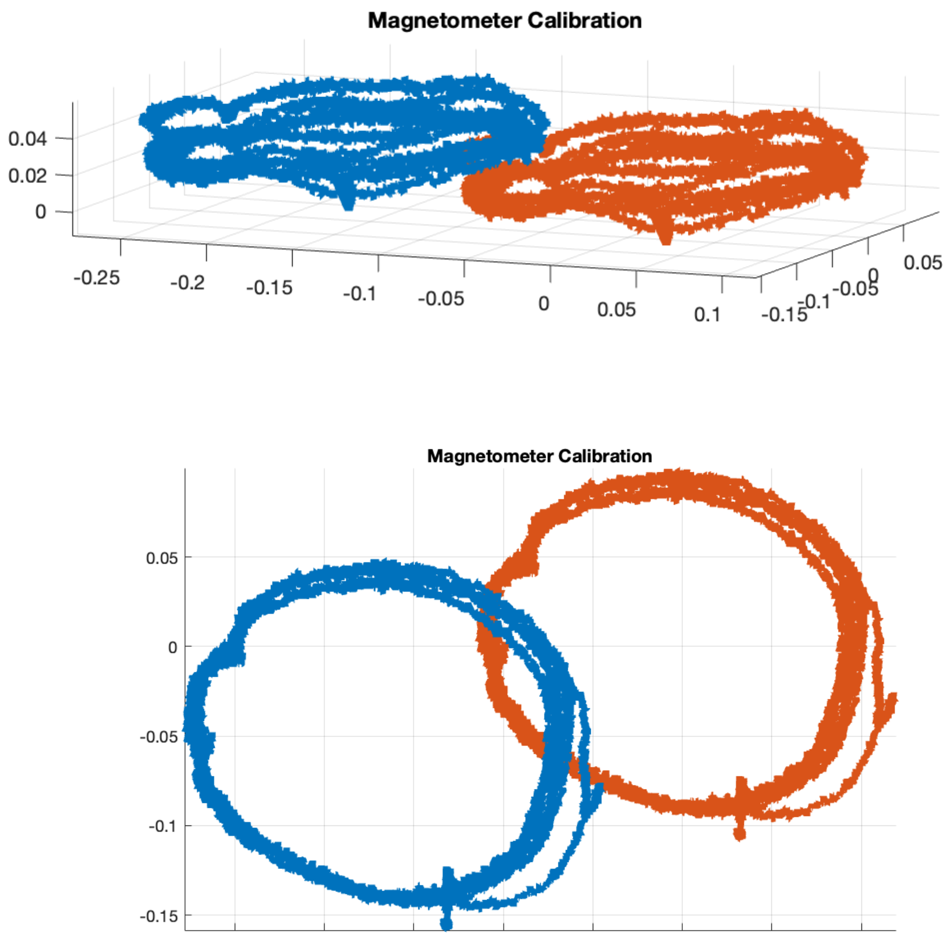


Figure 2 Magnetometer Calibration. Blue-before calibration; Orange-after calibration.

Figure 2 shows the magnetometer calibration before and after calibration. The blue line shows the data before calibration and the orange one shows after. There is no significant deformation in the images, only phase differences. So, we can easily found that most of the errors were caused by hard iorn.

ii. Yaw angle comparison from Magnetometer and gyro.

After corrected the magnetic field, we can compare yaw angles from GPS and IMU, we integrated the angular rate from IMU to get yaw and using atan2d to get yaw from magnetic field, the result figure showed below.

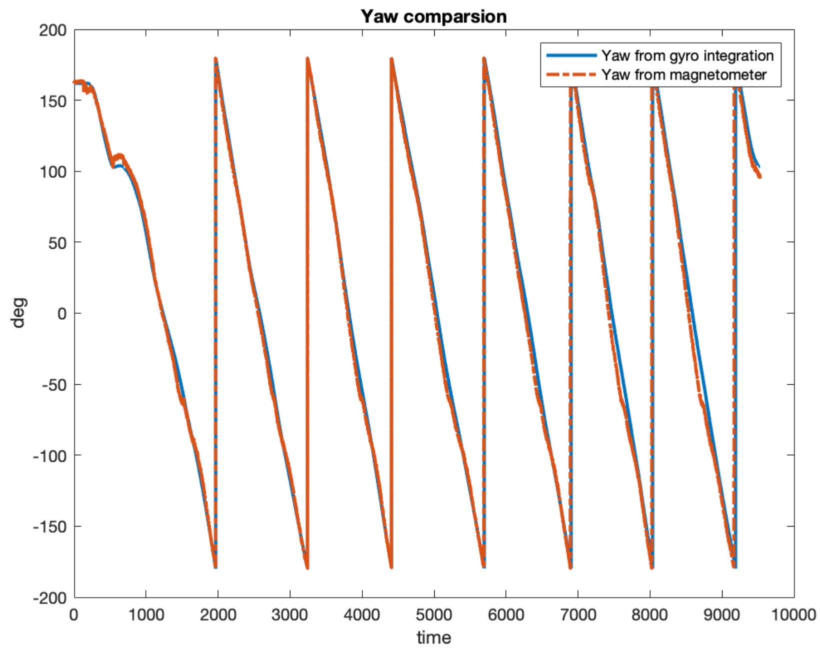


Figure 3 Magnetometer vs. Yaw Integrated from Gyro

Which we can notice from the graph that there is only a very small difference between the two figures. But data here is still noisy. To reduce the impact of noise on the data, we filtered the magnetometer using lowpass filter and the gyro using highpass filter. The filter result shows below.

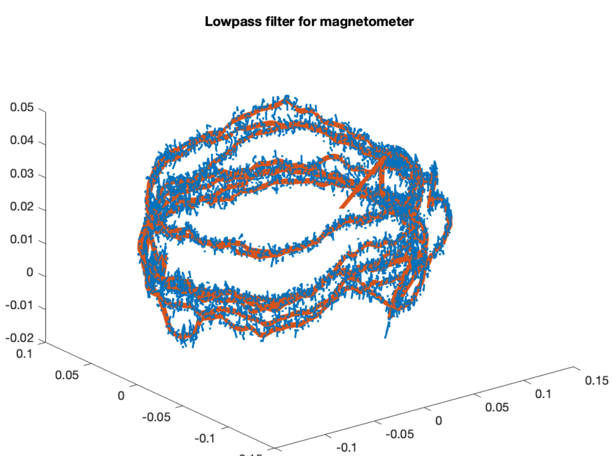


Figure 4 Lowpass filter for magnetometer. Blue-before; Orange-after.

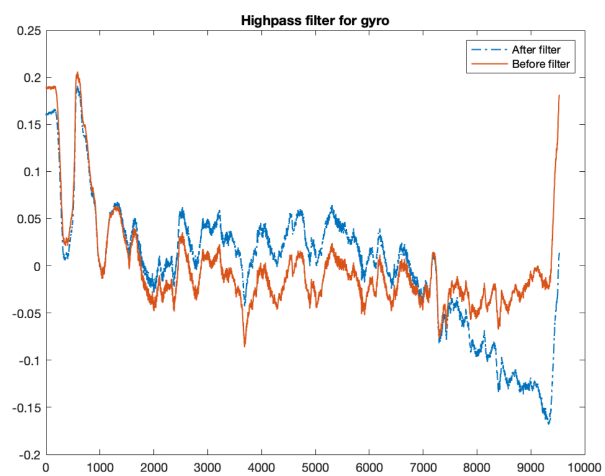


Figure 5 High pass filter for gyro.

After filtering the data separately, Complementary filter was used for both data to combine the measurements from the magnetometer and yaw rate as described in class to get an improved estimate of yaw angle. The figure below shows the comparison of yaw which directly from IMU and yaw after fusion.

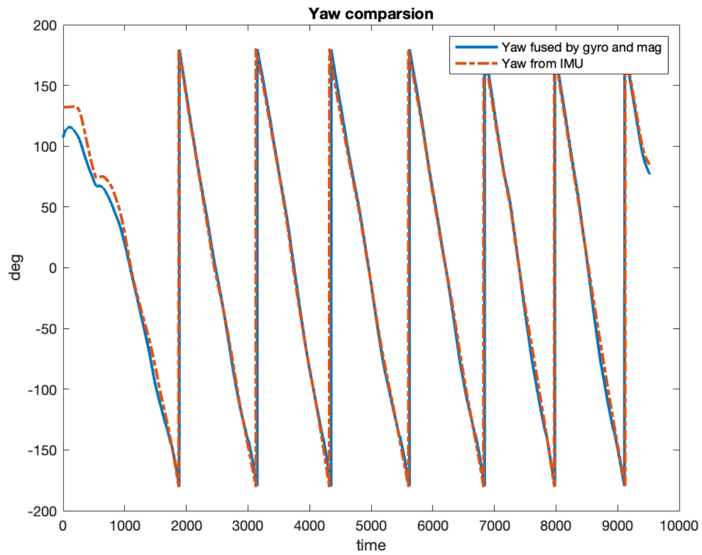
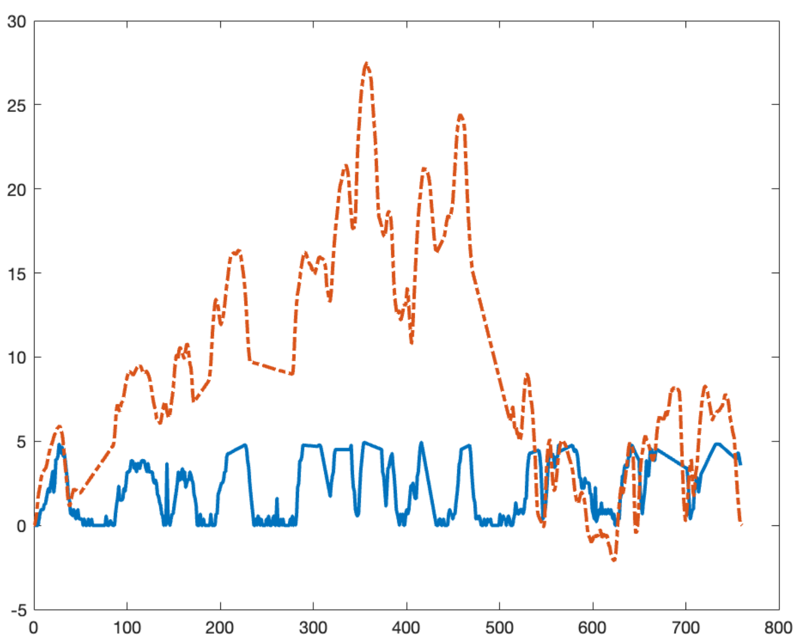


Figure 6 Yaw after fusion vs. Yaw from IMU

b. Estimate the forward velocity.
   i. Pythagorean theorem was used to get the velocity form GPS, and the velocity from IMU was integrated from forward acceleration. The comparison result shows below.



We can see the bias of data is large due to the high frequency noise of IMU. So I deigned a function to determine if the car is at a stop or not. Theoretically, more high-frequency noise is generated only when the car is moving, so I set the acceleration at the moment of lower high-frequency noise to zero. The result of this function shows below. We can see that the results are much more reasonable than the above results.

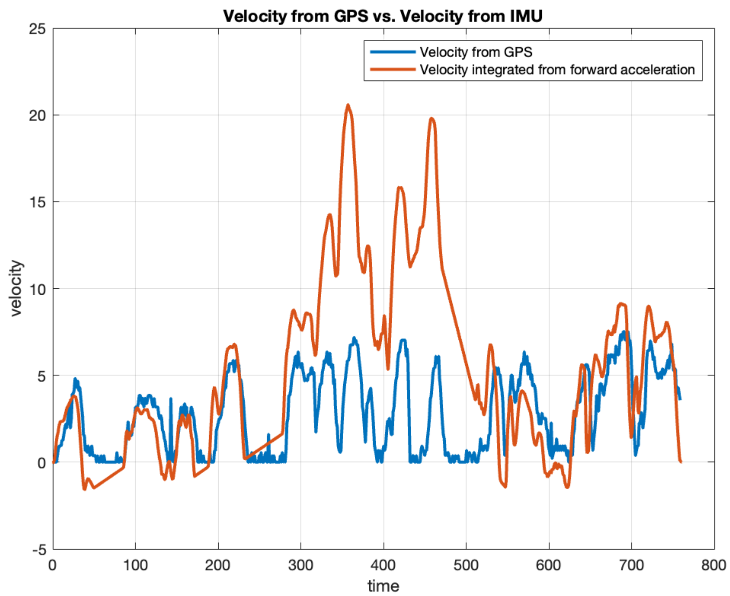


Figure 7 Velocity from GPS vs. Velocity from IMU.

c. Estimate the forward velocity.
    i. Compute $\omega\dot{X}$ and compare it to $\ddot{y}_{obs}$.

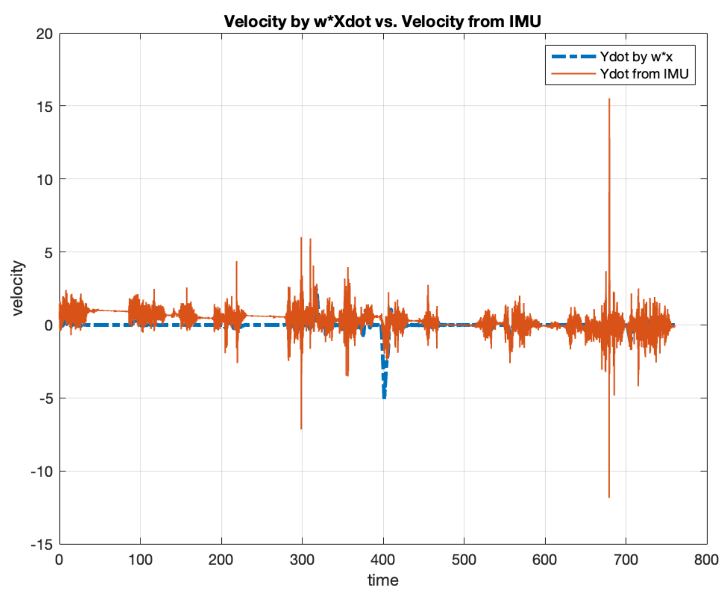


Figure 8 Estimation of forward velocity

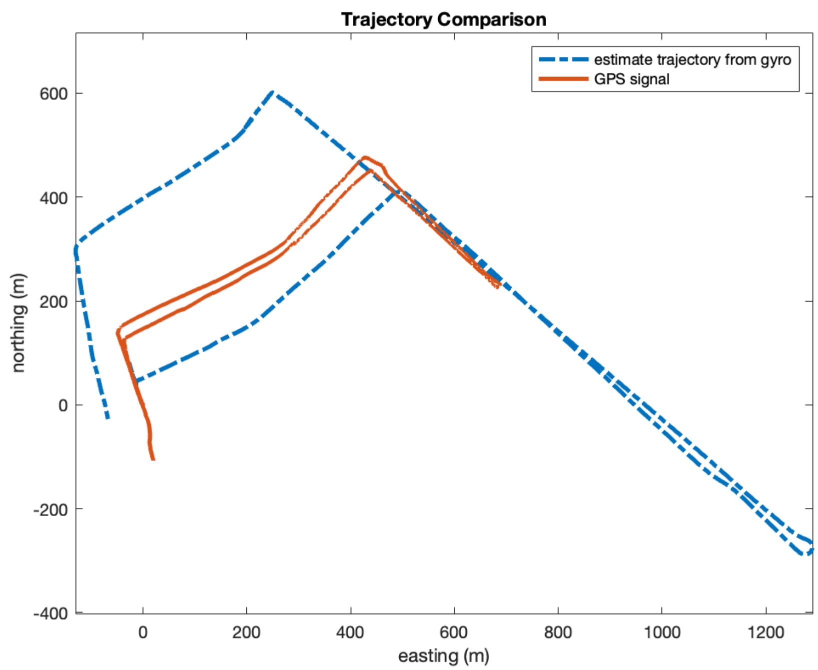
I used two methods to obtain two Ydot, one directly from IMU and the other through $\omega\dot{X}$,the comparison graph is shown above.

ii. Estimated trajectory Comparison

I used the heading from the magnetometer to rotate into a fixed (East, North) reference frame. Denote this vector by (ve,vn). Integrate it to estimate the trajectory of the vehicle (xe,xn). The following is the equation used.

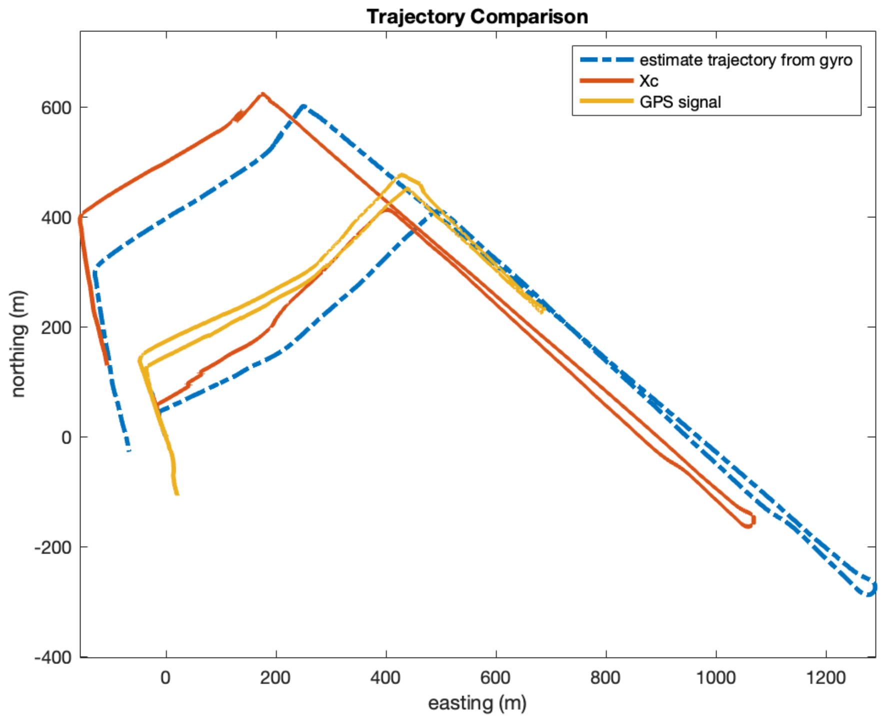
$$\ddot{x} = \dot{v} + \omega \times v = \ddot{X} + \dot{\omega} \times r + \omega \times \dot{X} + \omega \times (\omega \times r)$$

The comparison of estimated trajectory and ground truth from GPS shows below. The stop detection function is used here to reduce the noise.



iii. Xc Estimation

The inertial sensor is displaced from the CM by r = (xc,0,0) that the vector is constant in the vehicle frame. I used the above formula to do the difference to the numerical solution of Xc = 0.20376. The Visualization result shows below.


Trajectory Comparison
estimate trajectory from gyro
Xc
GPS signal
northing (m)
easting (m)
600
400
200
0
-200
-400
0
200
400
600
800
1000
1200