Robot Sensing and Navigation

Lab 4 - Navigation with IMU and Magnetometer

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1 Introduction

There were two datasets that were collected. The first dataset was recorded for calibration of the magnetometer, by driving around in circles. The calibration process was carried out on the data set and then applied to the second data set, collected by driving around. Yaw estimates from magnetometer and gyroscope were computed and filtered and added to get a better estimate of Heading. Forward velocity was obtained by integrating forward de noised acceleration and compared with GPS velocity. Finally, the route was reconstructed using the estimated heading and velocity.

2 Magnetometer Calibration

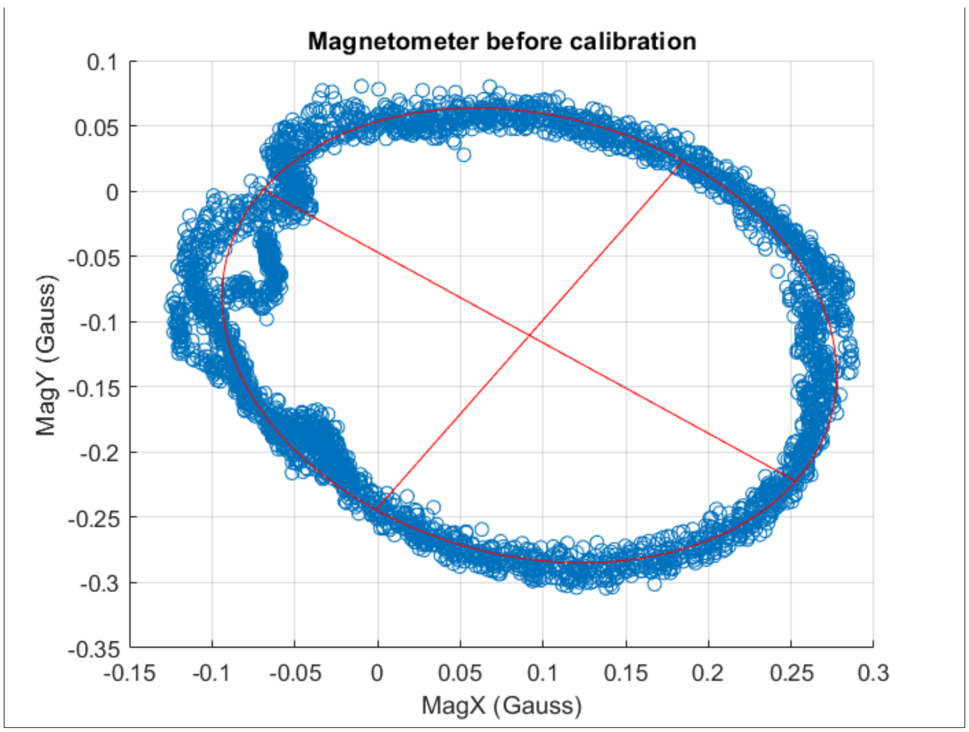

Figure 1 : Magnetometer data, uncalibrated

The magnetometer was data was collected by driving around the circle in front of Ruggles Train station. A calibrated magnetometer plotted is a circle centered at the origin. From fig 1, we can conclude presence of hard iron and soft iron distortion. Hard iron distortion generates an offset and soft iron distortion deforms the circle into an ellipse.

Calibration was carried out by performing the following mathematical operations – translation (to remove hard iron distortions) and rotation and scaling (to remove soft iron distortions). For this purpose, an ellipse was fitted to the data. Tilt angle = 0.6067 radians, scaling factors - major axis = 0.3917 and minor axis = 0.3254, and an offset of [0.0918, -0.1106] was calculated. Fig.2 shows data before and after calibration.

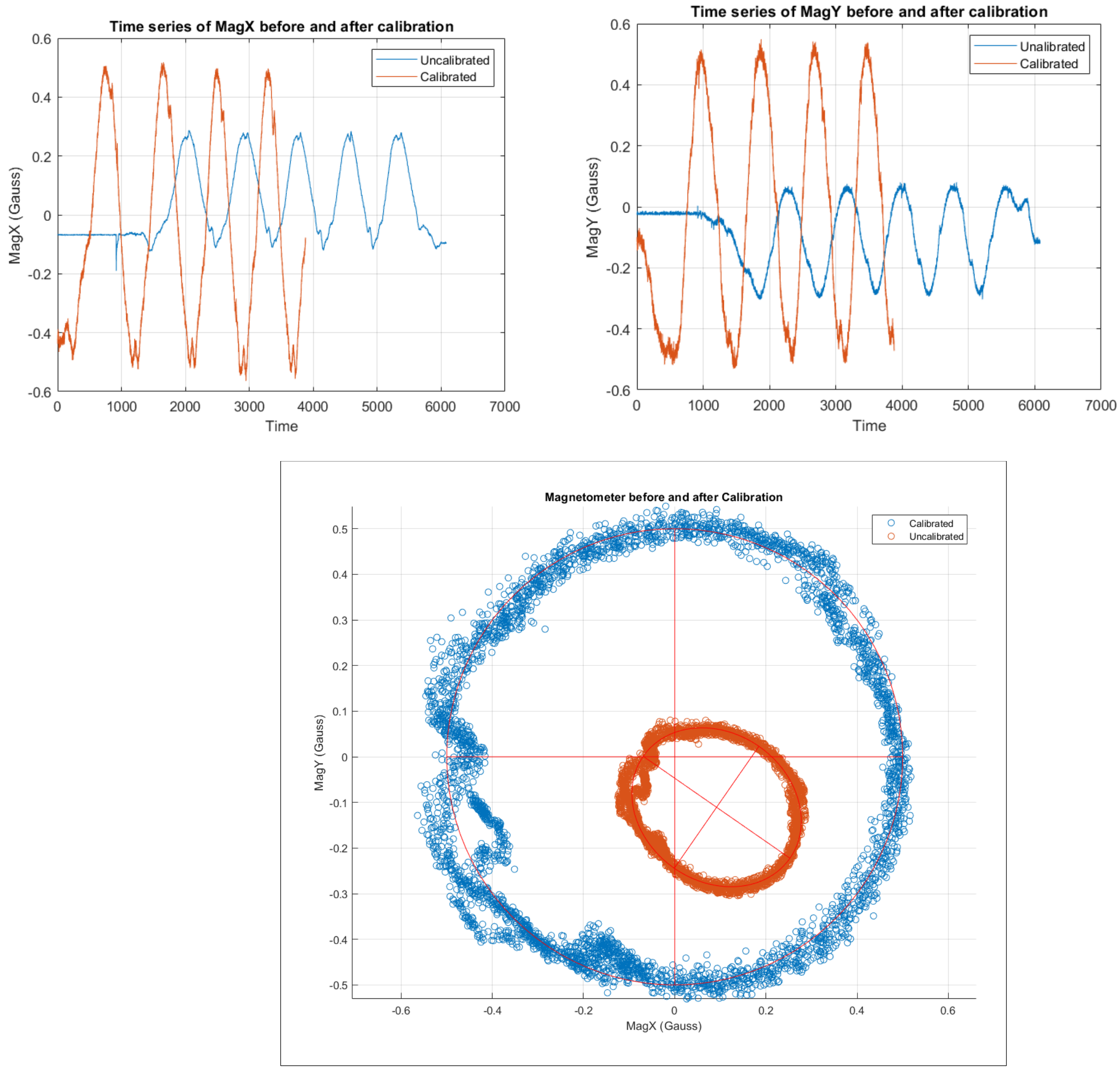

Figure 2: Comparison of Magnetometer data, uncalibrated and calibrated.

3 Estimation of Heading

The data of the magnetometer when the car is driven was calibrated by the same process. The yaw estimate from magnetometer was calculated using the equation $yaw = arctan\left(-\frac{magy}{magx}\right)$.

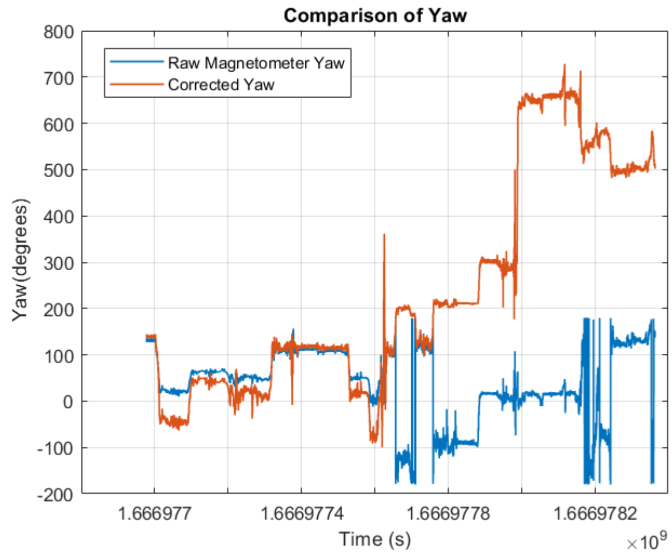

Figure 3: Comparison of Yaw from Magnetometer, calibrated and uncalibrated.

There is a big jump in the graph of magnetometer, as can be observed from fig4 and fig3. This may have been magnetic that the magnetometer picked up, such as train or some other magnetic interference (that was not present near the Ruggles station during calibration). Thus, the calibration is unable to correct these errors. This was an important factor in deciding the value of the weights assigned to the low pass and high pass values while fusion.

The yaw estimate from the gyroscope was found out by integrating rate of change of z-component of angular velocity. The two estimates were filtered using a low pass and high pass filter respectively. The final estimate of yaw was the weighted sum of both these estimates. The low pass filter helps remove the jittery nature of the magnetometer and high pass filter removes the drift present in the gyroscope.

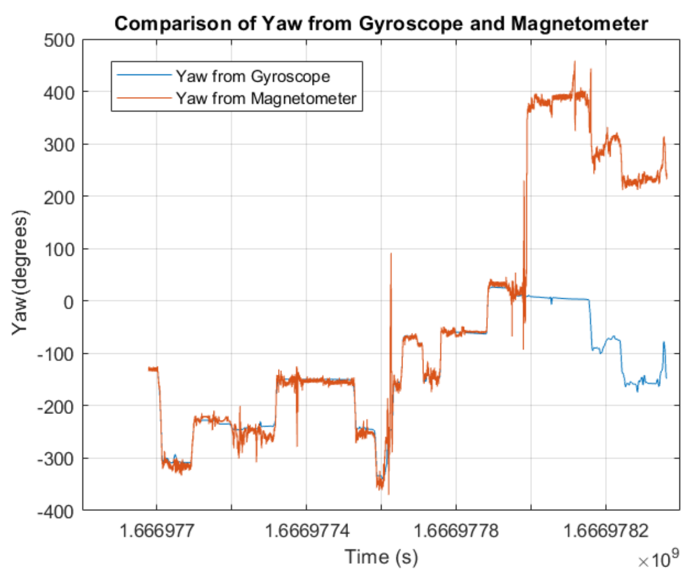

Figure 4: Comparison of Yaw from Magnetometer and Gyroscope

The filter has three components – Filter Order, Sample Rate and Cut Off Frequency. For this specific data, filter order of 6 yields the best results. The cut off frequencies for low pass and high pass were set as 0.85 and 0.05.

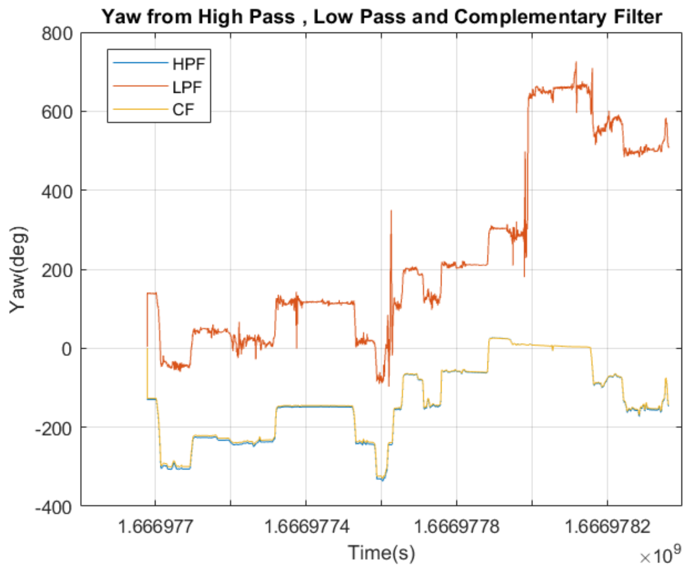

Figure 5: Comparison of Yaw from High Pass, Low Pass and Complementary Filter

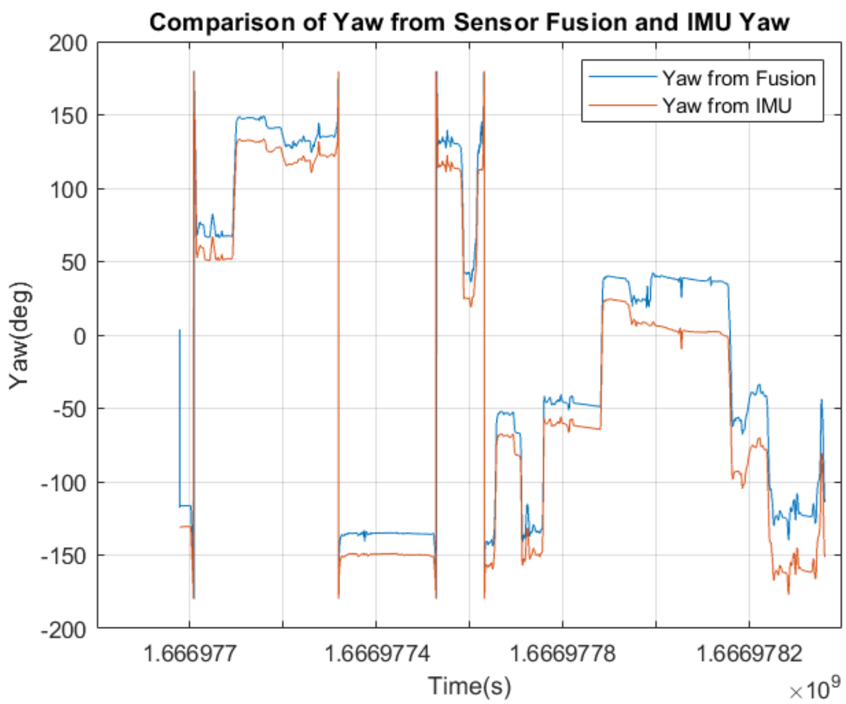

Figure 6: Comparison of Yaw from IMU and Sensor Fusion result

The magnetometer is extremely sensitive and therefore the yaw estimate from the magnetometer can be unreliable in the presence of magnetic disturbances. However, due to its sensitivity it can pick up on fast and small turns better than the gyroscope. The gyroscope on the other hand measures the rate of change of yaw and thus can drift over time, therefore requires correction periodically. It would also fail to record sharp turns or changes in trajectory. Therefore ideally the yaw estimate that combines both these estimates. from sensor fusion would be must accurate and reliable for long term navigation.

4 Estimation of Forward Velocity

The x component of acceleration integrated theoretically should give the forward velocity. However, there are a lot of biases and noise present in the acceleration data. Integrating without removing them will lead to them being amplified, as observed in fig. 7. GPS velocity was obtained by calculating the resultant of velocities in easting and northing respectively.

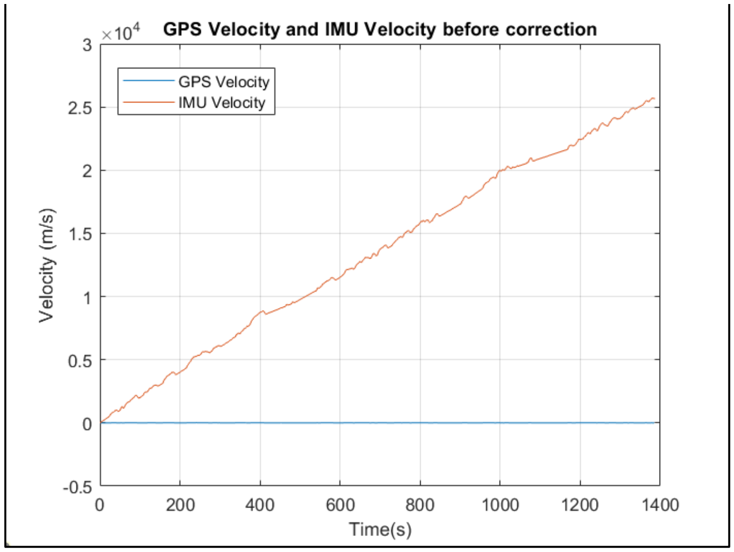

Figure 7 : GPS Velocity and integrated velocity before adjustment

To remove the biases, a program was implemented that could detect points when the resultant acceleration is less than '*g*' and the car is moving, calculate the bias of the group and remove it from that specific set of data. The bias is not constant here as the y and z components of acceleration can affect the x-component when the roads are not completely flat, or the IMU tilts ever so slightly. This causes components of y and z acceleration to act in the direction of x.

After denoising the acceleration, while integration, any negative velocities were set to zero. Negative velocities would signify driving in reverse (which is not something that was performed). After these adjustments we obtain the results in fig 8.

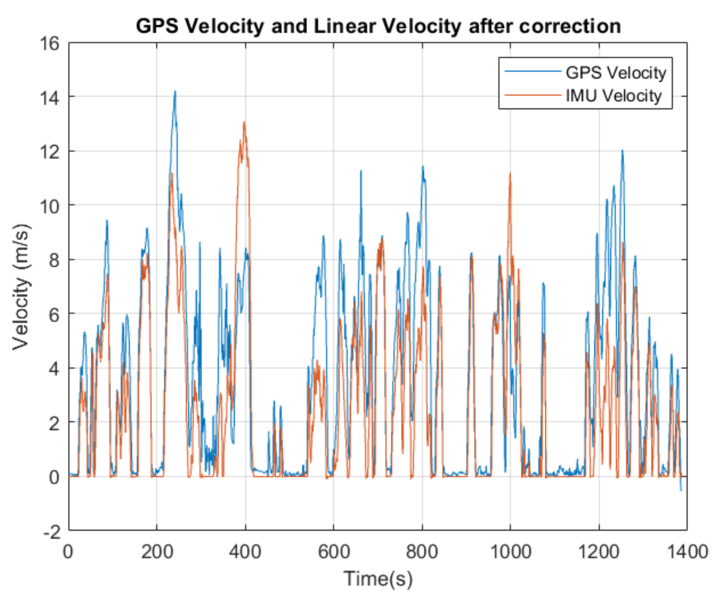

Figure 8: GPS Velocity and integrated velocity after adjustment

From the graph, we can infer that there are places where the bias was not removed correctly. The route followed during data acquisition had a lot of skyscrapers with reflective windows. The GPS velocity was also adjusted to account for errors due to multipath errors, all the outlier points were removed, and replaced with the nearest value.

5 Dead Reckoning

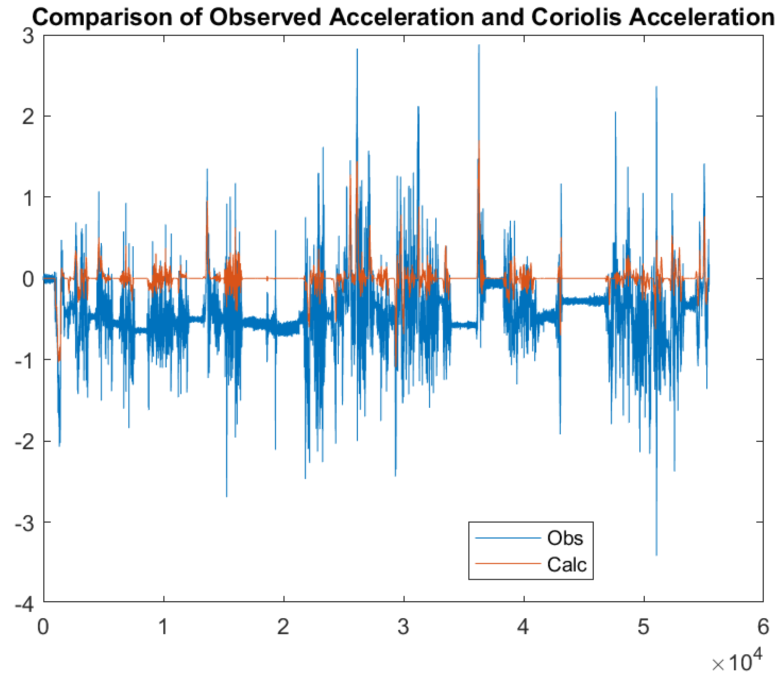

Figure 9 : Comparison of observed and calculated acceleration

The forward acceleration is the acceleration in x axis. The acceleration acting on the z axis is 'g'. The component of acceleration acting in y axis is the Coriolis Acceleration, $\alpha = \omega \cdot \dot{X}$, where $\dot{X}$ is the forward velocity. The difference between observed and calculated acceleration is due to components of X and Z acting in the Y direction, due to tilted roads, slopes or slight tilting of the IMU during braking or turning, and the inherent biases of the accelerometer as well.

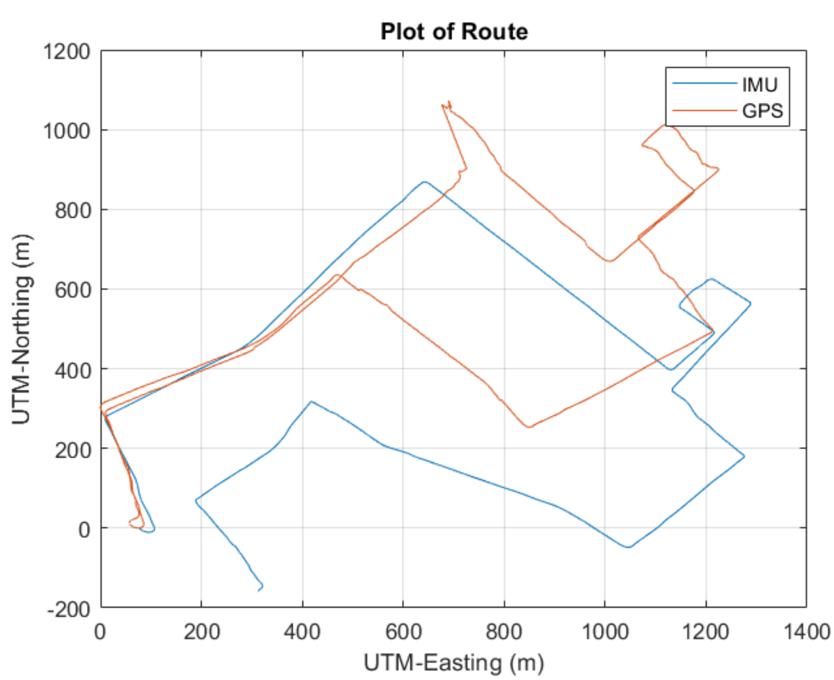

Figure 10: Dead reckoning plot

Dead reckoning was performed and the following plot, fig.10 was obtained. The IMU plot was scaled by a factor of 1.3 and trajectories were aligned.

From fig 10, we can observe that the IMU and GPS follow almost the same route, but after time, there is an offset observed between the two plots. One reasoning can be incomplete removal of biases from the velocity. Since magnetometer is used to correct the gyroscopic measurements periodically, and as observed in fig 3, the spike in readings may not have completely removed the drift of the gyroscope as well.

From the VectorNAV Primer, page 65, for an industrial grade IMU, error of 20kms within 10 minutes can be obtained if yaw estimate is not corrected. To mitigate errors, fixing the yaw estimate is crucial. This specification is not in accordance with results shown in fig 10. This may be due to the method of heading estimation – the VectorNAV primarily uses Kalman Filters and makes use of the accelerometer data to estimate the heading.

6 Conclusions

- For navigation, a yaw estimate that combines magnetometer and gyroscope estimates is the most accurate estimate of yaw.
- Magnetometer data is extremely sensitive to ferromagnetic materials in the surroundings and gyroscope drifts over time.
- Biases must be removed from the acceleration data to get velocity from the IMU and GPS velocity to be comparable. These biases are not constant.
- Coriolis acceleration acts on the sensor during driving.