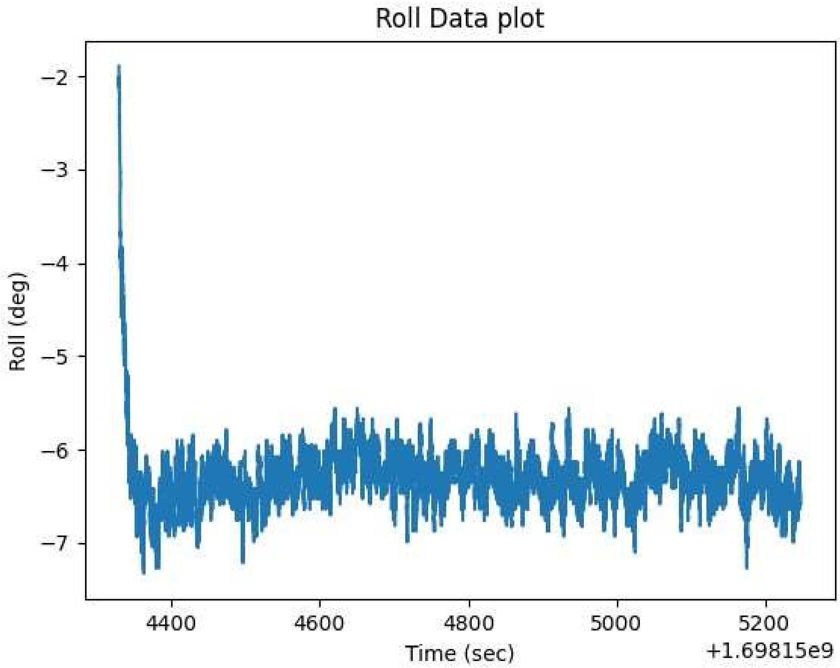
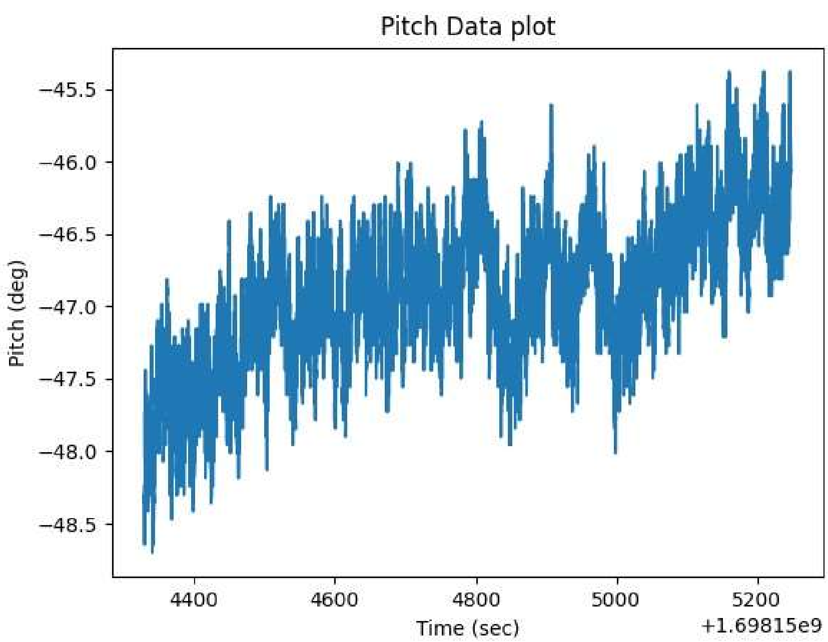
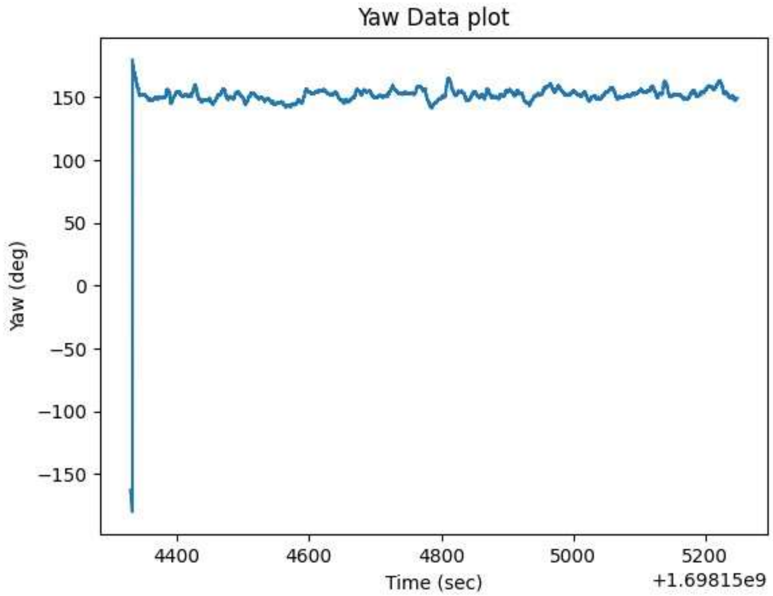
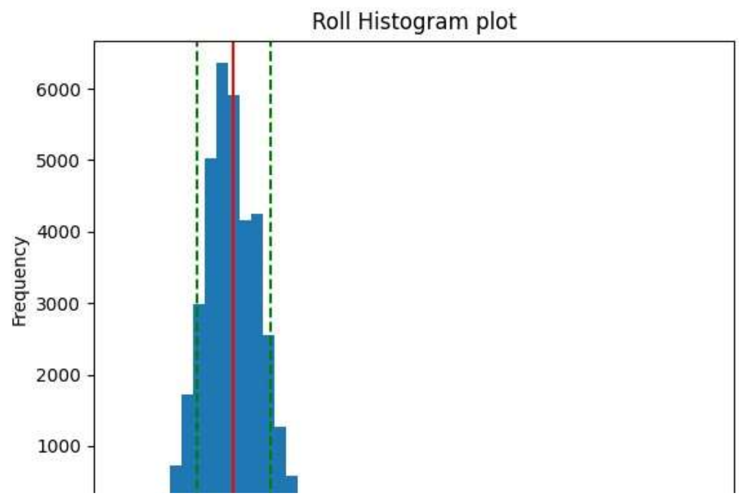
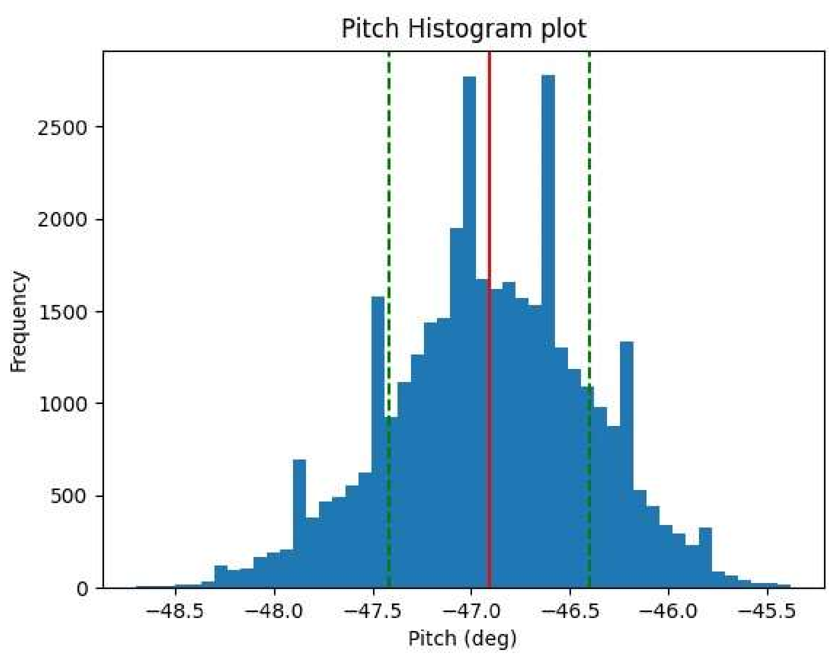
Lab3
IMU noise characterization with Allan Variance

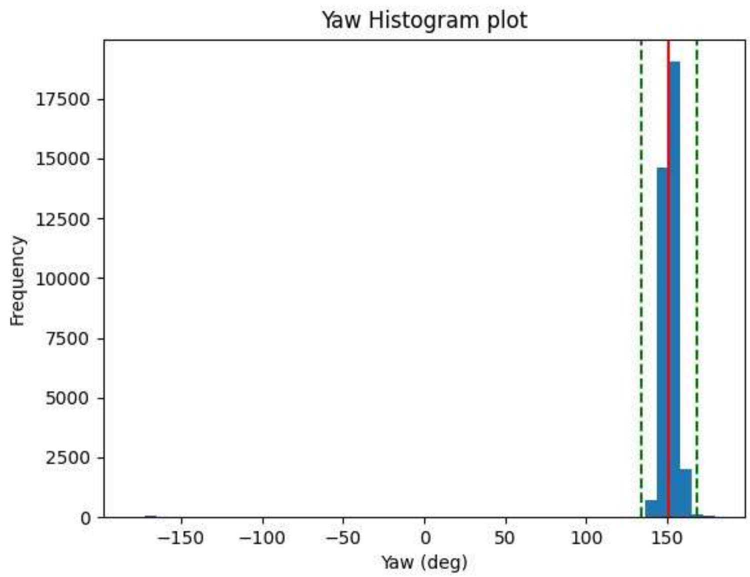


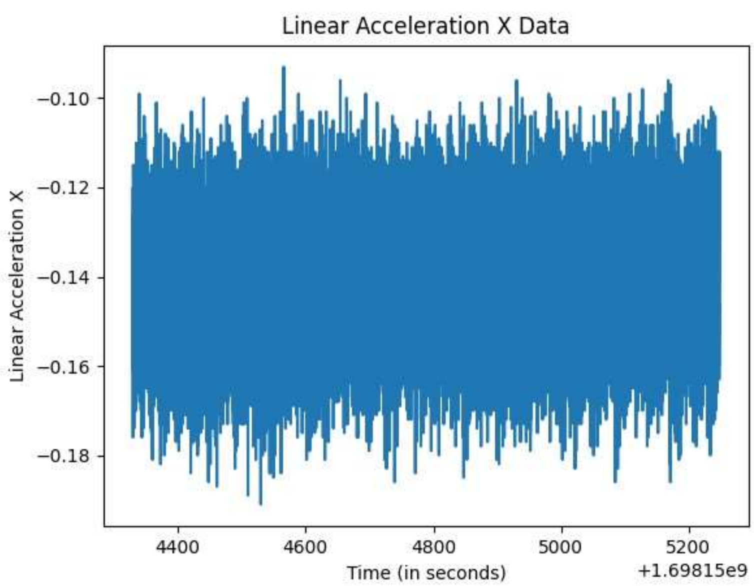


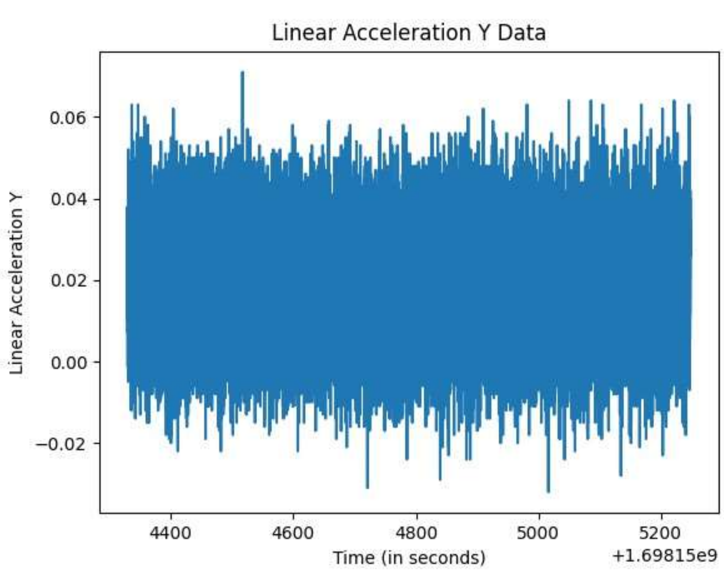

Yaw Data plot
150
100
50
0
−50
−100
−150
Yaw (deg)
4400
4600
4800
5000
5200
Time (sec)
+1.69815e9

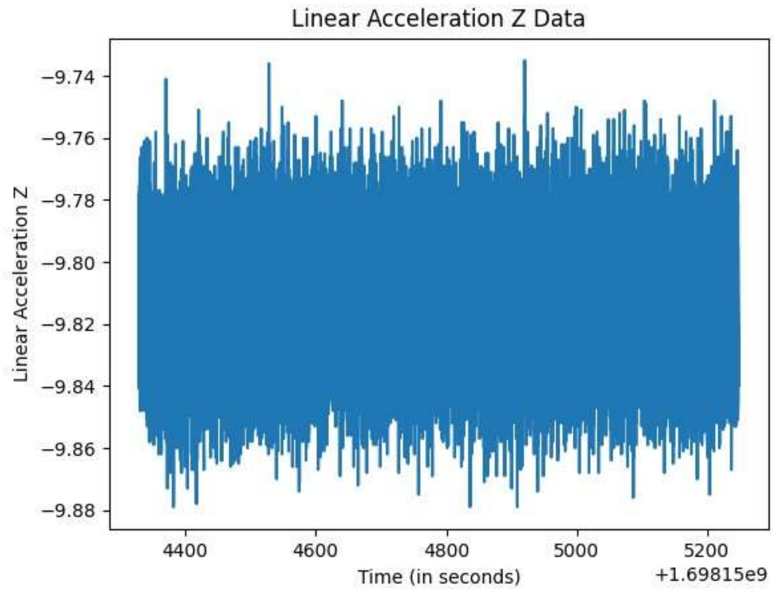

Roll Histogram plot
6000
5000
4000
3000
2000
1000
Frequency


Pitch Histogram plot
2500
2000
1500
1000
500
0
Frequency
−48.5
−48.0
−47.5
−47.0
−46.5
−46.0
−45.5
Pitch (deg)

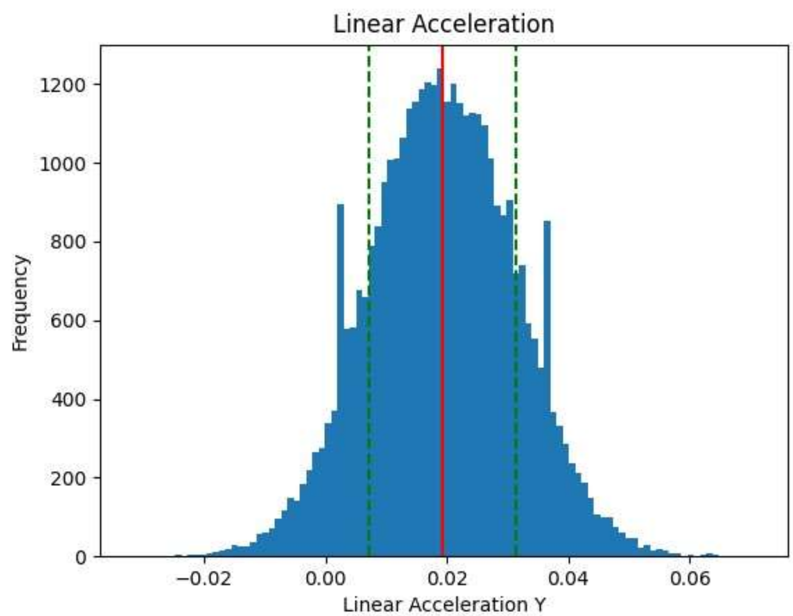

Yaw Histogram plot
Frequency
17500
15000
12500
10000
7500
5000
2500
0
−150
−100
−50
0
50
100
150
Yaw (deg)


Linear Acceleration X Data
Linear Acceleration X
−0.10
−0.12
−0.14
−0.16
−0.18
4400
4600
4800
5000
5200
Time (in seconds)
+1.69815e9


Linear Acceleration Y Data
Linear Acceleration Y
0.06
0.04
0.02
0.00
−0.02
4400
4600
4800
5000
5200
Time (in seconds)
+1.69815e9



Linear Acceleration Z Data
Linear Acceleration Z
−9.74
−9.76
−9.78
−9.80
−9.82
−9.84
−9.86
−9.88
4400
4600
4800
5000
5200
Time (in seconds)
+1.69815e9



Linear Acceleration
Frequency
1200
1000
800
600
400
200
0
−0.02
0.00
0.02
0.04
0.06
Linear Acceleration Y

Error analysis (Individual data)

Sources of errors in the IMU data can be attributed to:

- Sensor Noise
- Calibration Error
- Magnetic Interference
- Mounting and Installation Errors
- Sensor Drift

A significant portion of the data errors can be attributed to various factors related to the setup and data collection process during testing. These errors are a natural consequence of the testing conditions. The configuration of the test setup led to discrepancies in the results, primarily because the IMU device is highly sensitive to changes in motion. To mitigate these errors, it would have been beneficial to securely affix the equipment to a stable surface, reducing the potential for inaccuracies. Furthermore, the lack of a proper foundation for the surface on which the device was placed also contributed to the errors.

The histogram plots of the IMU data demonstrate a Gaussian distribution, which suggests the presence of Gaussian error. This observation is further supported by time series plots, which show that the data is dispersed around the mean and mostly falls within the range of plus or minus one standard deviation, indicating a Gaussian distribution of the data.

Regarding orientation data, the mean value represents the orientation of the sensor at the time of data collection.

In terms of linear acceleration, the negative mean values for the y and z axes may indicate errors resulting from sensor biases, misalignments, or external forces like gravity acting in the opposite direction of these respective axes.

When examining angular velocity data, the negative mean values for the x and z axes are concerning. A positive angular velocity in the y axis implies that the IMU is rotating counterclockwise around the y axis. However, negative angular velocity values in the x and z axes suggest that the IMU is rotating clockwise around these axes, which is physically impossible and points to errors in the data.

In the case of magnetic field data, a positive magnetic field in the y and z axes suggests that the IMU is correctly oriented with respect to Earth's magnetic field. Conversely, a positive mean value for the magnetic field in the y and z axes, coupled with a negative mean value for the x axis, indicates that the IMU is flipped around the x axis and is not aligned correctly with Earth's magnetic field.

Error analysis (group data) for 5hrs basement data
Allan deviation

The Allan Deviation serves as a valuable tool for characterizing and visualizing the presence of noise within a dataset, allowing us to filter out systematic errors. It is computed based on the dataset's sample count, the frequency of data collection, and the total data collection duration.

Gyroscope Noise:
1. **Bias Instability**: Gyroscopes inherently exhibit a bias or offset in their output, even in the absence of rotation. This bias can gradually shift over time, akin to a random walk process with a continuously changing bias.

2. **White Noise**: Gyroscopes also exhibit random noise across all frequency components. This noise is typically represented by a zero-mean Gaussian distribution.

Accelerometer Noise:
1. **Bias Instability**: Similar to gyroscopes, accelerometers experience bias instability, characterized by a slowly shifting bias that affects accelerometer readings. This can also be conceptualized as a random walk process.

2. **White Noise**: Accelerometers, like gyroscopes, feature white noise components, typically modeled as zero-mean Gaussian noise.

Magnetometer Noise:
1. **Bias Instability**: Magnetometers, like gyroscopes and accelerometers, are susceptible to bias instability. This instability can be described as a random walk process, where the bias gradually changes over time.

2. **White Noise**: Magnetometers contain white noise components, and this noise is often represented as zero-mean Gaussian noise.

In summary, the Allan Deviation helps us understand and visualize noise in datasets, specifically for gyroscope, accelerometer, and magnetometer data. Each of these sensor types exhibits bias instability as well as white noise, which can be effectively characterized using the Allan Deviation.