IMU Stationary Data Analysis Report

Introduction

The goal of this experiment is to develop and test a device driver for an Inertial Measurement Unit (IMU) and to analyze the stationary noise characteristics of the IMU data. Specifically, we parse and analyze IMU data from a VectorNav sensor, using a custom ROS message structure. We examine the accelerometer, gyroscope, and magnetometer readings, and convert Euler angles into quaternions to understand the behavior of the IMU during stationary data collection.

Objective

This analysis evaluates an IMU's stationary noise characteristics based on accelerometer, gyroscope, and orientation (Euler angles) data collected over a period of time. It provides insights into the IMU's performance and stability in a static environment, which can serve as a baseline for further dynamic testing.

Materials and Methodology

Device Driver Development

The IMU driver is developed using Python. We open a serial connection to read the $VNYMR string, which contains the accelerometer, gyroscope, orientation, and magnetometer data. The script parses this string, extracts the required parameters, and publishes them as a custom ROS message named “Vectornav.msg”.

Custom ROS Message

The custom message “Vectornav.msg” includes the following:
- Header with the name 'header', including timestamp and frame id ('imu1_frame').
- ROS sensor_msgs/IMU message for acceleration and gyroscope data.
- ROS sensor_msgs/MagneticField for magnetometer data.
- A string for storing the raw IMU string.

Quaternion Conversion

To further process the orientation data, the Euler angles obtained from the IMU are converted into quaternions. This conversion was done without using external libraries, ensuring a deeper understanding of the underlying mathematical transformations.

Data Collection and Stationary Analysis

The IMU was configured to output data at 40 Hz by writing to the respective register of the VectorNav sensor. The setup was then used to collect approximately 10 minutes of stationary IMU data, which was logged using ROS bags. The collected data were later processed and analyzed.

Plots and Analysis

To understand the noise characteristics and evaluate sensor performance, we plotted several time-series and statistical analyses of the collected IMU data:

Figure 1: Gyroscope Data

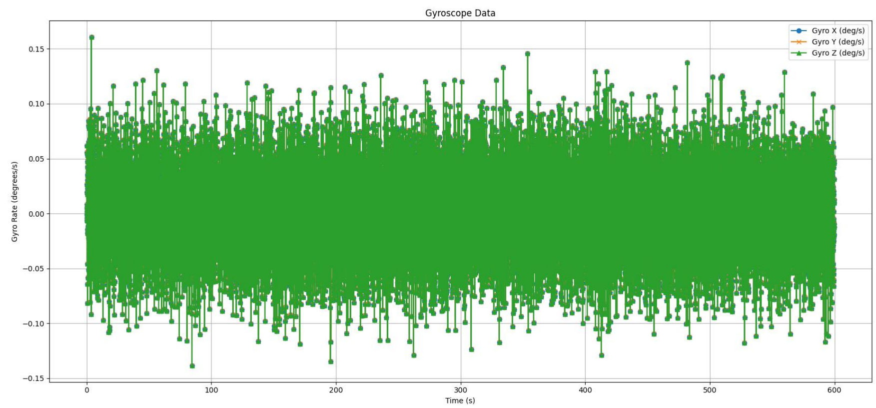


Figure 2: Accelerometer Data

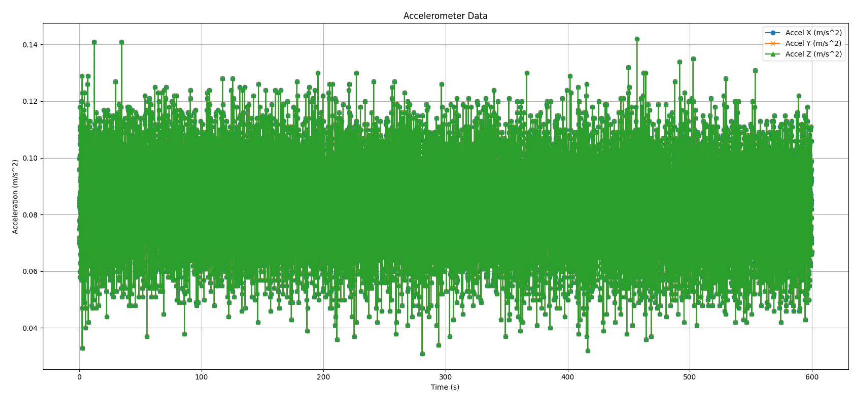


Figure 3: Orientation Estimation

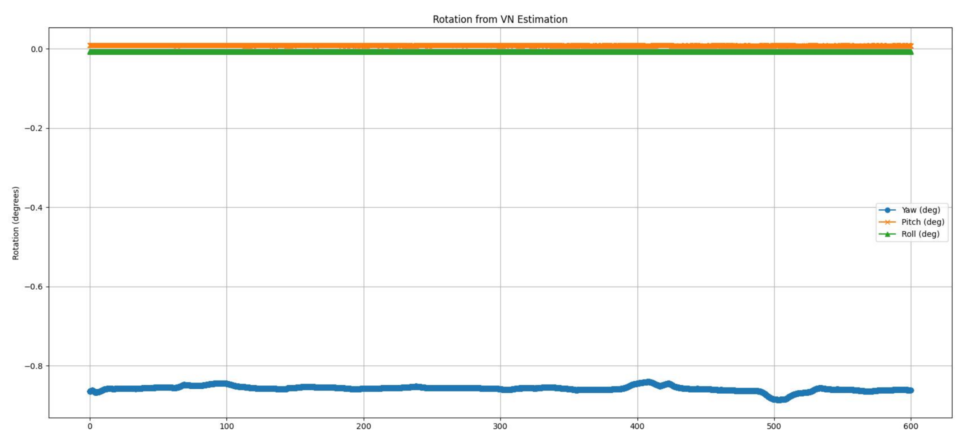


Figure 4: Histograms of Rotation

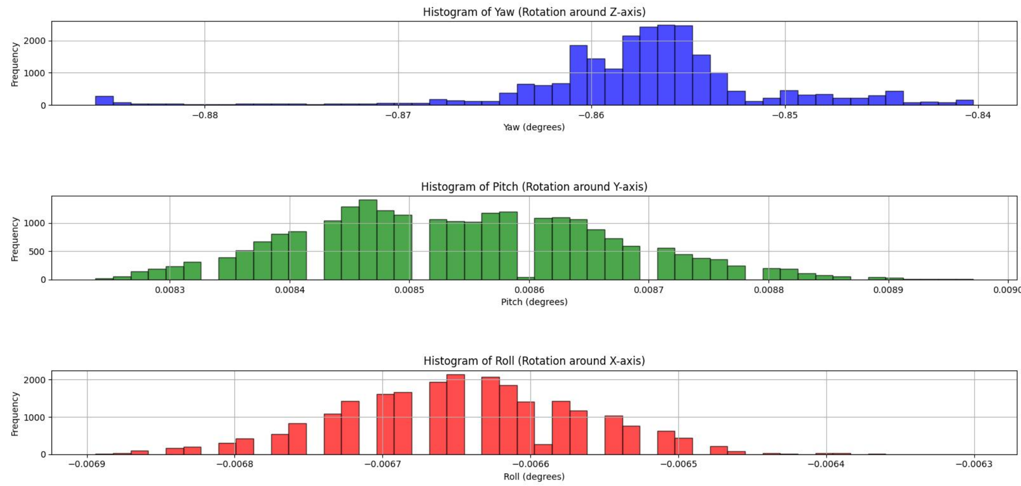


Figure 5: Allan Deviation for Gyroscope

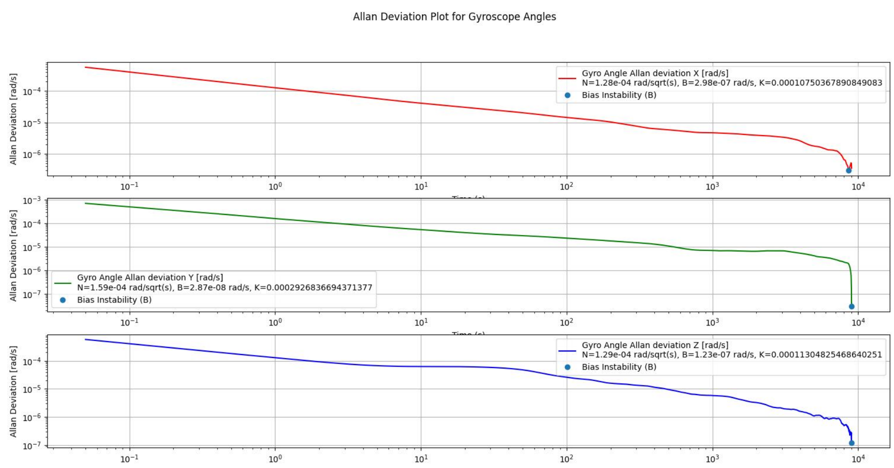
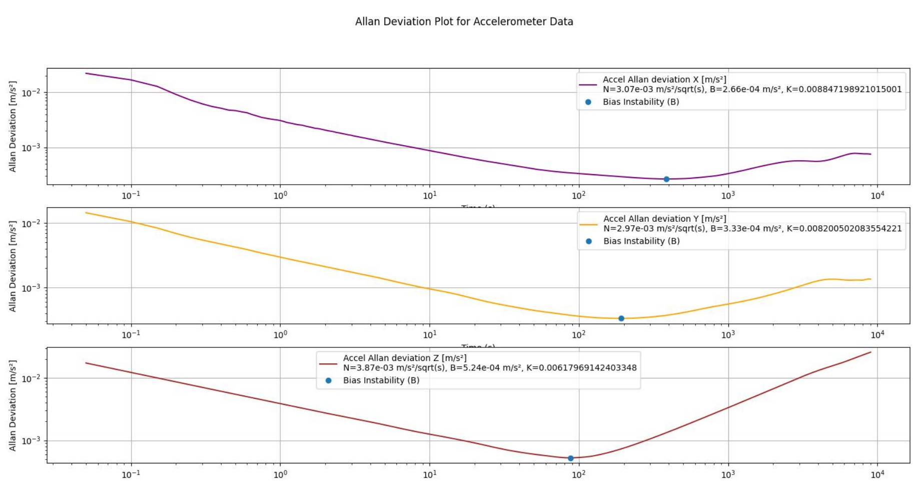


Figure 6: Allan Deviation for Accelerometer



Results and Discussion

Acceleration Analysis: The analysis of linear acceleration on the X, Y, and Z axes shows minor noise, consistent with expected behavior in a stationary environment. The Z-axis has a mean value close to -9.8 m/s^2, reflecting the effect of gravity. The X and Y axes display small values, suggesting minimal lateral or forward movement in the stationary setup.

Gyroscope Analysis: The gyroscope data from the Allan deviation plot indicates that the noise performance is consistent with expected behavior for a stationary sensor. Bias instability (B) is seen at long time intervals, with rate random walk (N) dominating at intermediate time scales. The gyroscope data along X, Y, and Z axes maintains a mean near zero with very low standard deviation, indicating that the IMU is not experiencing any noticeable rotational movement, as expected in a stationary state.

Orientation Stability: The orientation (Euler angles: Yaw, Pitch, Roll) derived from the IMU data remains stable with minimal variations. Yaw exhibits a mean of approximately -139.4 degrees, while pitch and roll are close to zero degrees. The histograms for roll, pitch, and yaw reveal a narrow distribution, indicating low variability in orientation. The relatively small range of rotation indicates that the IMU was stable and stationary, and any variations are due to inherent sensor noise.

Allan Variance Analysis

```
kamal@kamal:~/catkin_ws/src/imu/analysis$ python3 allan_analysis4.py
Gyro : Bias Instability = 2.977017256502665e-07, Angle Random Walk = 0.00012783481041848407, Rate Random Walk = 0.00010750367890849083
Gyro : Bias Instability = 2.869508834501329 6e-08, Angle Random Walk = 0.00015914391633137305, Rate Random Walk = 0.00029268366943713 77
Gyro : Bias Instability = 1.2323077941330143e-07, Angle Random Walk = 0.0001289260349395102, Rate Random Walk = 0.0001130482546864025 1
Accel : Bias Instability = 0.00026607377498935646, Angle Random Walk = 0.0030680251225869955, Rate Random Walk = 0.008847198921015001
Accel : Bias Instability = 0.0003330219340852745 4, Angle Random Walk = 0.0029654223861106644, Rate Random Walk = 0.008200502083554221
Accel : Bias Instability = 0.0005236636477898642, Angle Random Walk = 0.003869154041774962, Rate Random Walk = 0.006179691424 03348
```

Accelerometer Allan Variance: The Allan variance plots for the accelerometer data along the X, Y, and Z axes help identify key parameters such as rate random walk (K), angle random walk (N), and bias stability (B) for each axis (X, Y, and Z). The accelerometer shows reliable stability on all axes, with minor gravitational influence on the Z-axis, suitable for applications needing stable measurements.
- X-Axis: Low noise ($N=3.07\times10^{-3}$) and low drift ($B=2.66\times10^{-4}$, $K=0.0088$), suitable for stable short-term measurements.
- Y-Axis: Similar to X-axis with consistent noise and drift levels ($N=2.97\times10^{-3}$, $B=3.33\times10^{-4}$, $K=0.0082$).
- Z-Axis: Slightly higher noise and drift due to gravity ($N=3.87\times10^{-3}$, $B=5.24\times10^{-4}$, $K=0.0061$) but still stable overall.

Gyroscope Allan Variance: The Allan variance plots for the gyroscope data along the X, Y, and Z axes show very low noise and drift, making it ideal for precise, long-term rotational measurements.
- All Axes: Very low noise and drift (N values around 1.3×10^{-4}, B in the range of 10^{-7}), making it ideal for precise, long-term rotational measurements.

Conclusion

The IMU driver was successfully developed and validated, and data was collected and analyzed to evaluate stationary noise characteristics. The Allan deviation plots provide insights into the different types of noise present in the IMU measurements. The extracted parameters—rate random walk (K), angle random walk (N), and bias stability (B)—indicate that the IMU demonstrates high stability and low noise in a stationary environment. This information is crucial for applications involving precise inertial navigation, where understanding and compensating for noise is essential. Future work may involve integrating advanced filtering techniques, such as Kalman filters, to improve the sensor's overall accuracy.