VectorNav VN-100 IMU Data Analyzation

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Abstract

With all sensor measurements come sources of errors. These "sources of error" are often directly seen in datasets and are characterized as noise. Being able to visualize and understand the sources of noise within datasets is crucial when designing a system using specific technology and sensors. In this experiment, we used the VN-100 Inertial Measurement Unit (IMU) device to collect stationary angular, velocity, acceleration, and magnetic field data. We collected this data over 2 periods of time: 12.5 minutes and 5 hours. We plotted this time series data and calculated Allan Variances to visualize and draw conclusions about the effects of noise in our data.

Test Setup and Data Collection

IMU devices are sensors that incorporate the use of gyroscopes, accelerometers, magnetometers and pressure sensors to detect movement based on a 3-axis system. They are carefully calibrated and are able to effectively detect extremely small changes in orientation and movement. Due to its ability to detect these small displacements, there will be the presence of noise in recorded data. To eliminate this nose as best as we could, we collected stationary data in the basement of the visitor center located near West Village. We chose this location as it is relatively far from train lines compared to other locations, and the basement would provide less movement due to natural forces such as wind and other external vibrations.

We wrote a driver to collect orientation, angular velocity, linear acceleration and magnetic field data about all 3 axes from the IMU device. We converted orientation to quaternion coordinates and published this data to a ROS topic using standard ROS sensor messages. Stationary data was collected for both 12.5 minutes and 5 hours in the same location. The data is plotted below:

12.5 Minutes of Stationary Data

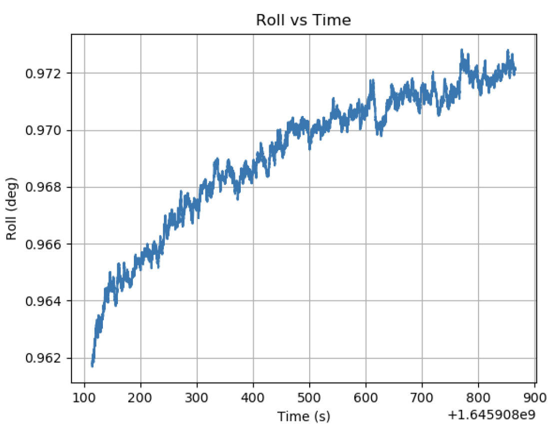

Figure 1: Roll Angle vs. Time

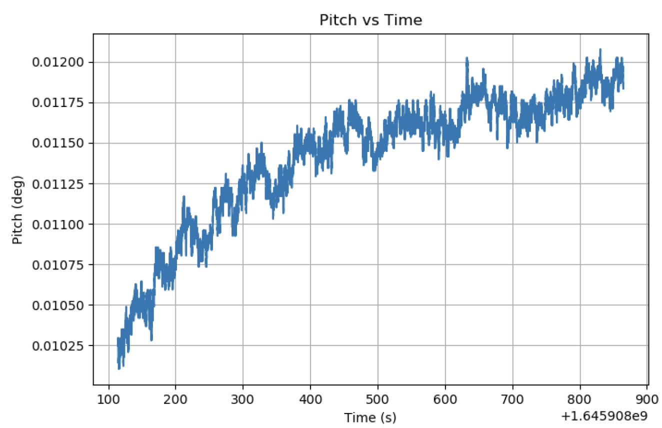

Figure 2: Pitch Angle vs. Time

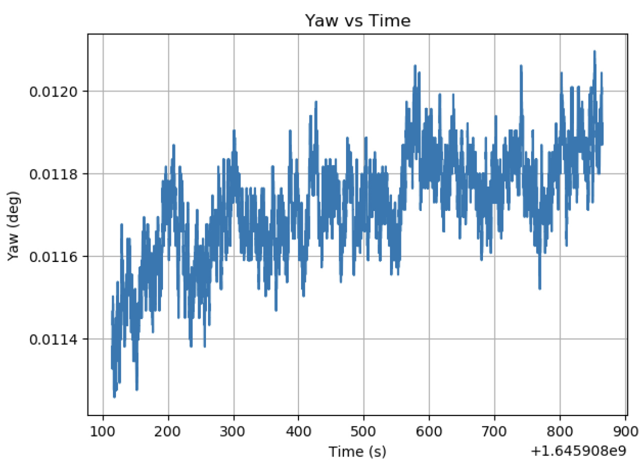

Figure 3: Yaw Angle vs. Time

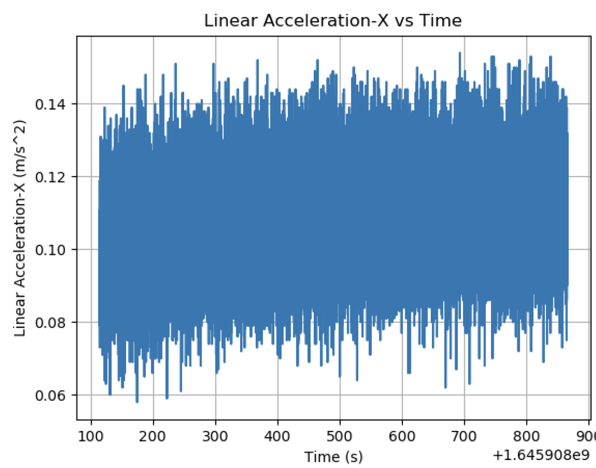

Figure 4: Linear Acceleration in X Direction vs. Time

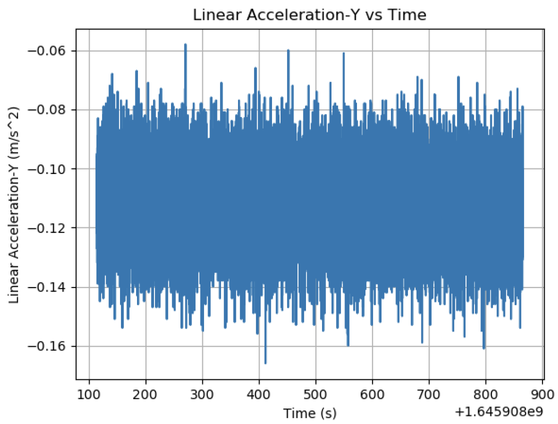

Figure 5: Linear Acceleration in X Direction vs. Time

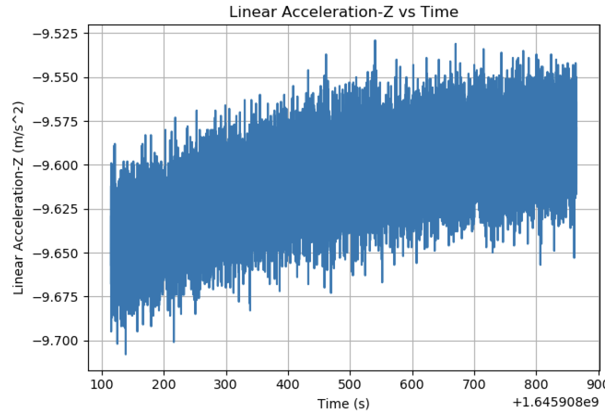

Figure 6: Linear Acceleration in X Direction vs. Time

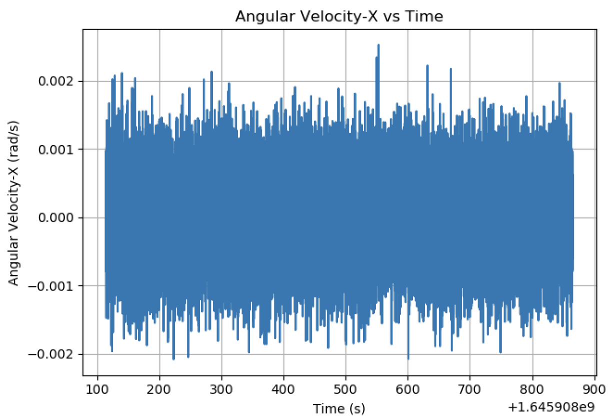

Figure 7: Angular Velocity about X-axis vs. Time

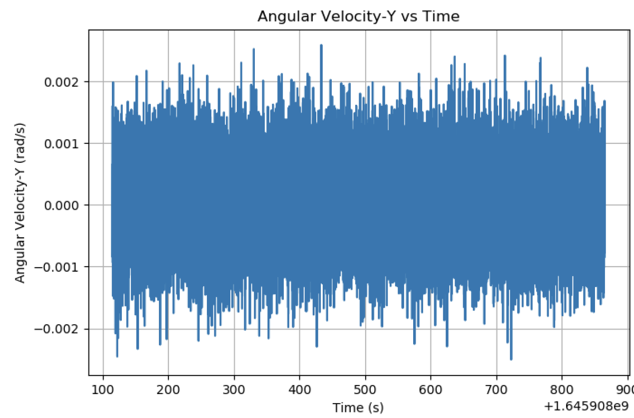

Figure 8: Angular Velocity about Y-axis vs. Time

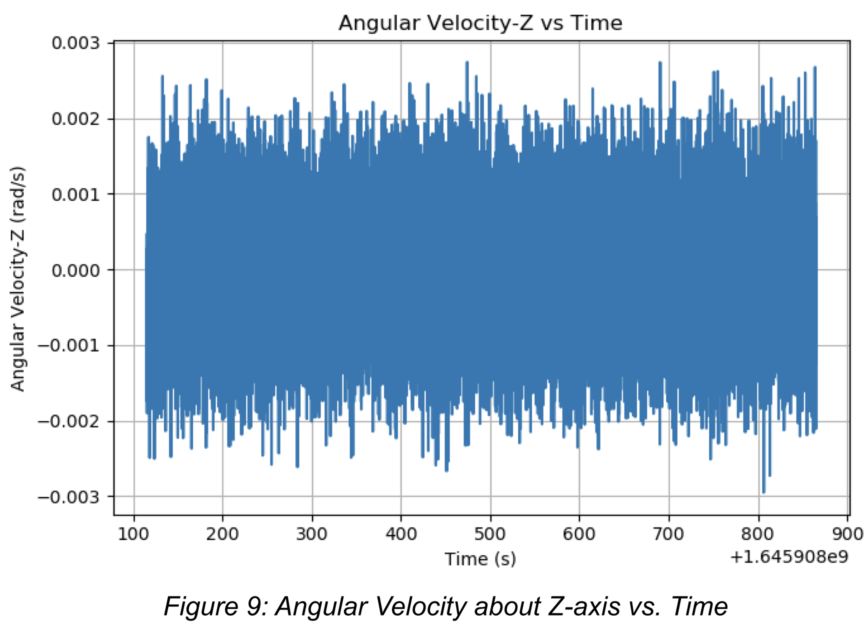

Figure 9: Angular Velocity about Z-axis vs. Time

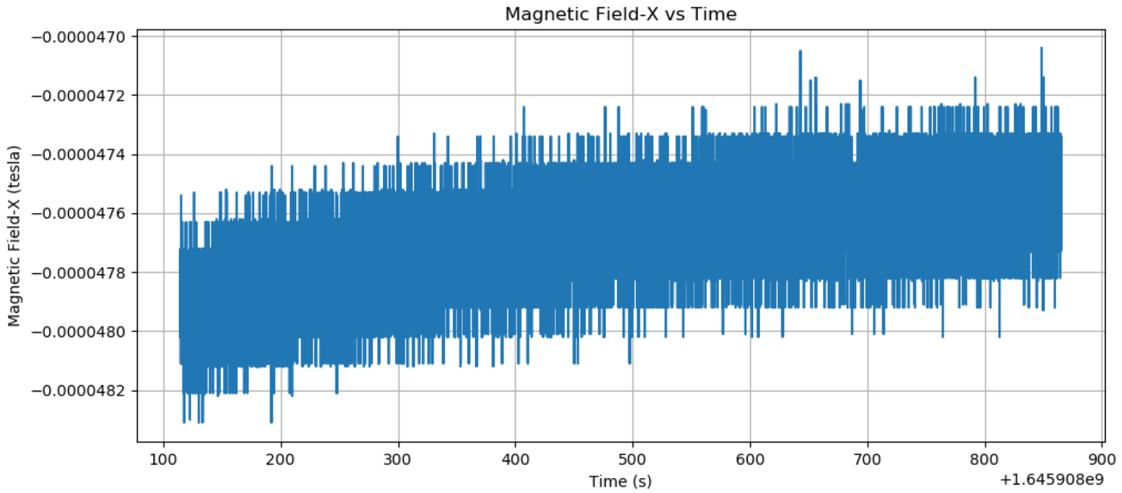

Figure 10: Magnetic Field about X-axis vs. Time

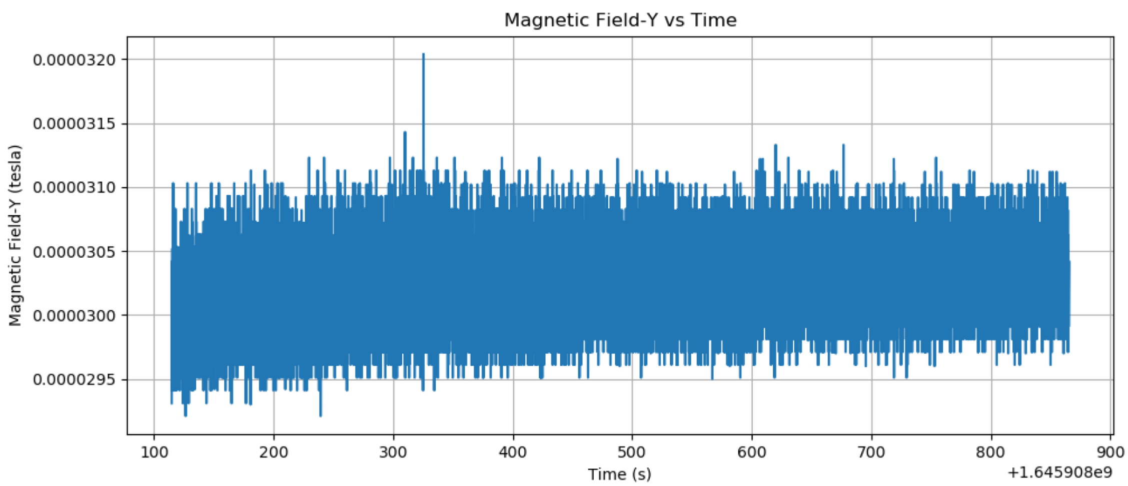

Figure 11: Magnetic Field about Y-axis vs. Time

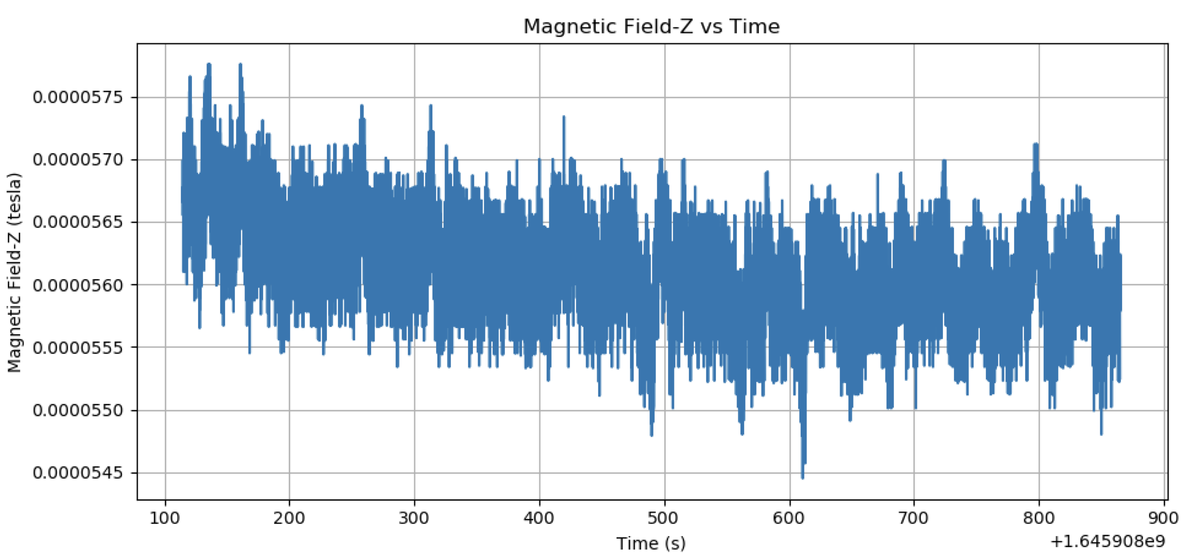

Figure 12: Magnetic Field about Z-axis vs. Time

<u>5 Hours of Stationary Data</u>

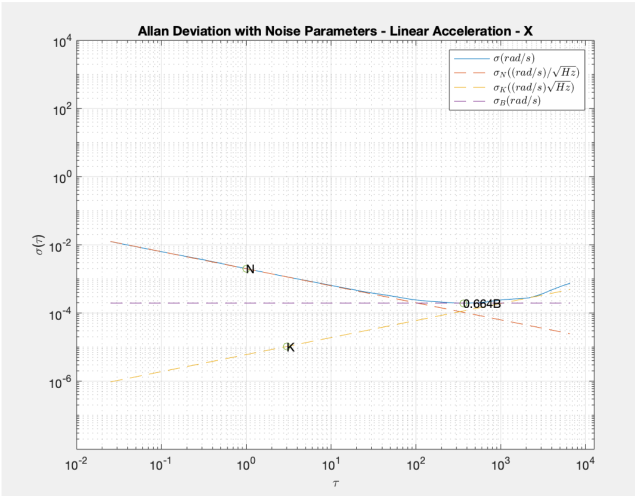

Figure 13: Allan Deviation - Linear Acceleration X-axis

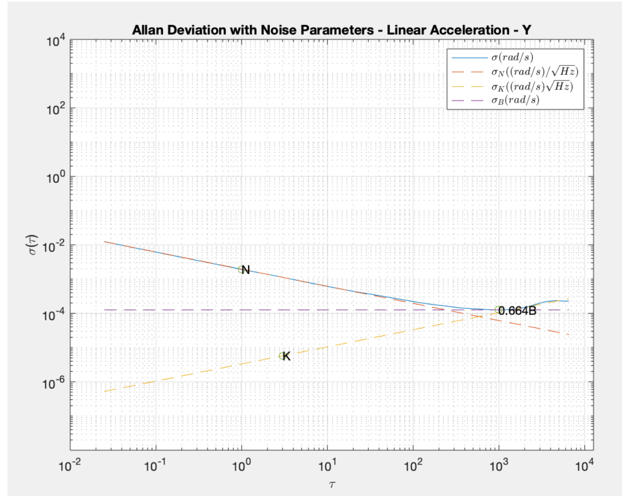

Figure 14: Allan Deviation - Linear Acceleration Y-axis

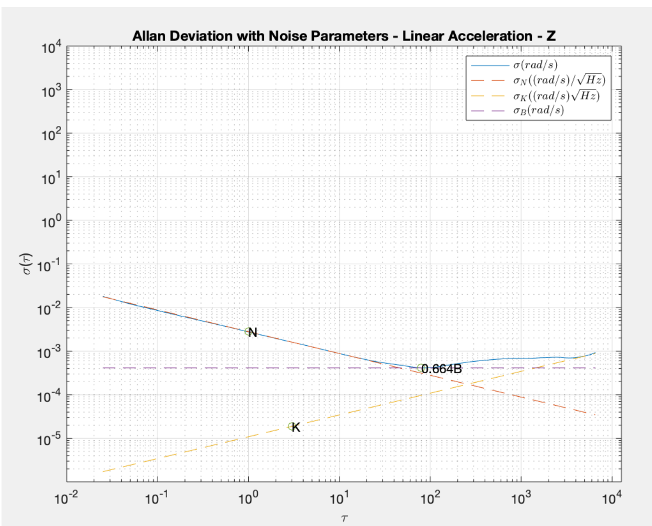

Figure 15: Allan Deviation - Linear Acceleration Z-axis

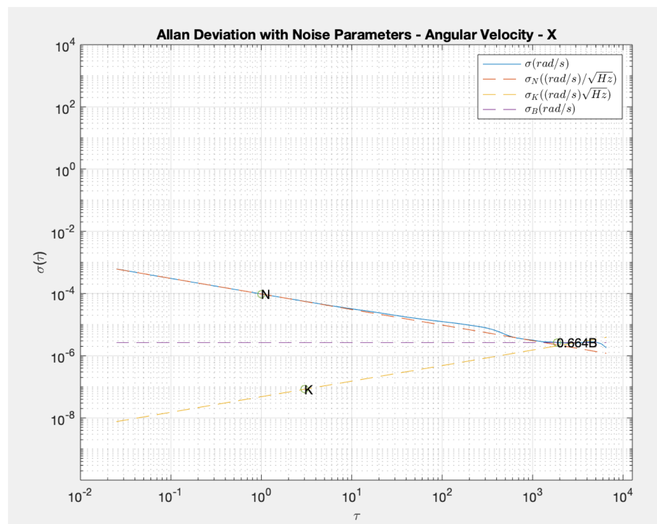

Figure 16: Allan Deviation - Angular Velocity X-axis

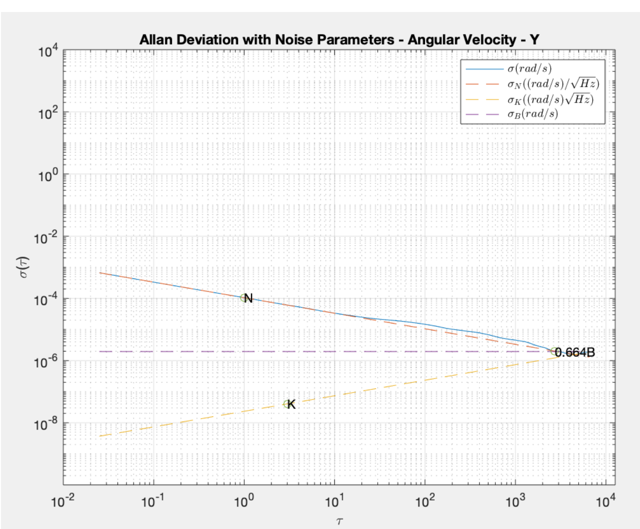

Figure 17: Allan Deviation - Angular Velocity Y-axis

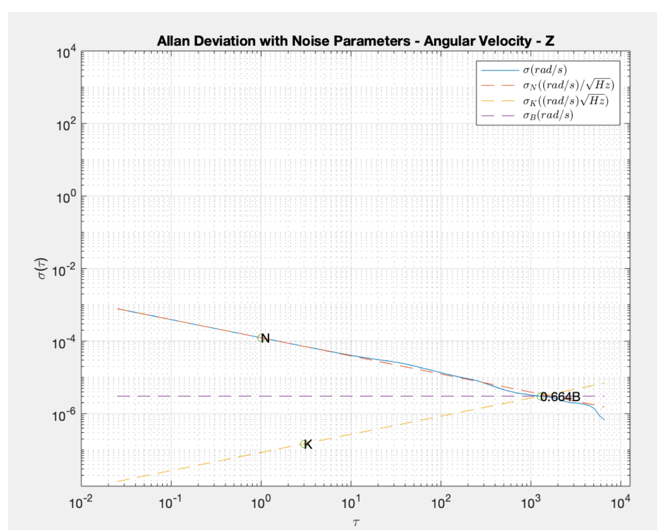

Figure 18: Allan Deviation - Angular Velocity Z-axis

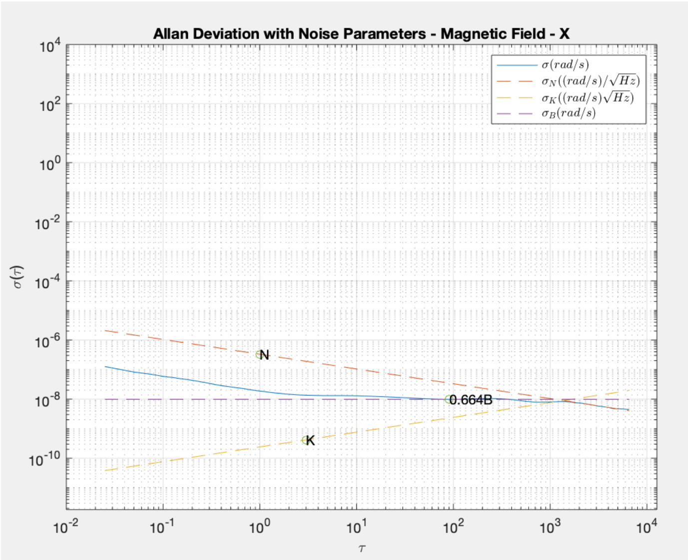

Figure 19: Allan Deviation - Magnetic Field X-axis

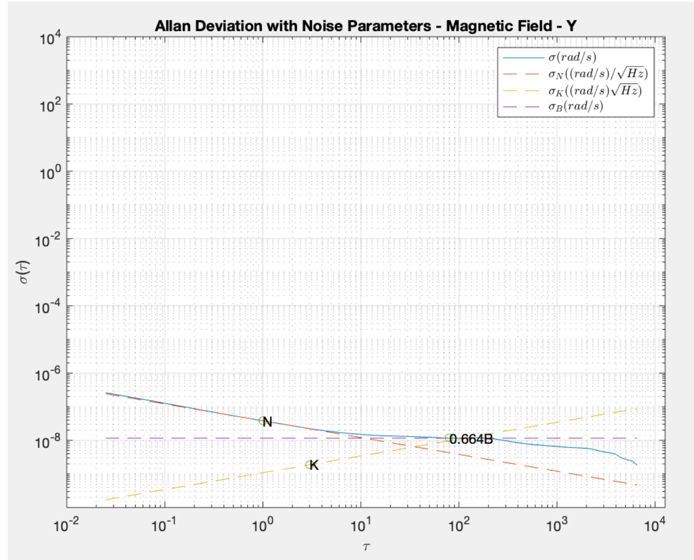

Figure 20: Allan Deviation - Magnetic Field Y-axis

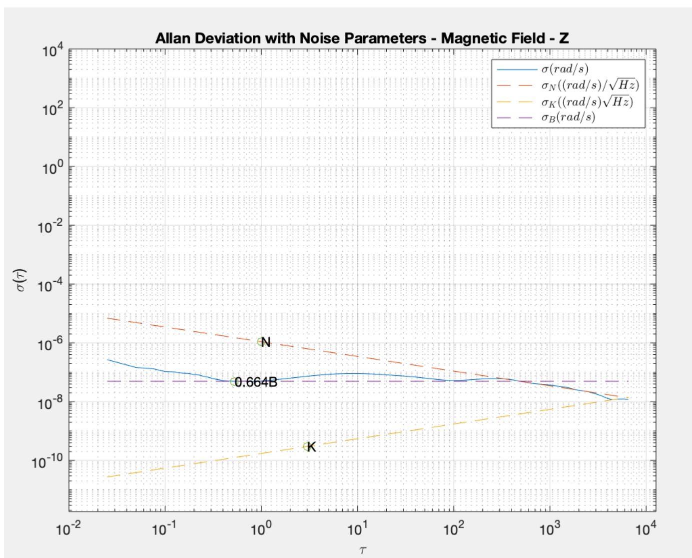

Figure 21: Allan Deviation - Magnetic Field Z-axis

Error and Noise Analysis

To analyze the error for the 12.5 minute long dataset, I calculated the mean and standard deviation for each variable. The calculations are displayed below:

	Mean	Standard Deviation
Roll (rad)	9.69112161e-01	2.47552474e-03
Pitch (rad)	1.14088404e-02	4.16715541e-04
Yaw (rad)	1.17182882e-02	1.30316424e-04
Linear Acceleration - X (m/s^2)	1.08837537e-01	1.30065684e-02
Linear Acceleration - Y (m/s^2)	-1.12501083e-01	1.21219896e-02
Linear Acceleration - Z (m/s^2)	-9.60921627	2.42824325e-02

Angular Velocity - X (rad/s)	2.95725186e-06	5.72475776e-04
Angular Velocity - Y (rad/s)	5.79168694e-05	6.31416765e-04
Angular Velocity - Z (rad/s)	-2.83509479e-05	7.56738697e-04
Magnetic Field - X (tesla)	-4.76845754e-05	1.65336197e-07
Magnetic Field - Y (tesla)	3.01785626e-05	3.00851588e-07
Magnetic Field - Z (tesla)	5.61623736e-05	3.91000786e-07

Table 1: Mean and Standard Deviations Calculations

Analyzing the above table displays relationships in our data. First, the orientation, angular velocity, and magnetic field of the device are all very close to zero, with values on the order of e-2,e-5, and e-5, respectively. These are all expected to be zero, as the device was on a flat surface, not moving, and had no magnetic devices near it. The orientation error is a little more due to the error of not being on an exactly flat surface, or lying at a very slight angle. Second, the linear acceleration in the Z direction of the device reads at around -9.6 m/s^2. This value is very close to the theoretical value of -9.81 m/s^2, or acceleration due to gravity. Some error may be dispersed in the X and Y direction as well, similar to the error in the orientation. Third and most important, most of the standard deviations are on the order of e-2 less than the mean, showing a strong accuracy towards the average and less variance in our data. Much of the error in this lab can be associated with natural error.

In analyzing the 5 hour long dataset, we can take a closer look at the Allan Deviation plots. The Allan Deviation is used to model and display the presence of noise in a dataset and neglect the presence of other systematic errors. It is calculated using the number of samples in a dataset, time frequency of those samples, and the total collection time. In *Figures 13-21*, the Allan Deviation is plotted for the linear acceleration, angular velocity, and magnetic field data, showing the different noise calculations taken into account. These noise calculations relating to the sources are Angle Random Walk (N), Rate Random Walk (K), and Bias Instability (B). Values for these calculations can be found below in *Table 2*. Angle and Rate Random walk are associated with the natural noise of the changing of data points oscillating around a value. This can be visually seen in *Figures 4-12* where the readings of the sensor are oscillating about the mean value. Bias Instability relates to the noise associated with stability of data measurements over a long period of time for the given sensor. This itself changes overtime, which is called Bias Drift. In *Figures 13-21*, we can see that the beginning of the Allan Deviation graphs show a strong correlation to the Angle Random Walk calculations. This represents the presence of white gaussian noise. Rate Random Walk and Bias Instability are calculated using time variables relating to the dataset.

	Angle Random Walk (N)	Rate Random Walk (K)	Bias Instability (B)
Linear Acceleration - X	0.0020	1.0435e-05	2.9372e-04
Linear Acceleration - Y	0.0019	5.7459e-06	1.8939e-04
Linear Acceleration - Z	0.0028	1.8832e-05	6.2184e-04
Angular Velocity - X	9.6677e-05	8.3419e-08	4.0031e-06
Angular Velocity - Y	1.0529e-04	4.0474e-08	2.9436e-06
Angular Velocity - Z	1.2387e-04	1.4797e-07	4.5892e-06
Magnetic Field - X	3.3011e-07	4.1826e-10	1.4813e-08
Magnetic Field - Y	3.8099e-08	1.8829e-09	1.7448e-08
Magnetic Field - Z	1.0906e-6	2.9988e-10	7.4146e-8

Table 2: N, K, and B values for each parameter

Much of the error seen in our data can also be associated with natural error in the test setup and data recording process. This IMU device is extremely sensitive to changes in motion and variations in our data are seen due to our test setup. To eliminate more error, the device should have been more strongly secured to the table, rather than loosely sitting on it. The table itself also acts as a second source of natural error due to it not being secured to the ground either.

Conclusion

IMU devices are useful pieces of technology in many different robotics applications due to their extreme sensitivity and accurateness. However, with this sensitivity comes the presence of noise factors among data measurements. Knowing the sources and magnitudes of these noise measurements is extremely important to effectively designing systems and ultimately using IMU devices in robotic applications. Through this lab, we were able to use an IMU device to detect and simulate these noise measurements through mathematical and graphical analysis of the Allan Deviation.