Stationary Noise Analysis
(Individual Work)

Introduction

Stationary noise analysis is a critical step in evaluating and improving the performance of Inertial Measurement Units (IMUs). IMUs are sensors used in a variety of applications to measure acceleration and angular velocity, however they are subject to noise. The purpose of this report is to characterize and quantify noise in IMU measurements when the sensor is at rest or moving evenly. It is critical for IMU precision, calibration, signal processing, and performance evaluation, ensuring their dependability and accuracy in a wide range of applications.

Analysis

The IMU (Inertial Measurement Unit) stationary noise analysis is based on the noise characteristics stated in the accelerometer, gyroscope, and magnetometer. The graph establishes the standard deviations and mean values. The graph is generated for the X, Y, Z of accelerometer, gyroscope, and magnetometer. The histogram are created for three types of data: Accelerometer, Gyroscope, and Magnetometer.

Analysis of Accelerometer

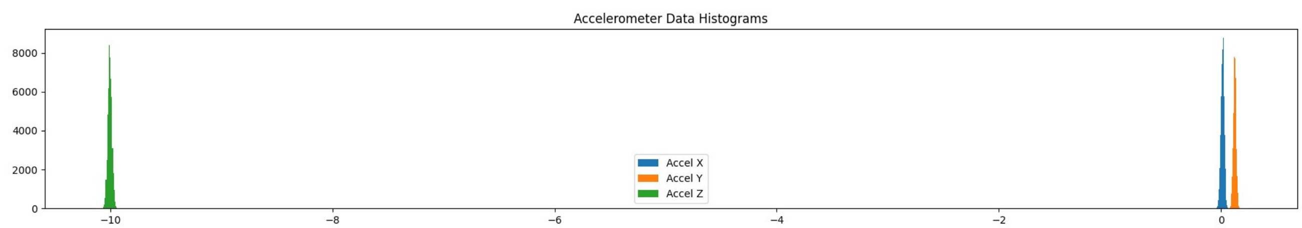

Fig 1: Accelerometer (X, Y, Z)

Figure 1 shows the Accelerometer for the data components X, Y, and Z. For each of the three accelerometer data components, a histogram is generated. The blue in the graph represents the Accelerometer X, the orange represents the Accelerometer Y, and the green represents the Accelerometer Z. The value for Accelerometer Z is negative, although the value for Accelerometer X, Y is positive. The x-axis in the Accelerometer graph represents acceleration, whereas the y-axis in the Accelerometer graph represents frequency. The Accelerometer for the data component X is shown in Fig. 1.1, the Accelerometer for the data component Y is shown in Fig. 1.2, and the Accelerometer for the data component Z is shown in Fig. 1.3. The individual analysis of the accelerometer is done below.

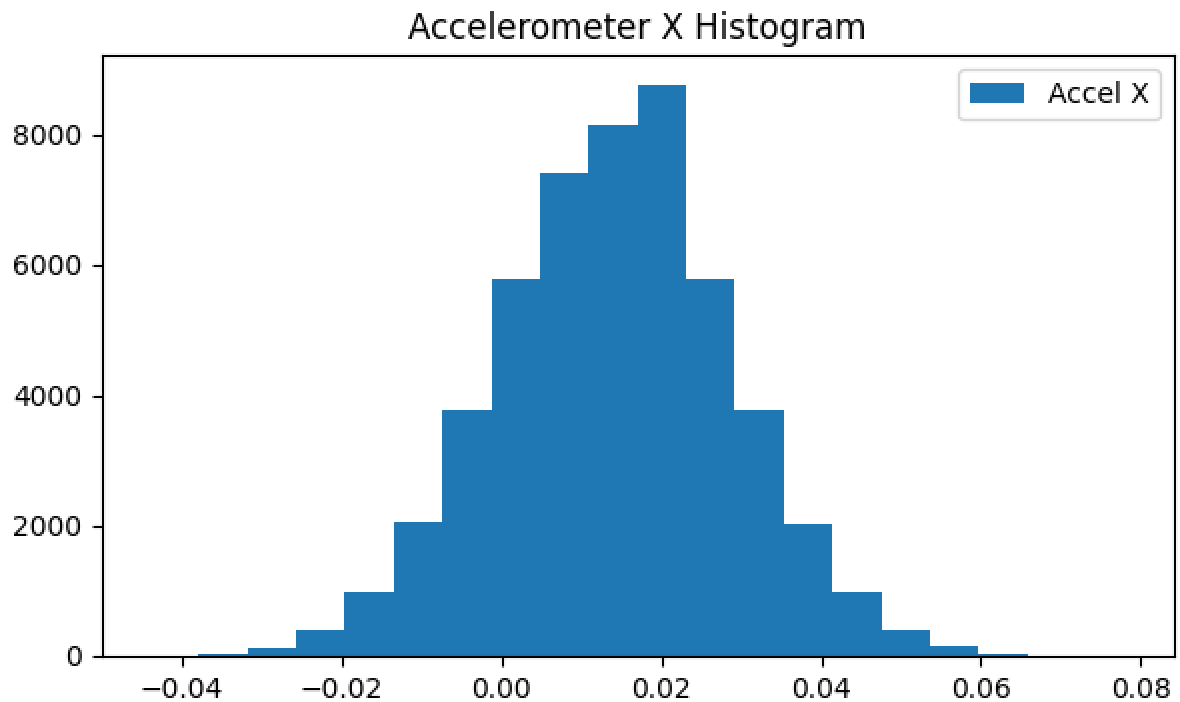

Fig 1.1: Accelerometer X

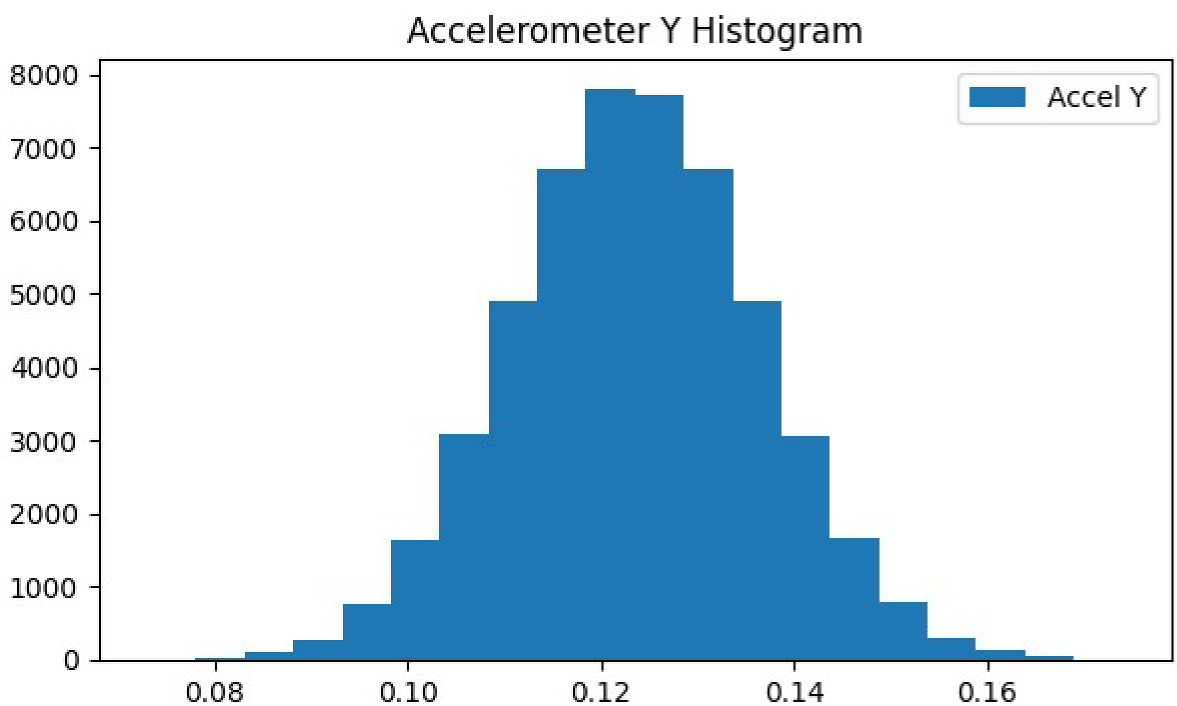

Fig 1.2: Accelerometer Y

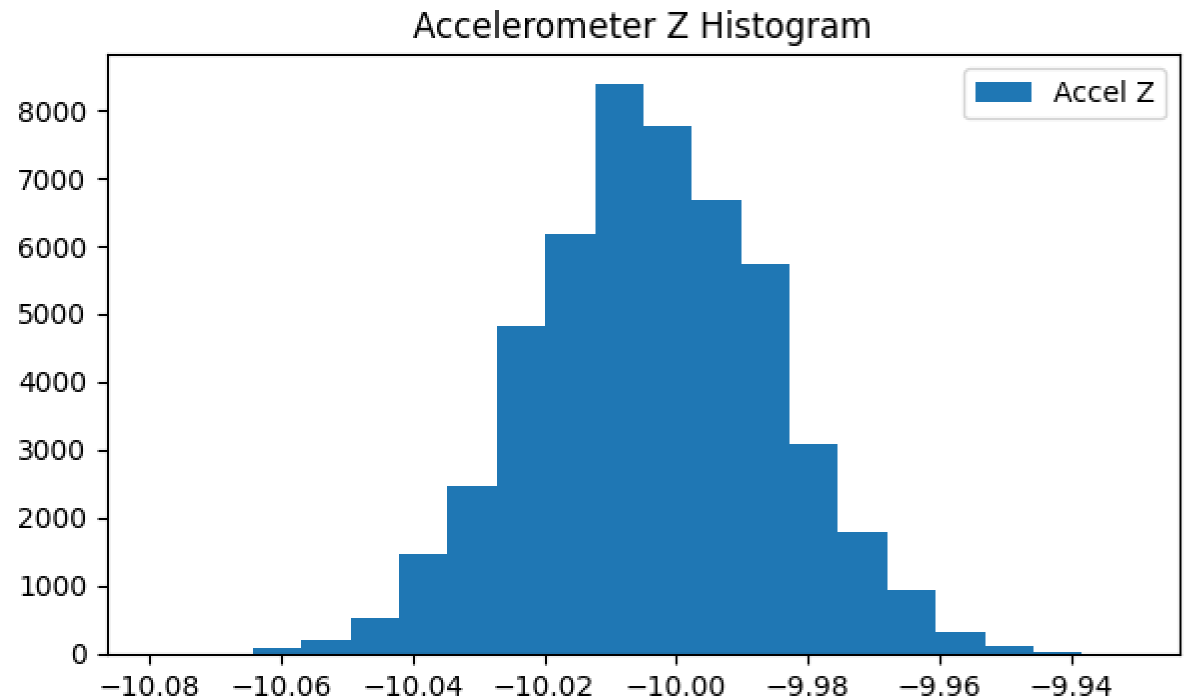

Fig 1.3: Accelerometer Z

The mean and standard deviation values for each component of the Accelerometer are as follows:

Accelerometer (X):

- Mean: 0.014002
- Standard Deviation: 0.014700

Accelerometer (Y):

- Mean: 0.123544
- Standard Deviation: 0.012674

Accelerometer (Z):

- Mean: -10.003519
- Standard Deviation: 0.018283

The graph from Fig 1 indicates a relatively low standard deviation, suggesting that the noise in these components is relatively small. The mean values are close to zero for X and Y, which is expected for a stationary IMU. The mean value for Z is approximately -10, which is close to the acceleration due to gravity.

Analysis of Gyroscope

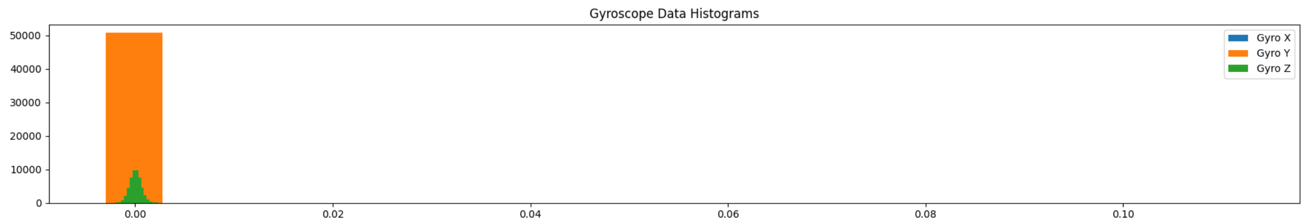

Fig 2: Gyroscope (X,Y, Z)

The Gyroscope for the data components X, Y, and Z is shown in Figure 2. A histogram is created for each of the three gyroscope data components. In the graph, blue indicates Gyroscope X, orange represents Gyroscope Y, and green represents Gyroscope Z. The data components of Gyroscope X, Y, Z are close to zero. The x-axis in the Gyroscope graph depicts angular velocity, while the y-axis reflects frequency. Figure 2.1 depicts the gyroscope for data component X, Figure 2.2 depicts the gyroscope for data component Y, and Figure 2.3 depicts the gyroscope for data component Z. The gyroscope individual analysis is done below.

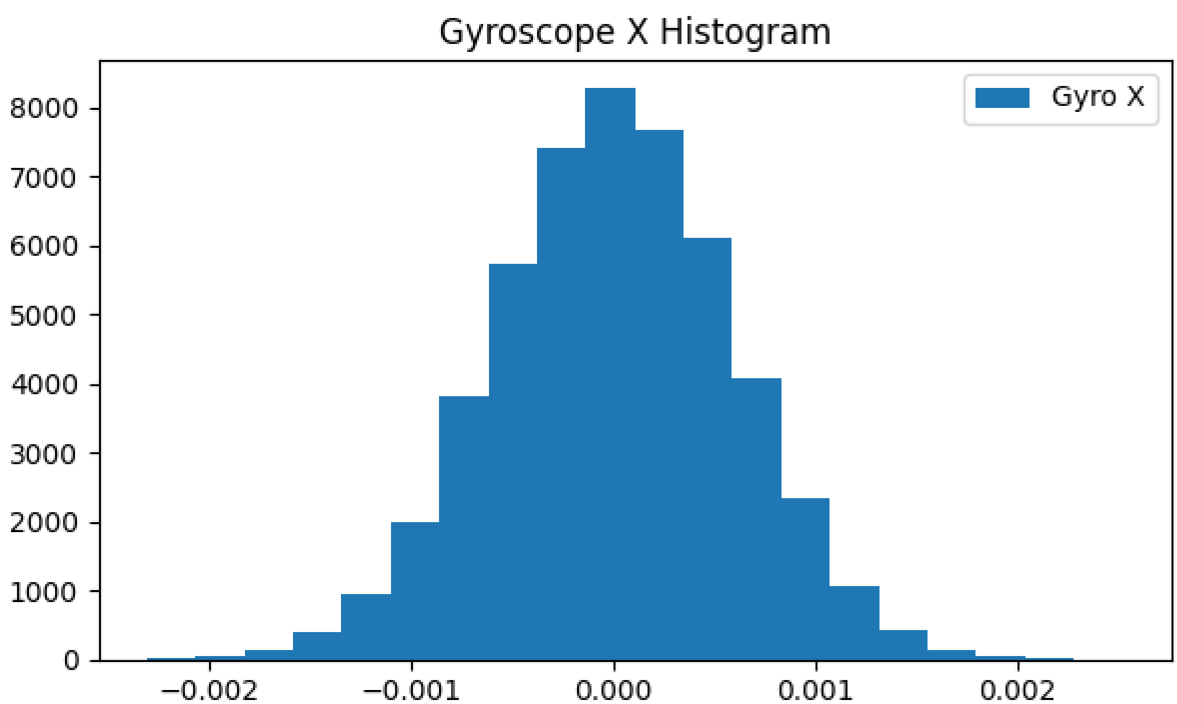

Fig 2.1: Gyroscope X

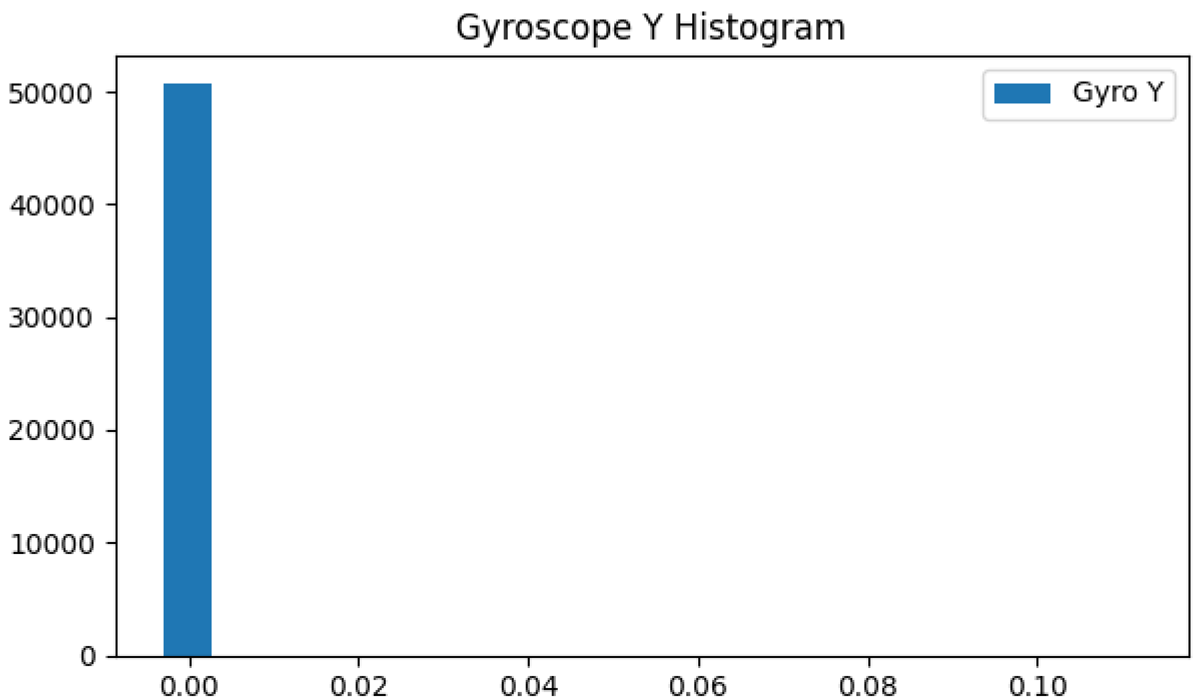

Fig 2.2: Gyroscope Y

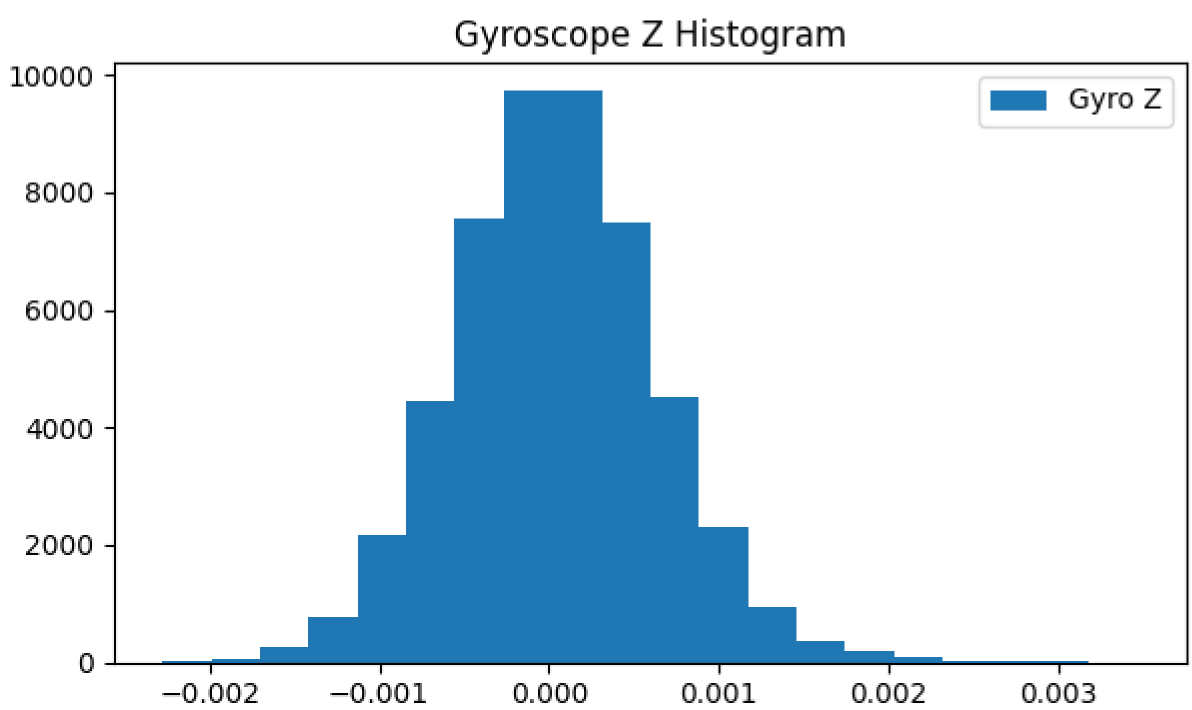

Fig 2.3: Gyroscope Z

The mean and standard deviation values for each component of the Gyroscope are as follows:

Gyroscope (X):

- Mean: 0.000006
- Standard Deviation: 0.000586

Gyroscope (Y):

- Mean: -0.000006
- Standard Deviation: 0.000874

Gyroscope (Z):

- Mean: 0.000043
- Standard Deviation: 0.000596

The gyroscope data also has low standard deviations, indicating low noise levels. The mean values for X, Y, and Z are very close to zero, indicating minimal drift in the gyroscope readings, which is desirable.

Analysis of Magnetometer

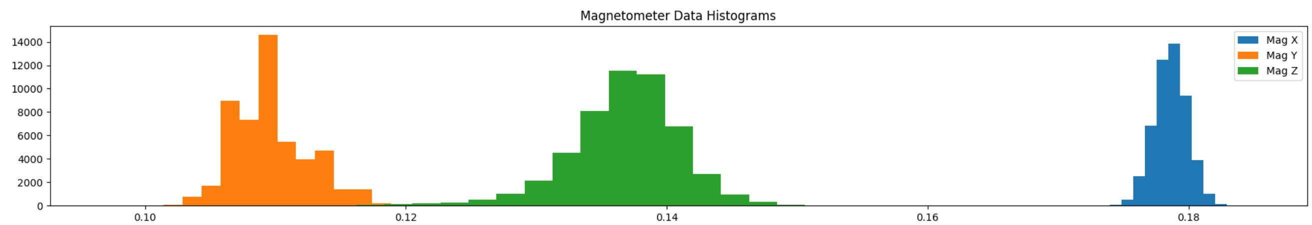

Fig 3: Magnetometer (X,Y, Z)

The Magnetometer for the data components X, Y, and Z is shown in Figure 3. A histogram is created for each of the three magnetometer data components. In the graph, blue indicates Magnetometer X, orange represents Magnetometer Y, and green represents Magnetometer Z. The data components of Gyroscope X, Y, Z are close to zero. The x-axis in the Magnetometer graph depicts magnetic field, while the y-axis reflects frequency. Figure 2.1 depicts the magnetometer for data component X, Figure 2.2 depicts the magnetometer for data component Y, and Figure 2.3 depicts the magnetometer for data component Z. The magnetometer individual analysis is done below.

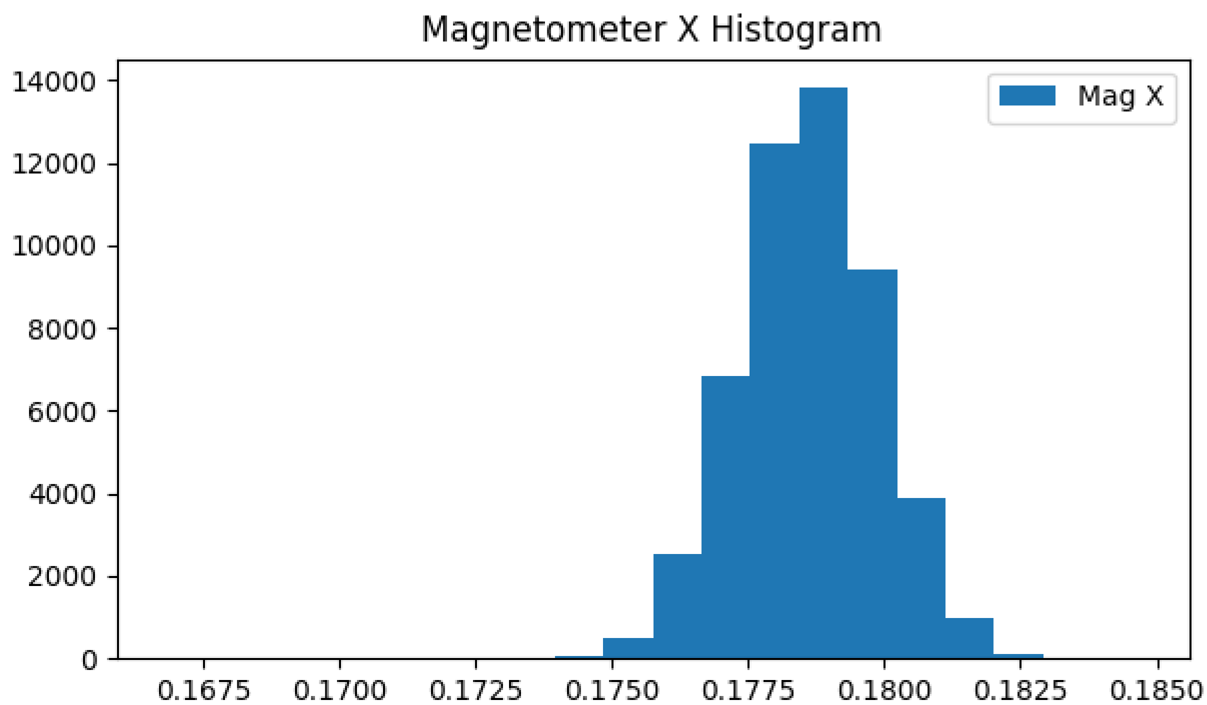

Fig 3.1: Magnetometer X

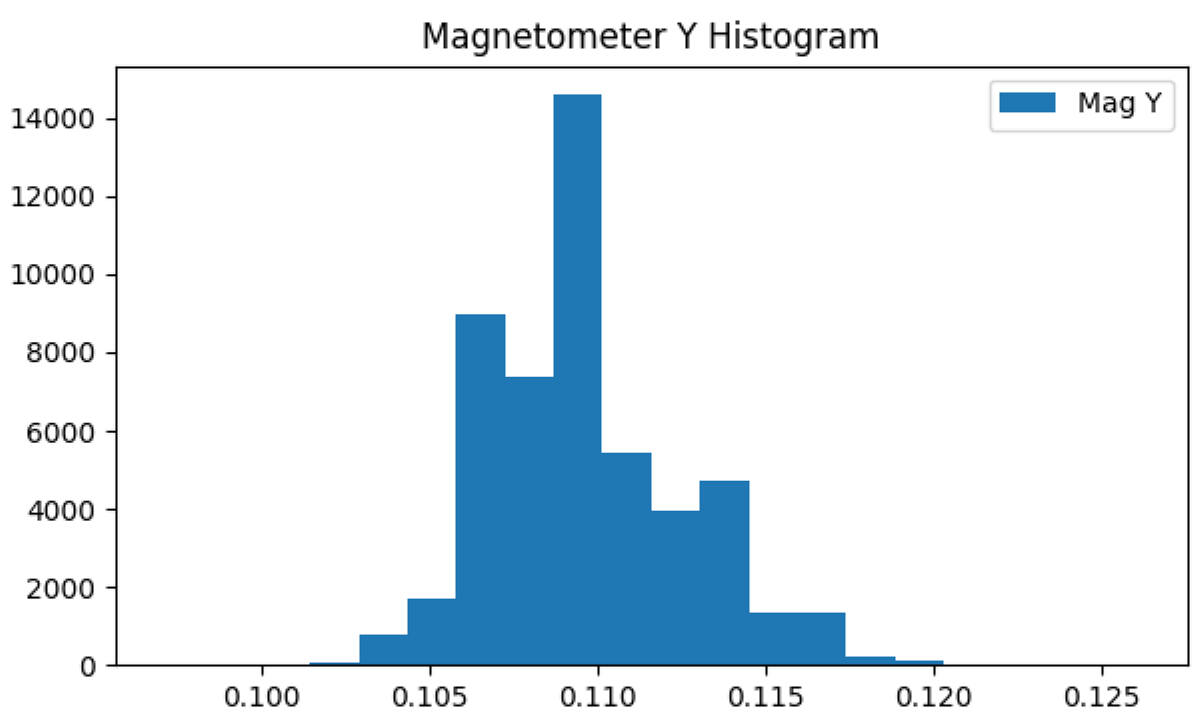

Fig 3.2: Magnetometer Y

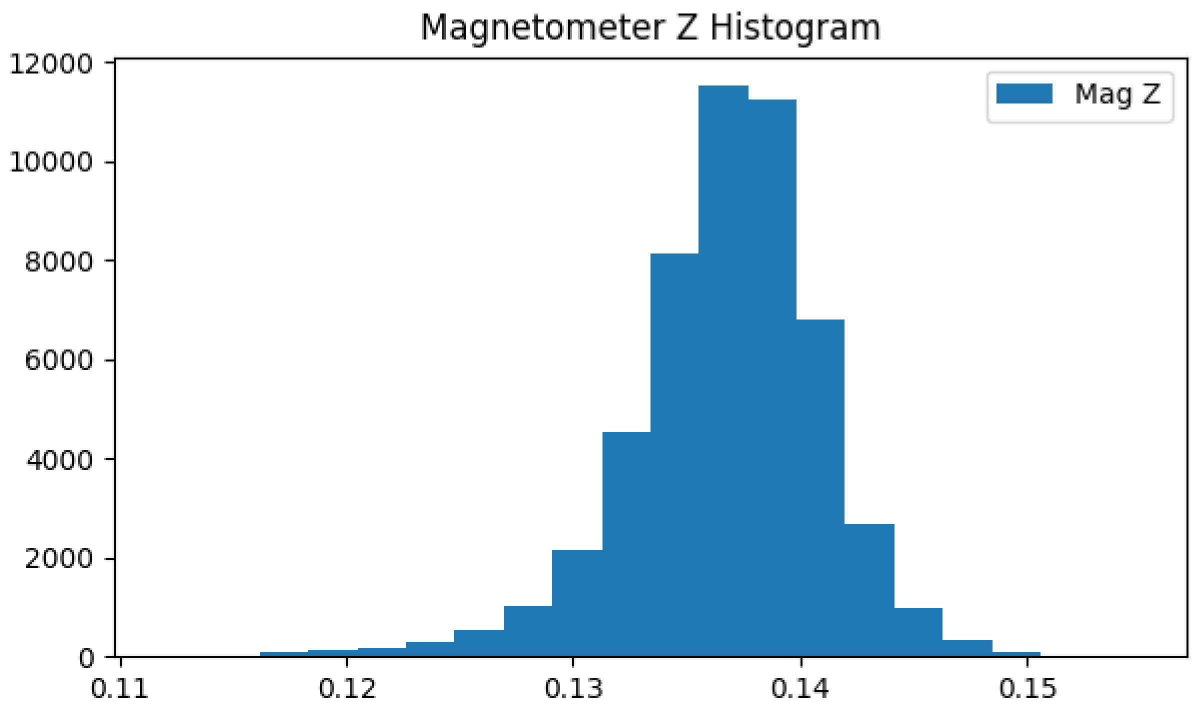

Fig 3.3: Magnetometer Z

The mean and standard deviation values for each component of the Magnetometer are as follows:

Magnetometer (X):

- Mean: 0.178718
- Standard Deviation: 0.001345

Magnetometer (Y):

- Mean: 0.109732
- Standard Deviation: 0.002818

Magnetometer (Z):

- Mean: 0.136913
- Standard Deviation: 0.004365

Magnetometer data has slightly greater standard deviations than accelerometer and gyroscope data. The mean values for X, Y, and Z range from 0.1 to 0.18, indicating that the magnetometer readings may be biased or offset.

The IMU data looks to be largely noise-free, with low standard deviations and mean values that are near to what would be expected for stationary settings. The noise characteristics indicate that the IMU data is adequate for applications requiring precise orientation and motion sensing. However, additional calibration or offset correction for the magnetometer data may be required to increase accuracy even more.

Allan Variance

Introduction

Allan deviation is a statistical method used to analyze the stability and noise characteristics of sensors, particularly gyroscopes and accelerometers. It provides valuable insights into the error and noise sources present in sensor data. Allan variance is a measure of the variance of the differences between consecutive measurements in a time series, divided by the time interval between the measurements squared. It is computed over various time intervals to capture different noise characteristics. It identifies various types of noise, such as white noise, random walk, and bias instability, which are critical in sensor applications.

Analysis

By plotting the Allan deviation against the time intervals (tau), patterns and characteristics of sensor noise can be visualized. The slope of the Allan deviation plot can be used to estimate the parameters of interest, such as Angle Random Walk, Rate Random Walk, and Bias Instability. For very short time intervals (tau), the Allan variance approximates the variance of white noise, which is uncorrelated random noise. For intermediate time intervals, the Allan variance characterizes the presence of random walk noise, which is a continuous accumulation of random errors. For longer time intervals, it captures bias instability, which represents drift or systematic errors in the sensor output over time.

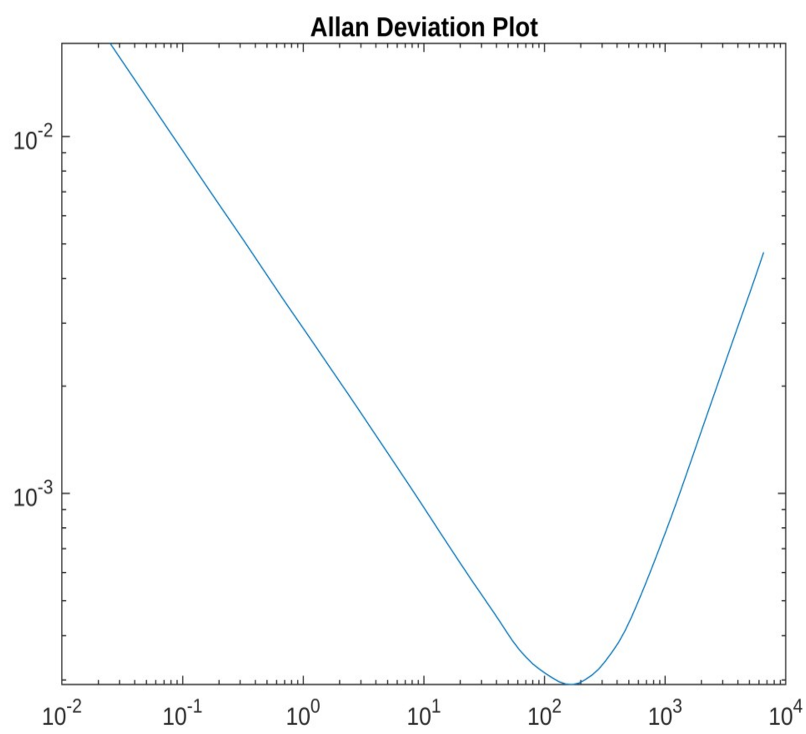

Fig 1: Allan Deviation Point

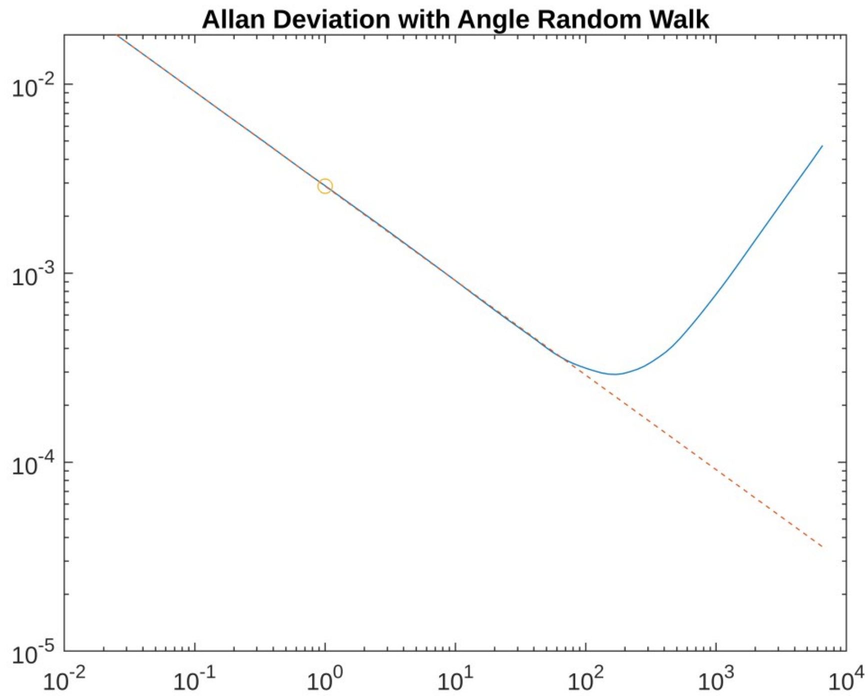

Fig 2: Allan Deviation with Angle Random Walk

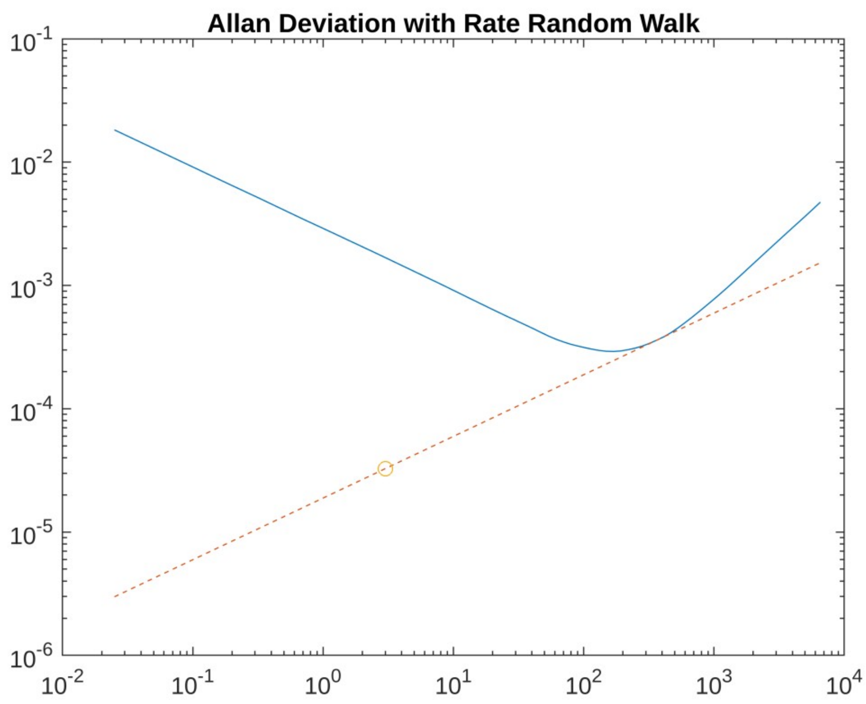

Fig 3: Allan Deviation with Rate Random Walk

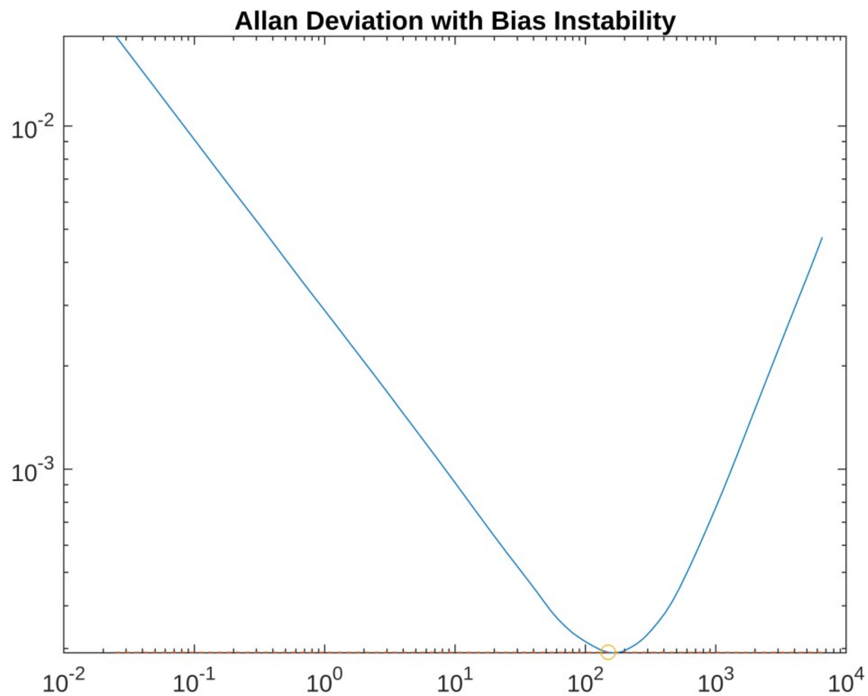

Fig 4: Allan Deviation with Bias Instability

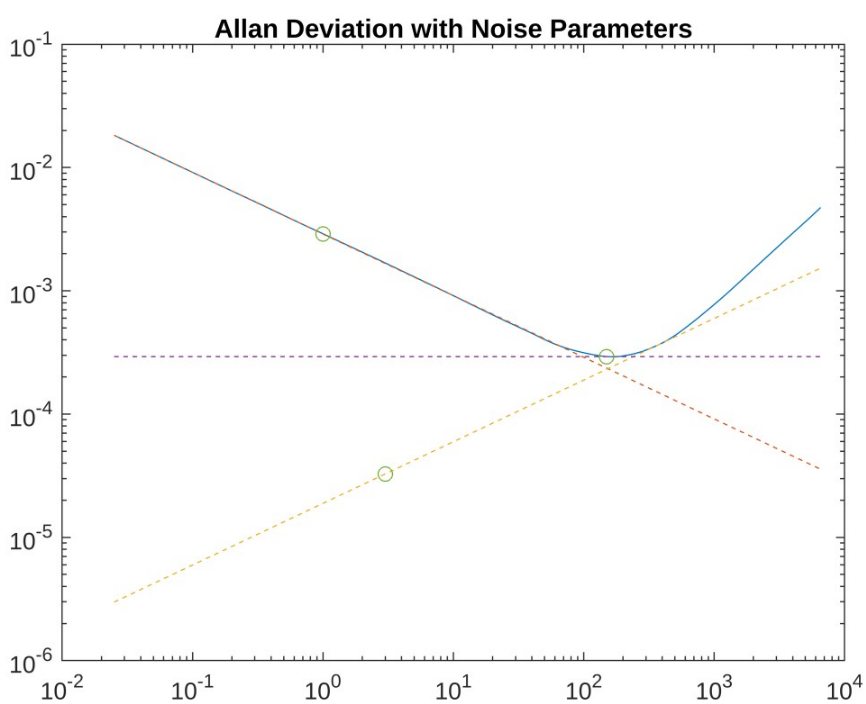

Fig 5: Allan Deviation with Noise Parameters

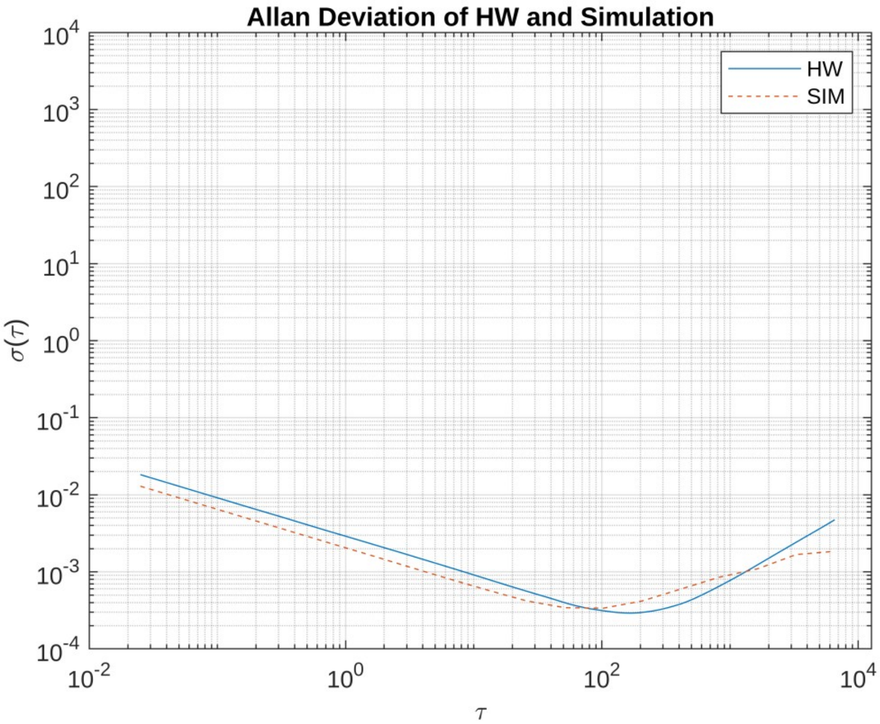

Fig 6: Allan Deviation of HW and Simulation

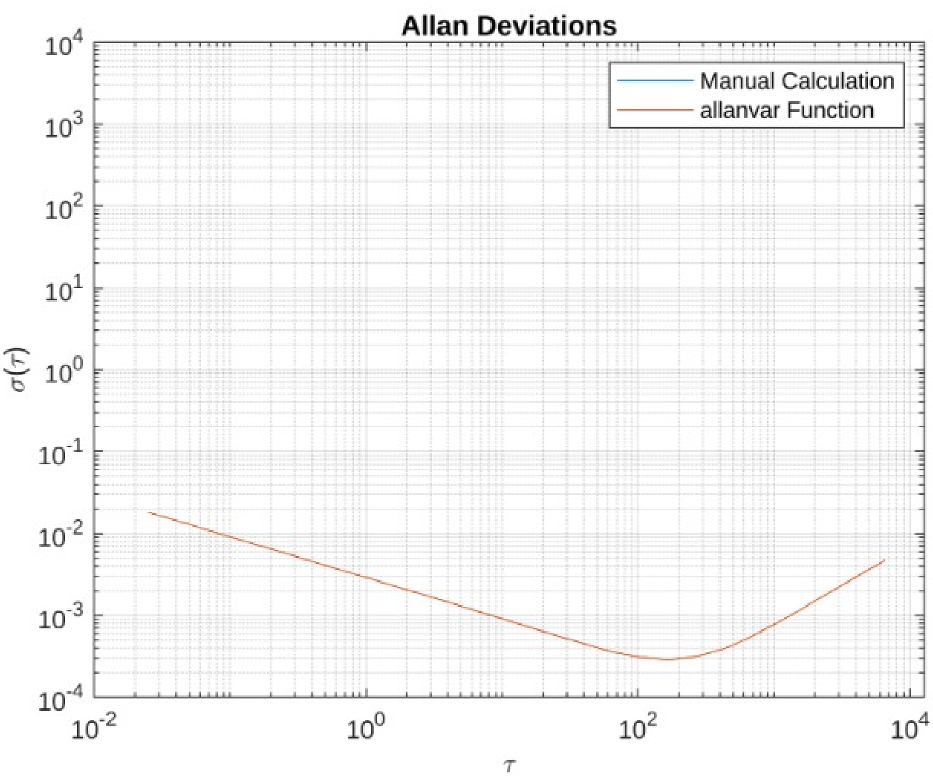

Fig 7: Allan Deviations

According to the graphs above, the Allan deviation grows with the time interval at a constant rate. This is the typical slope of flicker noise. At some point in time, the Allan deviation approaches a minimum. This is known as the Allan minimum, and it is often related with flicker noise.
Analyzing the graphs above reveals relationships with our data. First, the device's orientation, angular velocity, and magnetic field are all very close to zero. It is predicted to be zero because the device was on a flat surface, was not moving, and had no magnetic devices nearby. The orientation mistake is caused by not being on an entirely flat surface or lying at a very little incline. Second, the device's linear acceleration in the Z direction. Similar to the orientation error, some error may be scattered in the X and Y directions as well. Third, and most importantly, the majority of the standard deviations are on the order of e-2 smaller than the mean, indicating that our data is very accurate and has little volatility. Natural error accounts for a large portion of the mistake in this lab.
We may examine the Allan Deviation maps in greater detail while examining the 5-hour dataset. The Allan Deviation is used to model and visualize the presence of noise in a dataset while ignoring other systematic mistakes. It is estimated based on the amount of samples in a dataset, the frequency with which those samples are collected, and the total collection duration. Figures 1–7 exhibit the Allan Deviation for linear acceleration, angular velocity, and magnetic field data, illustrating the various noise computations used. Angle Random Walk (N), Rate Random Walk (K), and Bias Instability (B) are the noise calculations related to the sources. Angle and Rate Random walk are related to the natural noise of data points oscillating around a value.
Bias Instability refers to the noise associated with the long-term stability of data measurements for a certain sensor. Bias Drift refers to how something varies over time. Consider Random Walk and

Kind of Errors / Sources of Noise Present

The kind of errors or sources of noise present are as follows:

- **Angle Random Walk (ARW):** ARW quantifies the angular rate stability of the sensor. Angle Random Walk is a measure of the stability and noise characteristics associated with the angular rate or rotation rate data from sensors, such as gyroscopes. ARW is a parameter that quantifies the standard deviation of the random noise in the angular rate measurements over time. It characterizes the continuous, random variations in the sensor's output.
- **Rate Random Walk (RRW):** RRW quantifies the rate of change of the sensor's angular rate. Rate Random Walk is another parameter used to describe the instability and noise characteristics of angular rate sensors, especially gyroscopes. RRW represents the rate of change of the angular rate measurements over time. It quantifies the continuous accumulation of random errors in the sensor's measurements.
- **Bias Instability:** Bias Instability characterizes the sensor's bias drift over time. Bias Instability is a parameter that quantifies the drift or systematic errors in sensor measurements. Bias Instability represents the sensor's systematic error or bias in measurements, which can be constant or exhibit slow changes over time.

Modeling, Measurements and Measurements for VN100

To model and measure Angle Random Walk (ARW), Rate Random Walk (RRW), and Bias Instability, it is typically rely on sensor datasheets and data analysis.

1. Modeling:

Angle Random Walk (ARW):

- ARW can be modeled as the standard deviation of the angular rate noise over a unit square root of time. In mathematical terms, ARW (σARW) can be modeled as follows:
  - $\sigma ARW = k * \sqrt{(1 / \tau)}$
- Where τ is the time interval, and k is a constant specific to the sensor's performance.

Rate Random Walk (RRW):

- RRW can be modeled as the standard deviation of the rate of change of angular rate noise over a unit cube root of time. In mathematical terms, RRW (σRRW) can be modeled as follows:
  - $\sigma RRW = k * \sqrt[3]{(1 / \tau)}$
- Where τ is the time interval, and k is a constant specific to the sensor's performance.

Bias Instability:

- Bias Instability can be modeled as the standard deviation of the sensor bias drift over time. In mathematical terms, Bias Instability ($\sigma BIAS$) can be modeled as:
  - $\sigma BIAS = k * \sqrt{\tau}$
- Where τ is the time interval, and k is a constant specific to the sensor's performance.

2. Measurement:

Angle Random Walk (ARW):

- ARW is measured by observing the short-term variations in the sensor's angular rate data. The Allan deviation analysis, it can help to estimate the ARW parameter. By examining the slope of the Allan deviation plot for short time intervals, it can estimate ARW.

Rate Random Walk (RRW):

- RRW is measured by examining the intermediate-term variations in the angular rate data. The Allan deviation analysis can be used to estimate RRW. The slope of the Allan deviation plot for intermediate time intervals corresponds to RRW.

Bias Instability:

- Bias Instability is measured by observing the long-term drift or systematic errors in sensor data. The Allan deviation analysis can estimate Bias Instability by observing the plateau region of the Allan deviation plot for longer time intervals.

3. Relating to VN100 Datasheet:

The datasheet should contain specifications for ARW, RRW, and Bias Instability, which are essential parameters in characterizing the sensor's performance. Comparing the values obtained for ARW, RRW, and Bias Instability from the data analysis to the specifications in the datasheet. Ensure that the measurements are within the expected range or meet the sensor's stated performance characteristics.

The sensor performance may vary due to calibration or environmental factors. Ensure that the measurements are consistent with the sensor's intended use and calibration.

Conclusion

Because of their extraordinary sensitivity and accuracy, IMU devices are useful pieces of technology in a wide range of robotics applications. With this sensitivity, however, comes the prevalence of noise components in data readings.
Understanding the sources and magnitudes of these noise measurements is critical for efficiently designing systems and, eventually, employing IMU devices in robotic applications. We were able to detect and reproduce these noise readings using an IMU device and a mathematical and graphical analysis of the Allan Deviation in this lab.