Analysis Report of LAB 2 for EECE5554

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1. The Analysis for Stationary IMU Data:

The stationary dataset is collected in the basement of Snell Library. The size of dataset is about 17000, and we use the first 15000 IMU data points for plotting and analysis.

1.1. About a time series data of the 3 Accelerometers X Y Z from IMU :

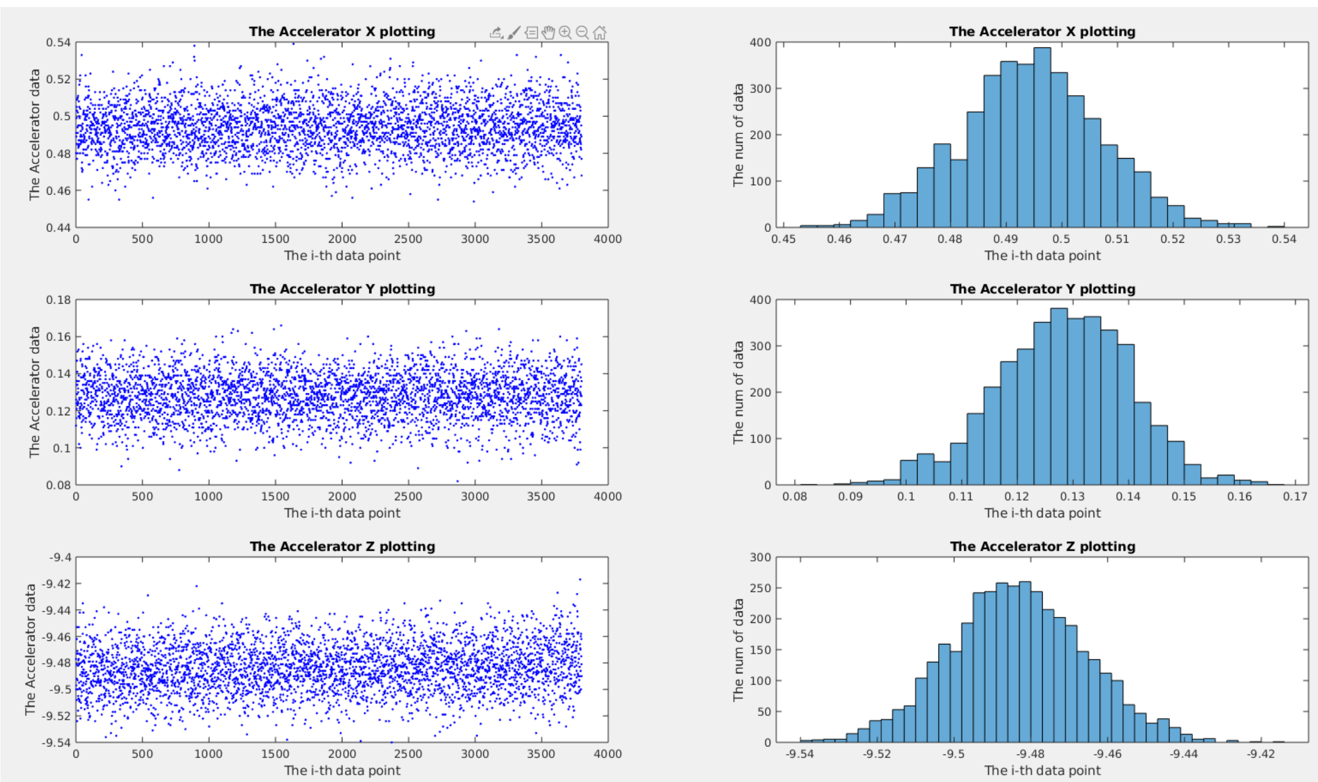


Figure 1. The Distribution about 3 Accelerometers

According to the plots of value distributions on right of figure 1, we could tell that the noise distributions of three accelerators are like Gaussian distribution in the whole space, although in some range the data doesn't fit the Gaussian so well(for example, value around 0.48 in Acc X or around -9.5 in Acc Z). The means and variances of each : Accelerometer X ~ N(0.4942, 1.5415e-04), Y ~ N(0.1279, 1.4574e-04), Z~N(-9.4840, 3.1363e-04).

According to the noise distributions on left of figure1 , the accelerator noise for stationary IMU has low variance, and we can see that the data of Accelerometer X and Y have a little bias because the IMU is stationary in reality that Ax and Ay should be zero but the mean of data collected is not zero. For Accelerometer Z, it also has a little noise and drift.

1.2. About a time series data of the 3 Gyroscopes X Y Z from IMU :

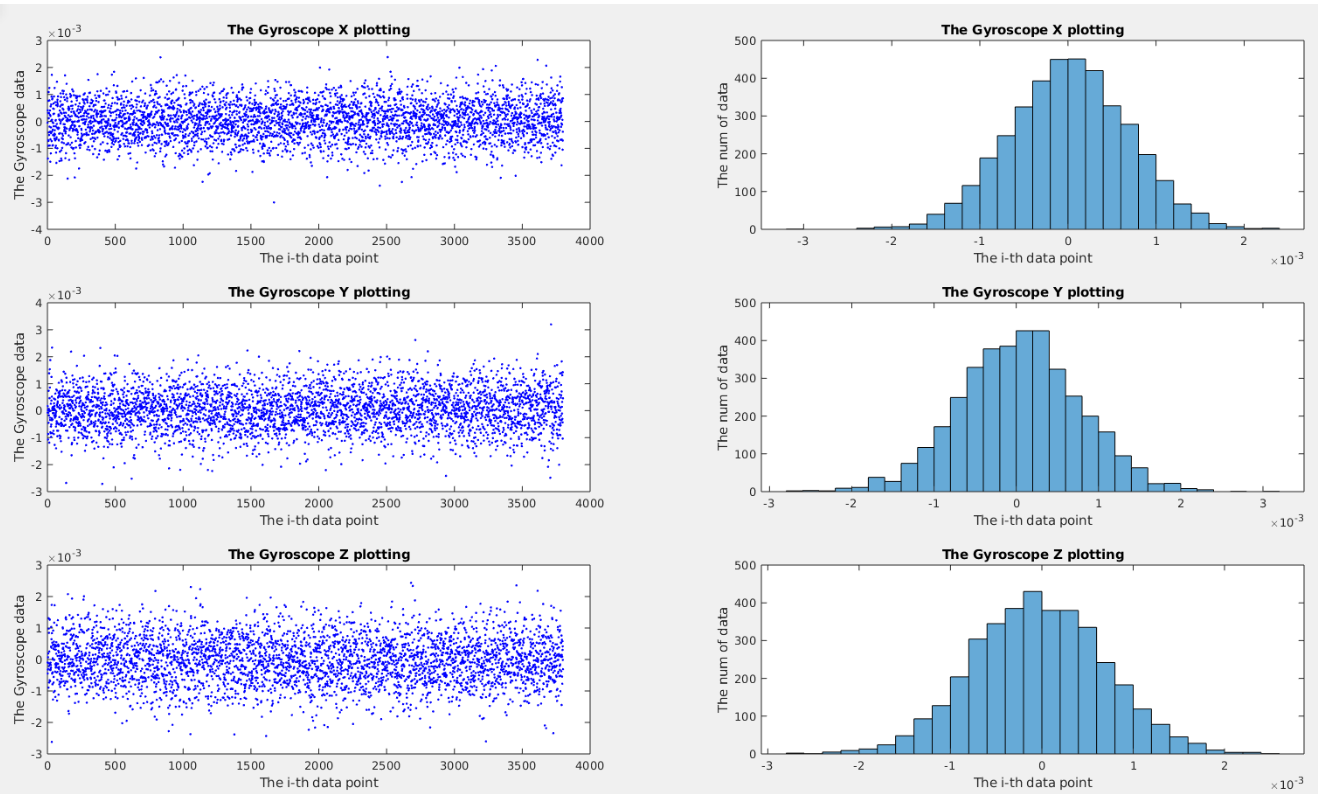


Figure 2. The Distribution about 3 Gyro Angular Rates

According to the plots of value distributions on right of figure 2, we could tell that the noise distributions of three Gyroscope are about the Gaussian distribution. The distribution of Gyro X fits Gaussian well, whereas Gyro Y and Gyro Z distribution, in whole space, is like Gaussian distribution. The means and variances of each : Gyroscope measurement X ~ N(1.1289e-05, 4.5289e-07), Y ~ N(4.2385e-05, 5.3791e-07), Z~N(-3.1637e-05, 5.1817e-07).

According to the mean value, we could tell that in stationary data Gyroscopes have little bias through whole distribution space, but the actual bias should not be zero.

1.3. About a time series data of the 3 Magnetometers X Y Z from IMU :

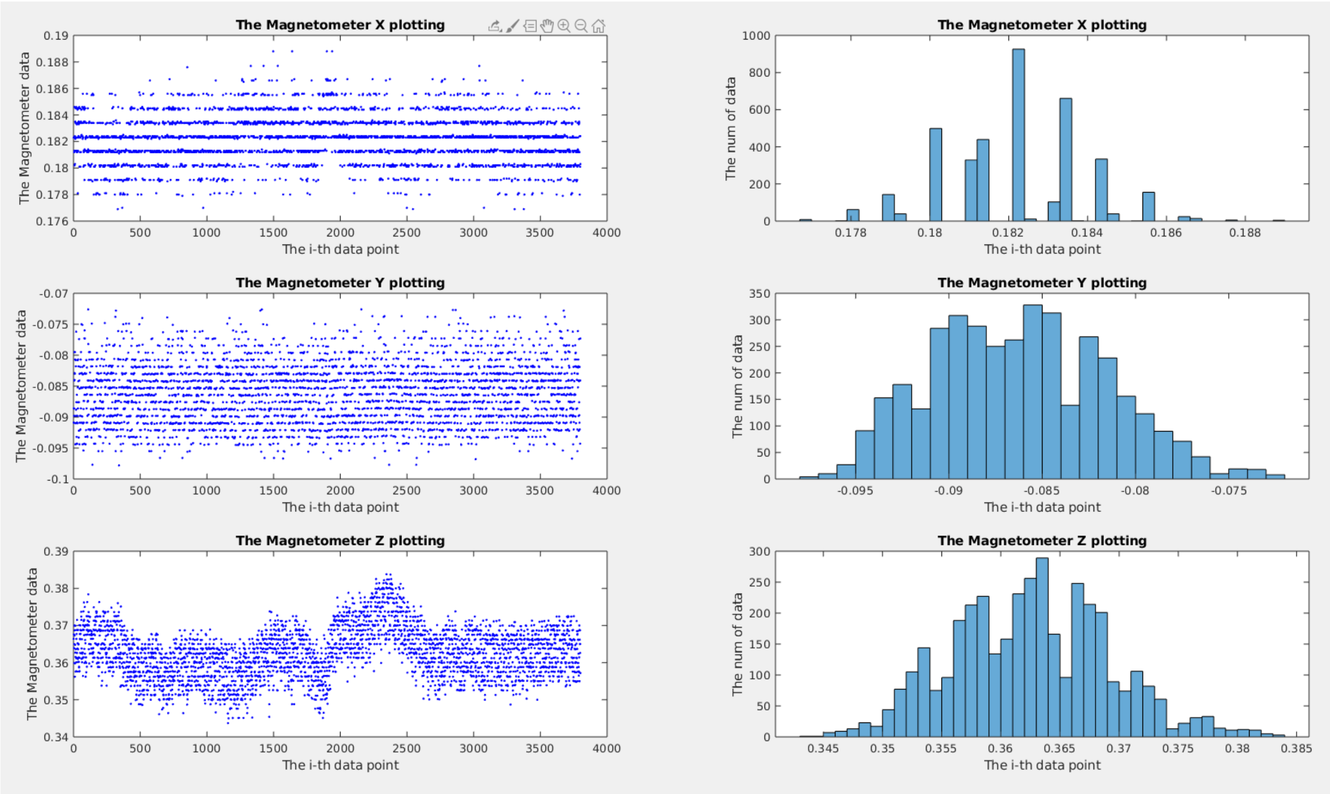


Figure 3. The Distribution about 3 Magnetometers

According to the plots of value distributions on right of figure 3, we can see that for magnetometer Y and Z, the distributions are like Gaussian distribution, but not good in some range. The magnetometer X distribution does not fit the Gaussian distribution pattern so well because we can see the data value is not so continuous, which lead to that in some value range there are no data points, but if we connect those columns' top which are with values, the distribution also seem like a Gaussian distribution generally, but with some noise.

It seems that the magnetometers also have some bias which may result from interference sources or the noise of the sensor itself.

2. The Analysis for Driving Data:

The driving dataset is collected around the Northeastern University. The size of dataset is about 47470, in which IMU data points from 552 to 4547 are about our first 4 driving circles, and in which the 40130th data points is about time we stop the car.

2.1. Estimate the heading (yaw)

2.1.1. Correct magnetometer readings for "hard-iron" and "soft-iron" effects using the data collected when going around in circles.

There are plots showing magnetometer data before and after corrections.

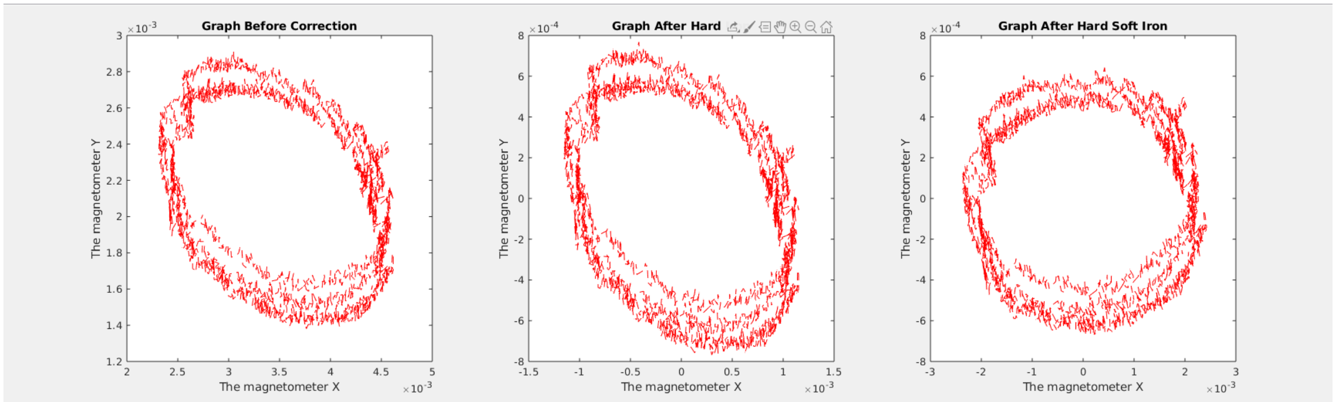


Figure 4. The magnetometer data before and after corrections

The data is about the first three and a half circles in the beginning of driving, and the data points are from 552 to 4541 of the whole dataset. Left plot is about the magnetometers before correction; the midden plot is about the magnetometers just after harden correction; the right plot is about the graph after hard and soft iron corrections.

2.1.2. Calculate the Yaw Angle from the corrected magnetometer readings and integrated from Gyro, and do comparison.

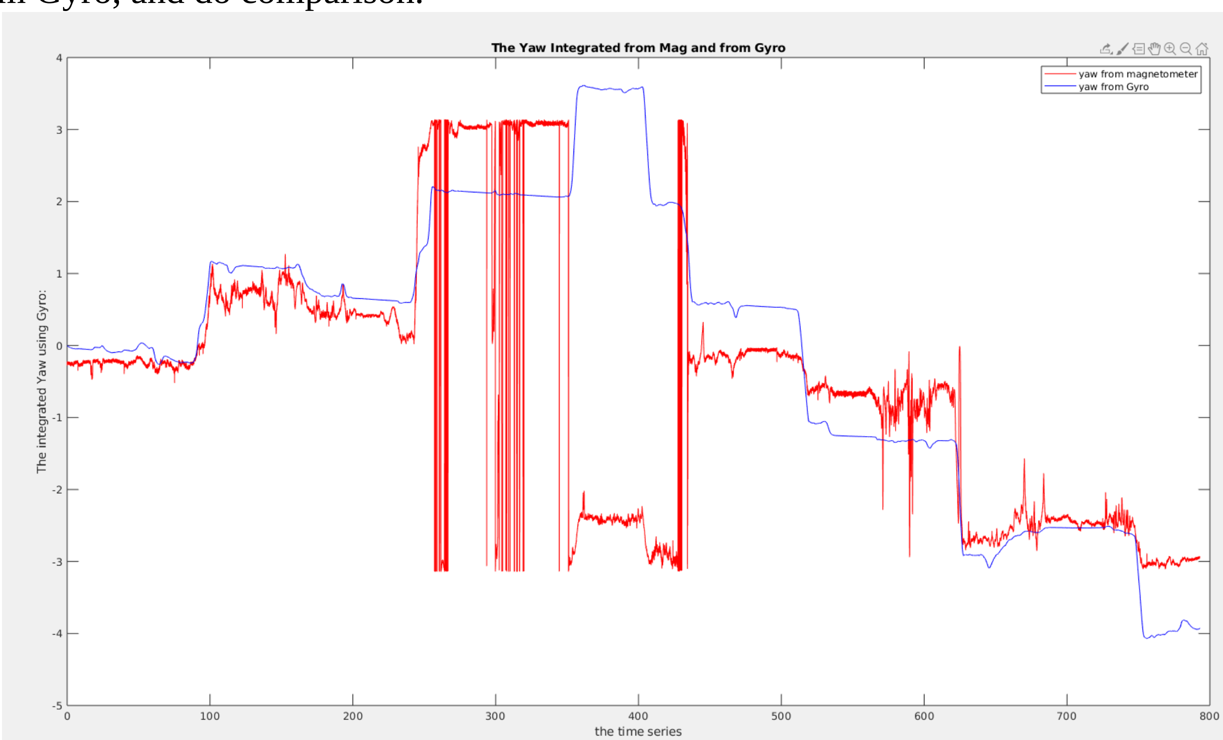
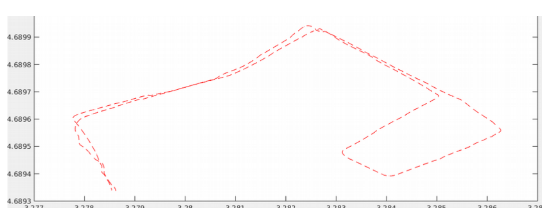


Figure 5. plots of Yaw Angle from magnetometer and from yaw Gyro Z

Above plots are about yaw angles from corrected magnetometer and integrated from GyroZ, of the straight driving line. The straight driving line shows like this:



That is our driving route apart from circles.

We could see that the yaw integrated from magnetometer has many noise, which may due to the noise in data collection or sensor itself would bring the noisy affect. And the yaw from magnetometer also have bias as we could see, that the beginning yaw is not zero which it should be. Perhaps the correction of magnetometer is not perfect yet for straight route. Also we there are some other sensors in vehicle, that could be potential interfere sources.

The plots of yaw from magnetometer and from GyroZ kind of agree generally, but still with the noise and bias talked above, and in some part the value does not match. This may because the same reasons that the sensor has bias, and there also could be some interference. Also, the rotation of sensor is about right hand coordinate, so we take the angle values, which are from magnetometer, negative here.

2.1.3. Complementary Filter combining the measurements from the magnetometer and yaw rate.

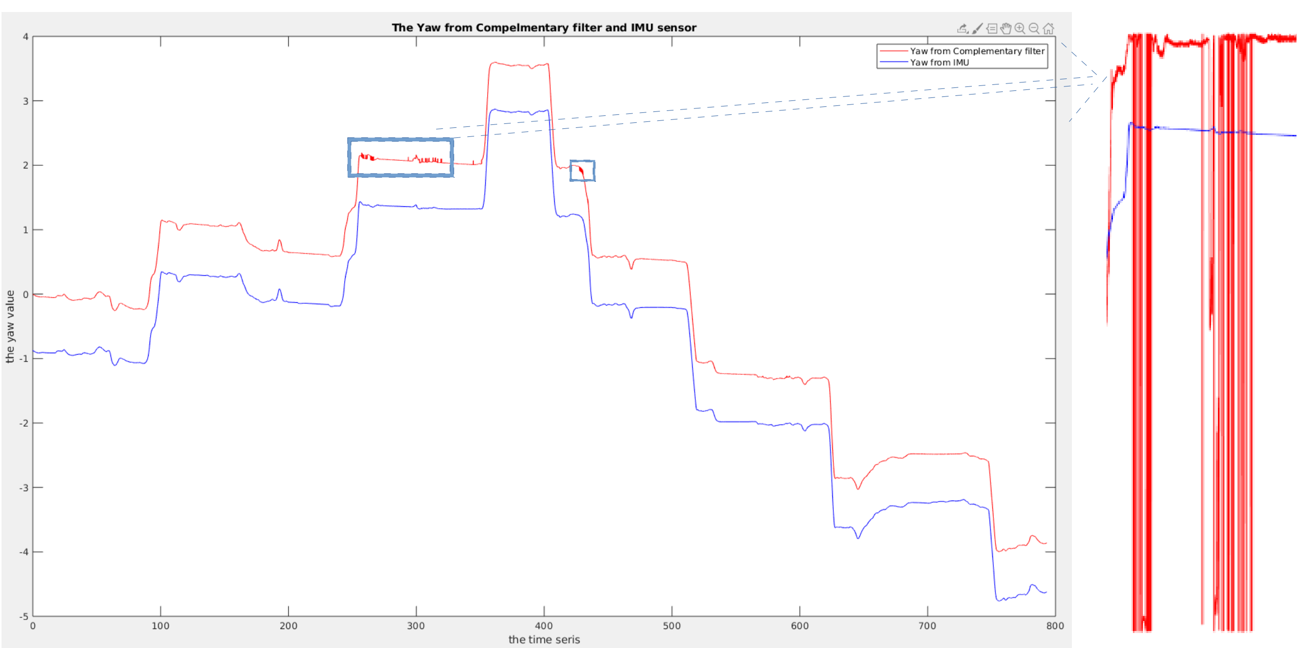


Figure 6. plots of Yaw Angle from Complementary Filter and from IMU data

The high pass filter has parameter 0.99, and the value of low pass filter is 0.01.

According to our plots above, the variation trend of filtered angles is very agree with that of IMU orientation, which shows that the combination of yaw results using complementary filter could eliminate many noise data and appropriately lower the data frequency, and the bias is also disappear. But the values do not match because the IMU values have the bias which also could be brought by sensor.

We could also see that there are still some small noise showed in blue squares, which could initiallly be very noisy part so that it is hard for filter to eliminate them completely.

2.2. Estimate the Forward Velocity

2.2.1. Integrate the forward acceleration to estimate the forward velocity && Calculate an estimate of the velocity from your GPS measurements.

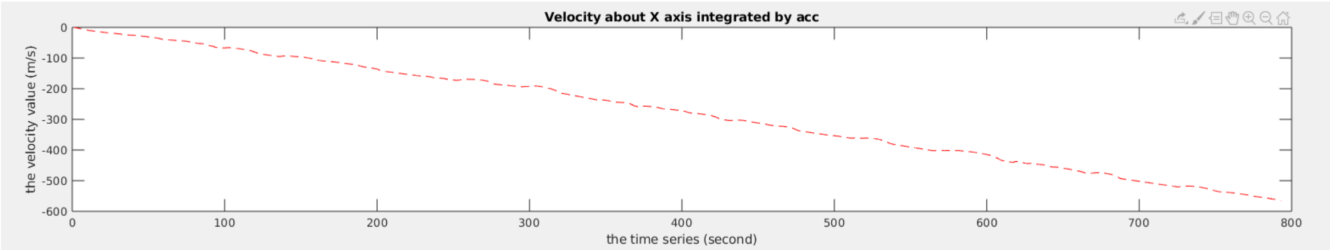


Figure 7. plots of Forward velocity integrated from raw accelerator X

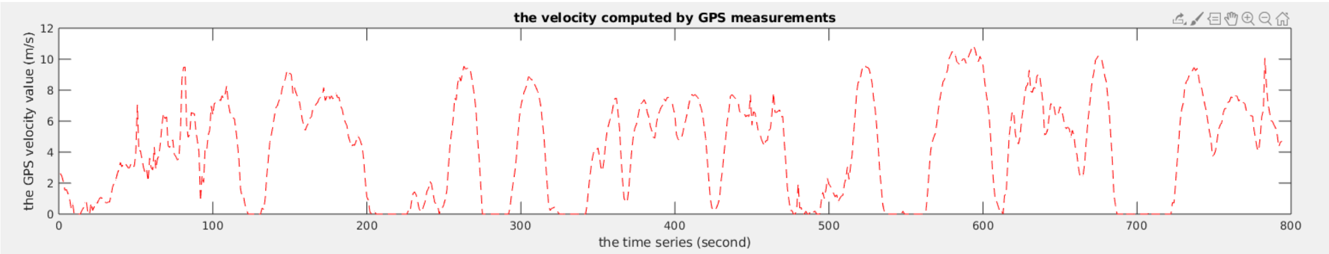


Figure 8. plots of Forward Velocity from GPS dataset

As shows above, figure 7 is about integrated forward velocity from accelerator X, and figure 8 is about GPS velocity. These both about the straight driving route.

For GPS velocity computation, we take advantage of latitude and longtitude to compute the real distance between two neighbor spots, and this distance is more accurate than that from UTM. Then we divide those distances by time between two spots to get the corresponding velocity

For velocity from accelerator X, because the sensor brought bias and our bias is negative, so the accelerator values are always negative that our velocity keeps going down. **Therefore, and Absolutely, this velocity from accelerator with bias does not make sense.**

2.2.3. Make adjustment to make velocity more reasonable

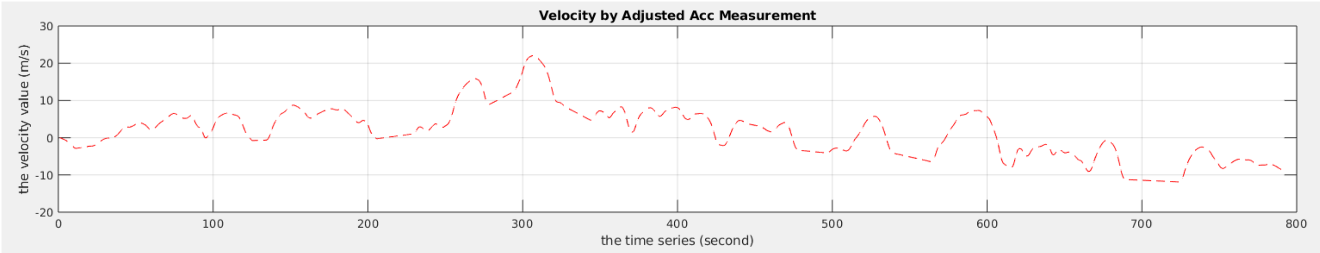


Figure 9. plots of Forward Velocity from Adjusted Accelerometer X

Figure 9 above is the plot of velocity after adjustment.

For adjustment, because the accelerator has the bias, we firstly compute the mean noise value, which could be seen as bias, of stationary data. Then, we subtract it from initial accelerator X. After that implement a low pass filter to avoid some noise and get data smoother.

We could see the variance trend makes sense now, but still with some negative value which should not be there. Perhaps it is because the actual negative bias is large, and we could not eliminate it efficiently just by subtractinging stationary bias. Or, in different situations the IMU could have different bias. For example, there was a road which is slant, so the negative bias could be larger.

2.3. Dead Reckoning with IMU

2.3.1 Compute wX' and compare it to y_{obs}''.

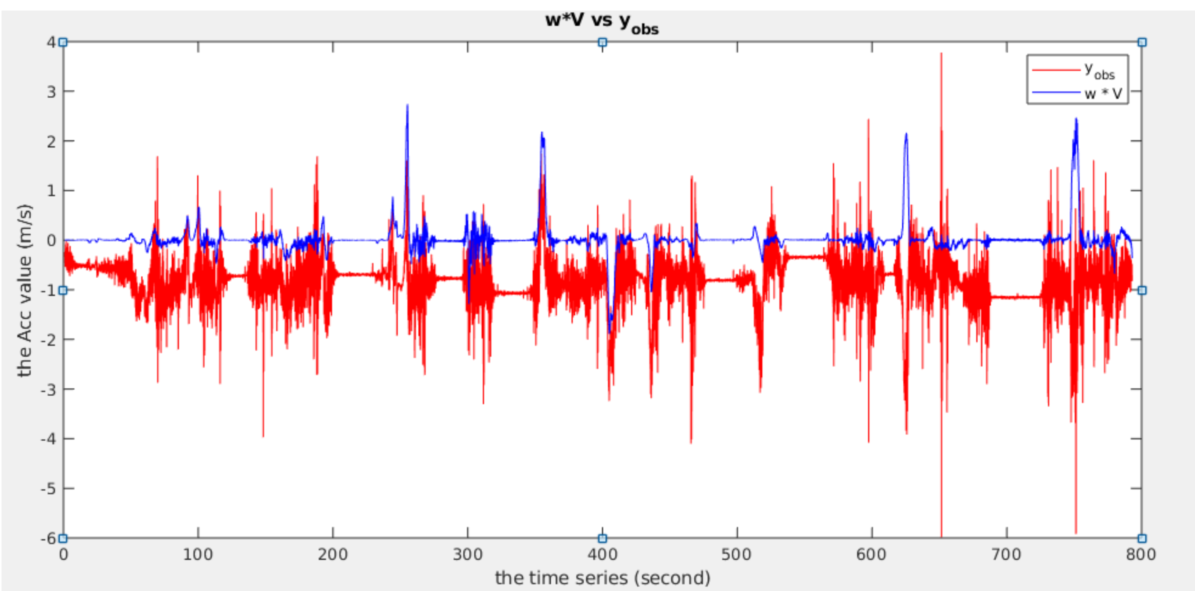


*Figure 10.   Plots of Y_{obs}'' and w * X'(w * V)*

Mathematically, w* X_dot equals w * V, and y''_obs equals accelerator Y. Generally, the variance trends of those two data are kind of agree, but still with some difference. First, y_obs has larger variance than w*V, because y_obs is raw accelerator data with high frequency and noise, whereas V is adjusted before that has less noise, and we also take the filter which lower the frequency. Second, the y''_obs itself has bias so we could see those two plots have bias between.

2.3.2. Integrate the (Ve, Vn) to estimate the trajectory && Compare it with GPS track

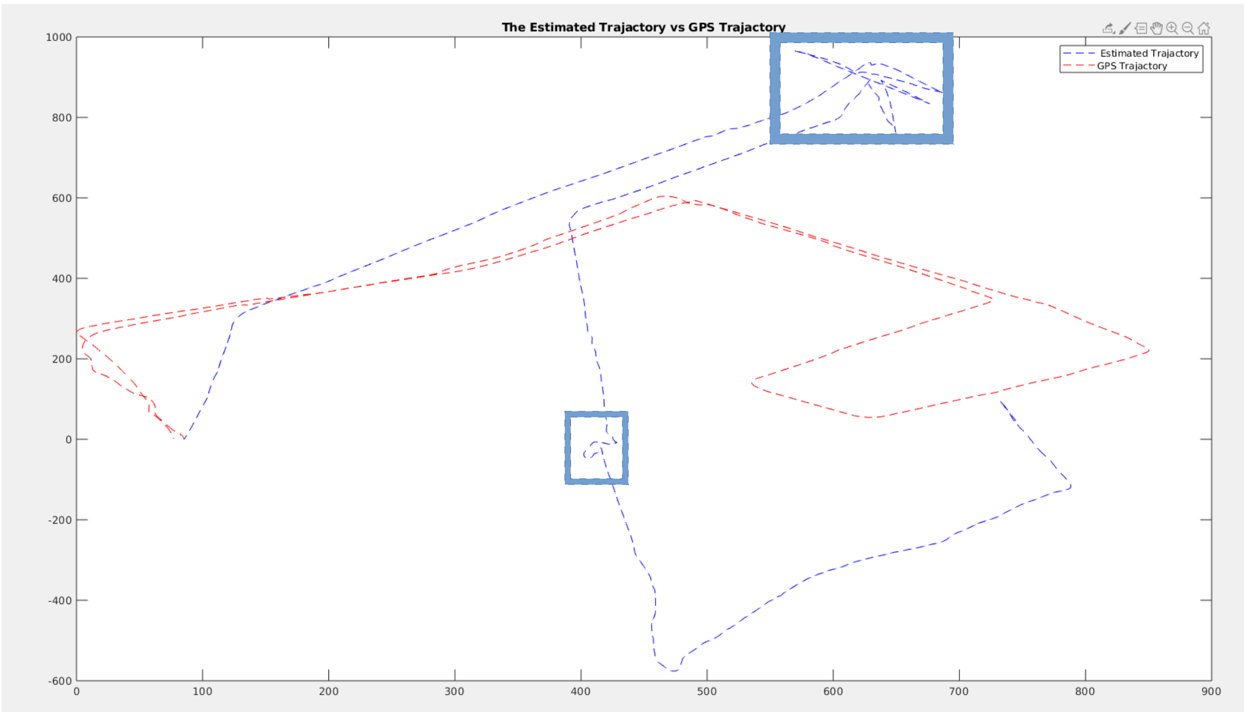
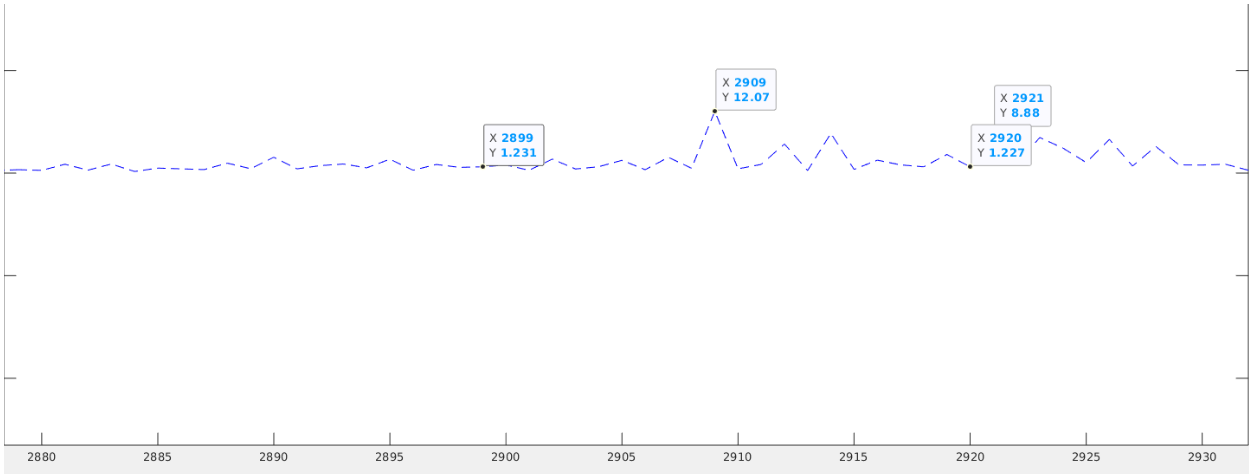


Figure 11. Plots of Trajectory from Integrated (Ve, Vn) and from GPS utm data

At the beginning, the estimated trajectory is appropriately on right track, and we could see the angle take at the first. But due to the not perfect correction of magnetometer, the first angle taken in estimated trajectory is smaller than that in GPS's. The beginning and end part of whole estimated trajectory is kind of agree with GPS trajectory, and at the end part it take some turns(blue flag like part) as in real world did, but because the adjustment of velocity is not good yet, we still have some negative velocity after adjustment, so the spot goes backward as showed in bigger square. We could also see a little circle in small square which may be caused by noise of velocity. Also, with the time goes by, the accuracy of IMU would decrease.

2.3.3. Estimation of Xc



This is estimated Xc from data 2880 to 2930. Because IMU at the beginning could bring relatively more accurate data than later, therefore we take Xc values in this point range to estimate the value. The estimated Xc value could be 1.3, which is still with bias because generally the distance from IMU and Center-of-Mass is half a meter.