Inertial Measurement Unit

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January 2026

Contents

1 Introduction **3**

2 Objectives **3**

3 Sensor Description **4**
3.1 Accelerometer 4
3.2 Gyroscope 5
3.3 Sensor Placement and Acquisition Conditions 5

4 Data Acquisition Protocol **6**
4.1 Activities and Recording Conditions 6
4.2 Acquisition Procedure 6
4.3 Exported Data Format and Organization 7

5 Raw Data Exploration **7**
5.1 Raw Accelerometer Signals 7
5.2 Raw Gyroscope Signals 10
5.3 Observations and Motivation for Preprocessing 13

6 Data Cleaning and Signal Preprocessing **13**
6.1 Temporal Alignment and Resampling 13
6.2 Handling Missing Values 13
6.3 Outlier Detection and Removal 13
6.4 Signal Smoothing 14
6.5 Summary of the Preprocessing Pipeline 14

7 Feature Extraction and Frequency-Domain Analysis **14**
7.1 Magnitude Computation 15
7.2 Rolling Statistics 15
7.3 Frequency-Domain Analysis Using FFT 15
7.4 Discussion 16

8 Visualization Results **17**
8.1 Raw vs. Clean Time Series (x, y, z) 17
8.2 Magnitude by Activity (raw vs. clean) 20
8.3 Activity Intensity via Rolling Standard Deviation 21
8.4 Rolling RMS vs. rolling STD (walking) 23
8.5 Feature distributions across activities: boxplots and histograms . 23
8.6 Normalized Histograms (z-score) 25
8.7 Correlation Heatmap (walking features) 26

9 Discussion and Limitations **27**
9.1 Discussion of Results 27
9.2 Limitations 28
9.3 Future Work 28

1 Introduction

Human Activity Recognition (HAR) using wearable sensors is an active research area with applications like in healthcare and fitness monitoring. In particular, Inertial Measurement Units (IMUs) embedded in smartphones provide acceleration and angular velocity signals that can be exploited to characterize human motion in a non-invasive and low-cost manner.

In this project, IMU data acquired from a smartphone were analyzed to study and compare different daily activities, namely sitting, walking, and ascending/descending stairs. The accelerometer and gyroscope signals were collected under different conditions (phone on table or in pocket), resulting in multivariate time-series data characterized by noise, sensor drift, and motion-induced variability.

The project follows a structured pipeline including data acquisition, raw data exploration, data cleaning, preprocessing and feature extraction, and visualization-based analysis, with the goal of understanding how different activities manifest in both the time and frequency domains.

2 Objectives

The main objectives of this project are:

1. Understand the characteristics of raw IMU signals
    - Explore accelerometer and gyroscope data in the time domain
    - Identify noise, outliers, and differences across activities and sensor modalities
2. Apply appropriate data cleaning and preprocessing techniques
    - Handle missing values and ensure temporal consistency
    - Reduce noise using filtering and interpolation
    - Obtain clean signals suitable for feature extraction and analysis
3. Extract meaningful time-domain features from IMU signals
    - Compute acceleration and angular velocity magnitudes
    - Derive rolling statistics (mean, standard deviation, RMS) to summarize local motion behavior
    - Use rolling windows to capture short-term dynamics relevant to activity recognition
4. Analyze and visualize feature distributions across activities
    - Compare activities using boxplots and histograms of rolling features
    - Address scale differences between activities through normalization when necessary

- Assess feature separability and variability across motion types

5. Investigate frequency-domain characteristics of walking activity
   - Apply Fast Fourier Transform (FFT) to accelerometer and gyroscope magnitude signals
   - Identify dominant frequency components associated with periodic walking patterns
   - Interpret frequency peaks in relation to step cadence and motion dynamics

6. Study relationships between extracted features
   - Compute correlation matrices for clean features
   - Visualize correlations using heatmaps to identify redundant or strongly related features

   Overall, the project aims to provide a comprehensive exploratory analysis of IMU data, highlighting how different activities influence sensor signals and derived features, and laying a solid foundation for future extensions such as activity classification or real-time motion analysis.

3 Sensor Description

The data analyzed in this project were acquired using the inertial sensors embedded in a modern smartphone, namely a triaxial accelerometer and a triaxial gyroscope, collectively referred to as an Inertial Measurement Unit (IMU). These sensors provide complementary information about linear and rotational motion and are widely used in Human Activity Recognition (HAR) applications.

Data acquisition was performed using a dedicated smartphone sensor logging application, configured to record inertial measurements (linear acceleration with gravity compensation and angular velocity) at a sampling frequency of 50 Hz. This sampling rate represents a common trade-off between temporal resolution and power consumption and is sufficient to capture the dynamics of daily human activities such as walking and stair climbing.

3.1 Accelerometer

The accelerometer measures linear acceleration along three orthogonal axes (x, y, z), expressed in meters per second squared (m/s^2). In the collected dataset, the accelerometer signal represents gravity-compensated (linear) acceleration, as the gravitational component is removed by the operating system prior to data logging.

In practice, small residual offsets may still be present due to imperfect gravity compensation and sensor bias. This effect is particularly noticeable in static conditions, such as sitting, where the signal fluctuates close to zero but may show a small non-zero mean, especially along the vertical axis.

In this study, accelerometer data capture:

- Static conditions, such as sitting, characterized by very low variability and residual sensor noise.
- Dynamic movements, such as walking and stair ascent/descent, characterized by periodic patterns and higher variability.
- Motion-induced effects related to device placement and orientation (e.g., phone on a table versus phone in a pocket).

To obtain an orientation-independent representation of motion intensity, the acceleration magnitude is computed as the Euclidean norm of the three acceleration components.

3.2 Gyroscope

The gyroscope measures angular velocity around three orthogonal axes (x, y, z), typically expressed in radians per second (rad/s). Unlike the accelerometer, the gyroscope is not directly influenced by gravity and primarily captures rotational motion of the device.

Gyroscope signals are particularly informative for:

- Capturing rotational dynamics during walking and stair negotiation.
- Distinguishing activities with similar linear acceleration but different rotational behavior.
- Complementing accelerometer measurements in activity characterization.

As for the accelerometer, a gyroscope magnitude is computed to summarize overall rotational activity independently of device orientation.

3.3 Sensor Placement and Acquisition Conditions

Data were collected under different placement conditions depending on the activity:

- **Sitting**: the smartphone was placed on a table, resulting in minimal movement and low signal variability.
- **Walking and stairs** the smartphone was carried in a pocket, introducing additional variability due to body motion and loose coupling between the device and the body.

These acquisition conditions reflect realistic usage scenarios and lead to IMU signals affected by noise, sensor drift, and motion artifacts, providing a representative dataset for exploratory analysis and feature extraction.

4 Data Acquisition Protocol

IMU data were collected using a smartphone running the Sensor Logger application. The app was configured to record triaxial accelerometer and triaxial gyroscope signals at a nominal sampling rate of 50 Hz. Although 50 Hz was set in the app, the effective sampling rate can slightly vary depending on the specific device, operating system scheduling, and sensor driver behavior; therefore, minor timing irregularities were expected and later handled during preprocessing.

4.1 Activities and Recording Conditions

Three daily activities were acquired:

- **Sitting (phone on table)**: the smartphone was placed on a stable table surface to minimize motion and isolate baseline sensor noise/drift.
- **Walking (phone in pocket)**: the smartphone was carried in a pocket to capture realistic body-induced motion and natural variability due to loose coupling and orientation changes.
- **Stairs (phone in pocket)**: the smartphone was carried in a pocket while walking on stairs, introducing periodic motion patterns and higher intensity changes compared to sitting.

Each trial was recorded continuously for a short session (on the order of minutes), aiming to capture representative segments of the activity rather than perfectly controlled laboratory conditions.

4.2 Acquisition Procedure

For each activity, the acquisition followed the same steps:

1. **Setup**: select the required sensors in Sensor Logger (accelerometer and gyroscope) and set the nominal sampling rate to 50 Hz.
2. **Start recording**: begin recording while the phone is already in the target placement (table or pocket).
3. **Perform activity**: maintain the target activity for the whole recording, without intentionally synchronizing steps or enforcing strict cadence.
4. **Stop recording and export**: stop the session and export the data as CSV files.

4.3 Exported Data Format and Organization

The exported CSV files contain timestamped samples with three axes (x, y, z) for each sensor. Files were organized by activity and sensor modality (accelerometer/gyroscope), and then used as input for subsequent stages (raw exploration, cleaning, and visualization). This organization allows direct comparison across activities and between raw and cleaned signals.

5 Raw Data Exploration

Before applying any cleaning or preprocessing steps, an exploratory analysis of the raw IMU signals was conducted in order to understand their structure, variability, and potential issues such as noise, outliers, and artifacts. This step is essential to motivate the subsequent preprocessing choices and to gain an initial qualitative understanding of how different activities manifest in the sensor signals.

The raw data consist of triaxial accelerometer and gyroscope measurements recorded during three activities: sitting, walking, and ascending/descending stairs.

5.1 Raw Accelerometer Signals

Figure 1 shows the raw accelerometer signals along the three axes (x, y, z) during the sitting activity. As expected, the signal exhibits very low variability, with values fluctuating close to zero. The z-axis presents a small offset compared to the other axes, likely due to imperfect gravity compensation and sensor bias. A brief high-amplitude spike is also visible, corresponding to a transient movement or handling of the device at the beginning of the recording.

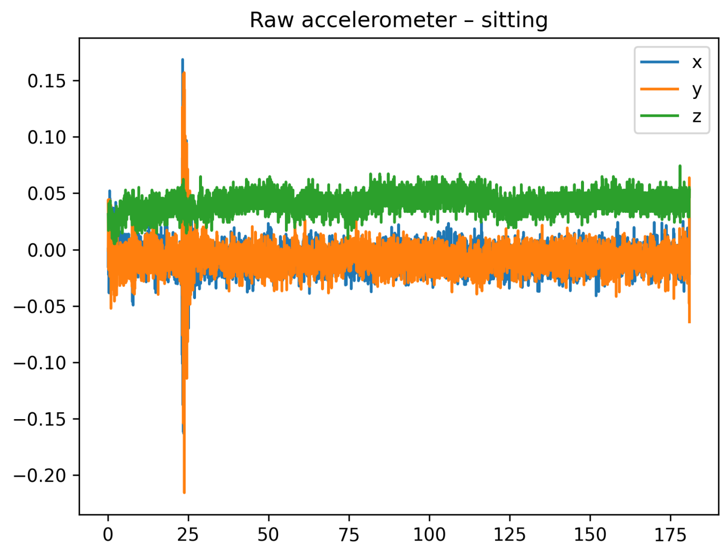

Figure 1: Raw accelerometer signals along the three axes during sitting.

To better characterize dynamic activities, the acceleration magnitude was computed for walking and stairs. Figure 2 shows the acceleration magnitude during stair negotiation, where frequent high-amplitude peaks reflect impacts and stronger body movements. The signal is highly variable and non-stationary, reflecting the increased physical effort and the more complex motion dynamics associated with stair ascent and descent, which combine vertical displacement and repeated movement cycles.

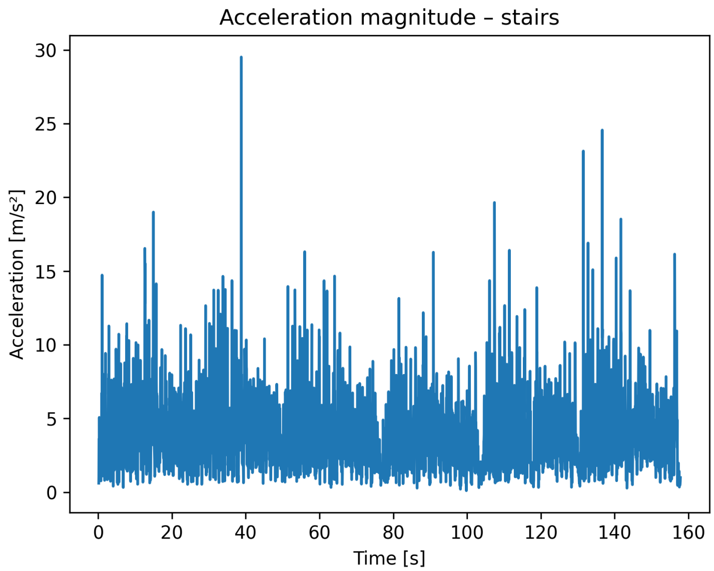

Figure 2: Acceleration magnitude during stairs activity.

Figure 3 shows the acceleration magnitude during walking. Compared to stairs, the signal appears more regular, with almost periodic peaks corresponding to steps. Occasional high-amplitude spikes are still present and may be attributed to abrupt movements or sensor artifacts.

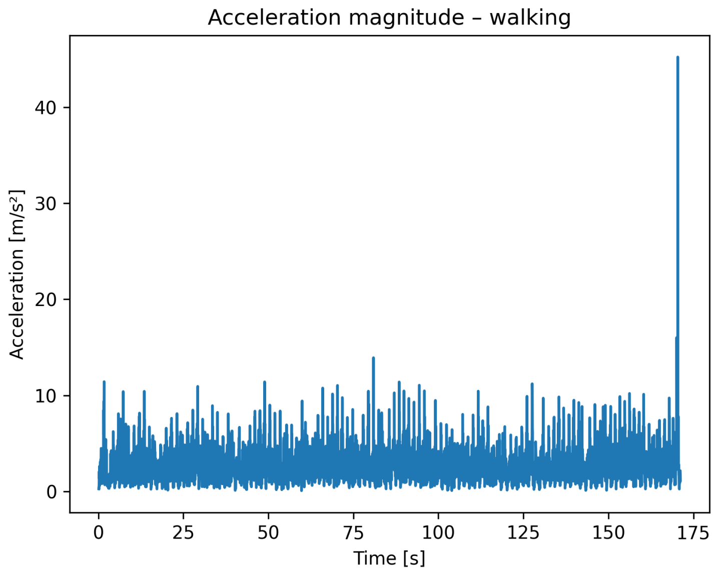

Figure 3: Acceleration magnitude during walking activity.

5.2 Raw Gyroscope Signals

The gyroscope magnitude provides a compact representation of rotational motion intensity. Figure 4 shows the gyroscope magnitude during sitting. The signal remains close to zero, indicating minimal rotational movement, with small fluctuations mainly due to sensor noise.

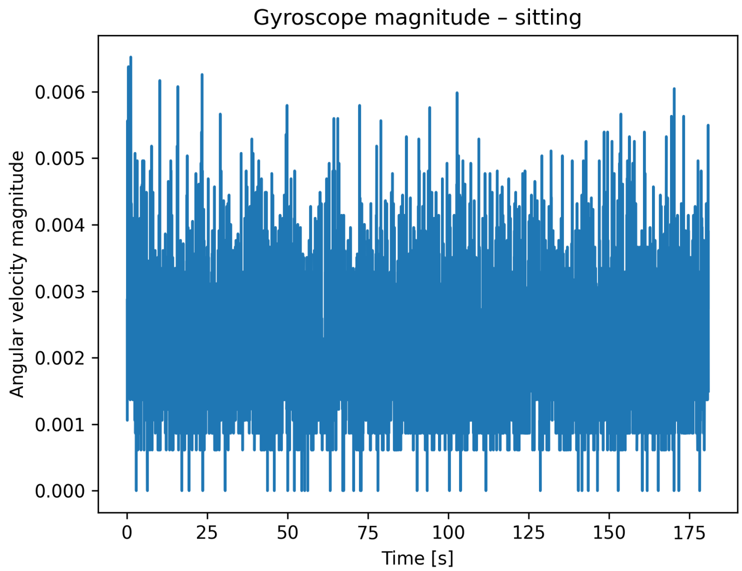

Figure 4: Gyroscope magnitude during sitting.

In contrast, Figures 5 and 6 show significantly higher variability during stairs and walking, respectively. Stair activity produces larger peaks and more complex fluctuations, reflecting frequent orientation changes and repeated ascent/descent cycles. Walking exhibits a more structured pattern, with repeated oscillations associated with the gait cycle.

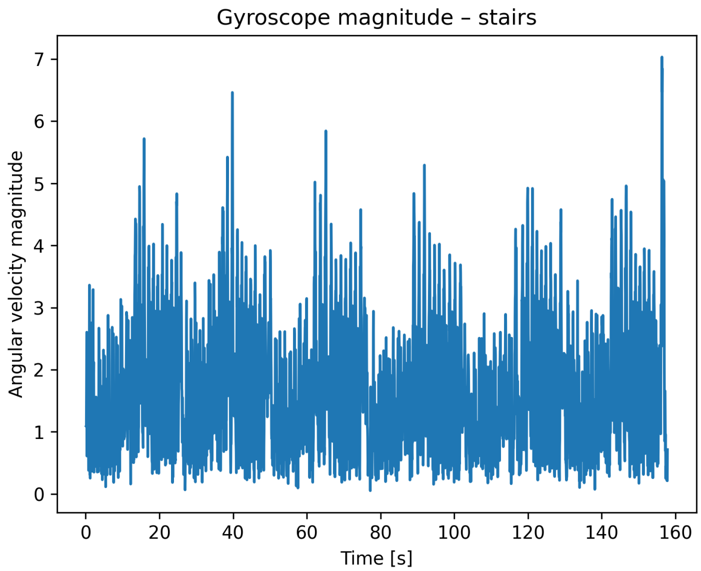

Figure 5: Gyroscope magnitude during stairs activity.

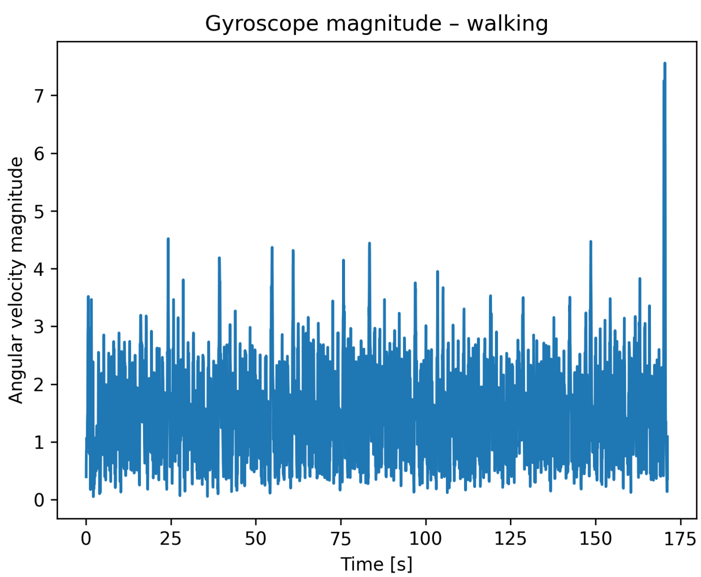

Figure 6: Gyroscope magnitude during walking activity.

5.3 Observations and Motivation for Preprocessing

The raw data exploration highlights clear differences between static and dynamic activities, as well as between walking and stair negotiation. At the same time, several issues emerge, including noise, transient spikes, and slight offsets in the signals. These observations motivate the preprocessing steps described in the next section, which aim to improve signal quality, ensure temporal consistency, and prepare the data for robust feature extraction and analysis.

6 Data Cleaning and Signal Preprocessing

Raw IMU signals acquired from smartphone sensors are inherently affected by noise, timing irregularities, and occasional artifacts due to sensor limitations and operating system scheduling. To ensure data quality and suitability for subsequent feature extraction, a structured cleaning and preprocessing pipeline was applied to all accelerometer and gyroscope recordings.

6.1 Temporal Alignment and Resampling

Although data acquisition was configured at a nominal sampling frequency of 50 Hz, the effective sampling rate exhibited small irregularities due to asynchronous sensor acquisition and operating system scheduling. In particular, individual sensor axes may be sampled at slightly different times, resulting in missing values when aligning measurements to a common timeline.

To enforce temporal consistency, all signals were resampled to a uniform sampling frequency of 30 Hz, representing a trade-off between temporal resolution and robustness to missing samples. Resampling was performed using a fixed time grid, which introduced missing values when no sensor measurement was available within a given resampling interval.

6.2 Handling Missing Values

Missing values introduced during resampling were handled using time-based interpolation. Interpolation was restricted to short temporal gaps (up to three consecutive samples, corresponding to approximately 100 ms) to preserve signal continuity while avoiding unrealistic reconstruction of long missing segments.

After this step, the missing values were removed.

6.3 Outlier Detection and Removal

IMU signals may contain impulsive spikes caused by sensor glitches, sudden impacts, or numerical errors. To mitigate the influence of such artifacts, outliers were detected independently for each sensor axis using the interquartile range (IQR) method.

Samples falling outside a predefined IQR-based threshold were considered outliers and replaced with NaN values. Following outlier removal, time-based interpolation was applied again, limited to short temporal gaps only. This two-step procedure (outlier detection followed by constrained interpolation) effectively reduces the impact of spurious values while preserving the physical plausibility of the motion signals.

Some missing values remain after this process, mainly associated with long gaps or extreme motion segments, which were deliberately not interpolated.

6.4 Signal Smoothing

Even after interpolation and outlier removal, IMU signals exhibit high-frequency noise that can negatively affect feature extraction. To address this issue, a rolling median filter was applied independently to each accelerometer and gyroscope axis.

A window size of five samples was used, with the window centered on the current sample. For each time instant, the signal value was replaced by the median of the two preceding samples, the current sample, and the two following samples. Compared to mean-based filters, the median filter is more robust to residual outliers and impulsive noise, ensuring that isolated spikes do not distort the smoothed signal.

Rolling median smoothing effectively reduces high-frequency noise while preserving the main motion patterns across all activities and sensor modalities.

6.5 Summary of the Preprocessing Pipeline

The complete preprocessing pipeline can be summarized as follows:

- Conversion of timestamps to datetime format, followed by sorting and removal of duplicate entries.
- Resampling of all signals to a uniform sampling frequency of 30 Hz.
- Time-based interpolation to fill short gaps introduced by resampling.
- IQR-based outlier detection applied independently to each sensor axis.
- Replacement of outliers with NaNs followed by constrained interpolation.
- Rolling median smoothing with a window of five samples.

The resulting cleaned and smoothed signals provide a reliable and consistent representation of human motion and form the basis for the feature extraction procedures described in the next section.

7 Feature Extraction and Frequency-Domain Analysis

After the cleaning and preprocessing stage, a set of features was extracted from the IMU signals in order to characterize human motion in both the time and frequency domains. Feature extraction aims to transform raw and cleaned time-series data into more compact and informative representations that highlight patterns relevant to activity analysis.

This section focuses on magnitude-based features and frequency-domain characteristics, with particular attention to the walking activity, which exhibits a pronounced periodic structure.

7.1 Magnitude Computation

To obtain an orientation-independent representation of motion intensity, both accelerometer and gyroscope magnitude signals were computed. For each time sample, the magnitude was calculated as the Euclidean norm of the three sensor axes:

$$|\mathbf{a}| = \sqrt{a_x^2 + a_y^2 + a_z^2}, \qquad |\boldsymbol{\omega}| = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2}$$

where a_x, a_y, a_z denote the accelerometer components and $\omega_x, \omega_y, \omega_z$ the gyroscope components.

Magnitude signals provide a compact summary of overall linear and rotational activity, reducing sensitivity to device orientation and axis-specific noise.

7.2 Rolling Statistics

To capture short-term dynamics and local variations in motion intensity, rolling statistics were computed on the magnitude signals using sliding windows. In particular, rolling mean, standard deviation, and root mean square (RMS) were calculated over fixed-length windows.

These time-domain features summarize the local behavior of the signal and are commonly used in Human Activity Recognition tasks to distinguish between activities with different intensity and regularity patterns. In addition, the use of rolling statistics preserves temporal variability that would be lost when computing global features, enabling a more detailed characterization of non-stationary motion patterns and supporting subsequent feature aggregation and analysis.

7.3 Frequency-Domain Analysis Using FFT

Walking is characterized by quasi-periodic motion patterns associated with the gait cycle. To investigate these periodic components, a frequency-domain analysis was performed using the Fast Fourier Transform (FFT) applied to the magnitude signals.

FFT analysis was restricted to the walking activity, as static activities such as sitting do not exhibit meaningful periodic behavior, while stair negotiation shows more irregular dynamics.

Figure 7 shows the amplitude spectrum of the accelerometer magnitude during walking. A clear dominant frequency component is observed at approximately 0.65 Hz, corresponding to the fundamental periodicity of the walking motion. Additional smaller peaks at higher frequencies represent harmonics and secondary motion components.

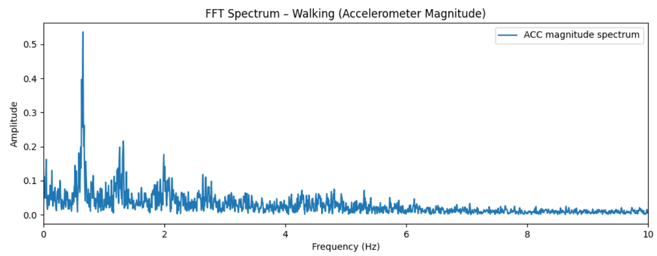

Figure 7: FFT spectrum of the accelerometer magnitude during walking.

Figure 8 reports the FFT spectrum of the gyroscope magnitude for the same activity. In this case, the dominant frequency is located around 1.33 Hz, indicating a stronger contribution of rotational motion at higher frequencies compared to linear acceleration. This difference reflects the distinct nature of rotational dynamics during walking, such as leg swing and torso rotation.

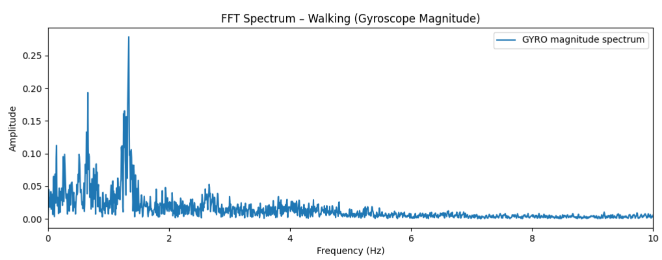

Figure 8: FFT spectrum of the gyroscope magnitude during walking.

7.4 Discussion

The dominant frequency observed in the accelerometer magnitude spectrum (approximately 0.65 Hz) corresponds to about 39 steps per minute, which is consistent with a slow to moderate walking pace. This result provides a direct physical interpretation of the frequency-domain analysis in terms of gait cadence.

The gyroscope magnitude exhibits a dominant frequency at approximately 1.33 Hz, which is close to twice the accelerometer dominant frequency. This behavior can be explained by the fact that rotational motion often presents two characteristic events per gait cycle, such as leg swing and foot contact, leading to a stronger harmonic component in the angular velocity signal.

These observations further confirm the complementary role of accelerometer and gyroscope measurements and highlight the ability of frequency-domain features to capture meaningful biomechanical aspects of human walking.

8 Visualization Results

This section reports the main visualization outcomes obtained from the cleaned IMU signals and from the derived magnitude-based features. The purpose is twofold: (i) verify that the preprocessing pipeline preserves meaningful motion patterns while reducing artifacts, and (ii) compare sitting, walking, and stairs in terms of intensity, regularity, and feature separability.

8.1 Raw vs. Clean Time Series (x, y, z)

Figures 9–14 compare raw and cleaned triaxial signals for accelerometer and gyroscope. In the sitting condition, signals are mostly stationary and dominated by small-amplitude noise, with occasional impulsive artifacts (e.g., brief spikes due to handling). In walking and stairs, the cleaning procedure attenuates high-frequency jitter and impulsive outliers while preserving the overall oscillatory structure of the motion, which is essential for subsequent feature extraction.

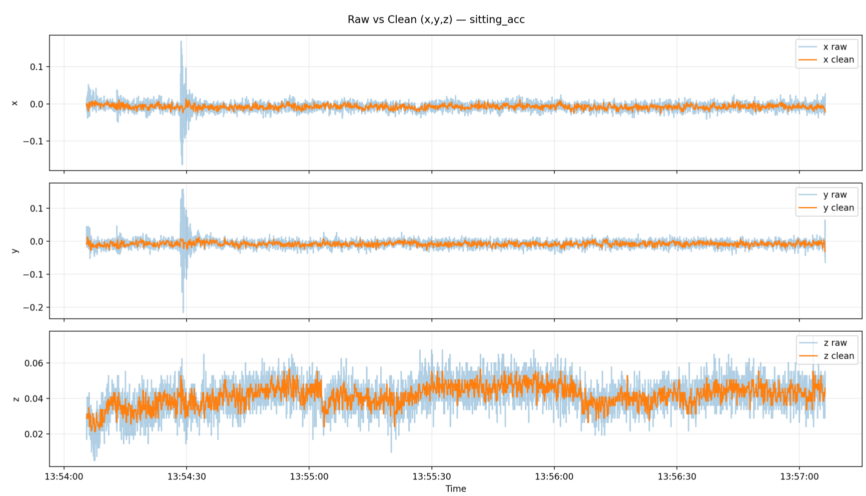

Figure 9: Raw vs. clean accelerometer signals (x, y, z) during sitting.

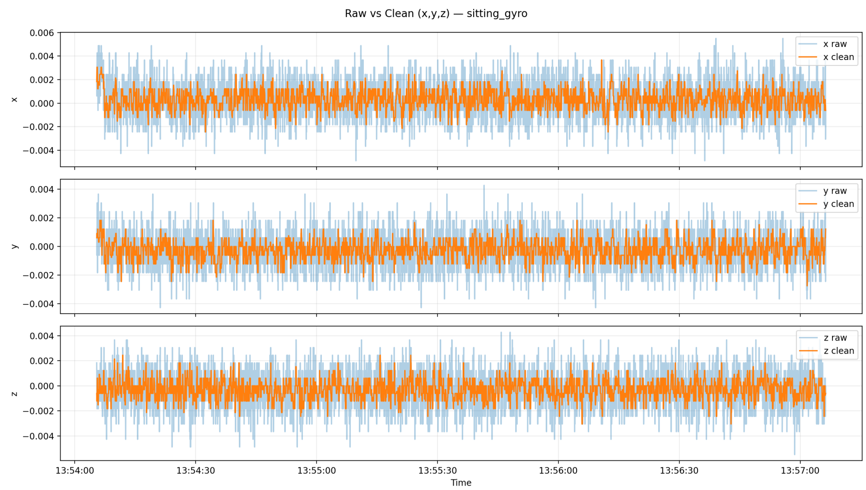

Figure 10: Raw vs. clean gyroscope signals (x, y, z) during sitting.

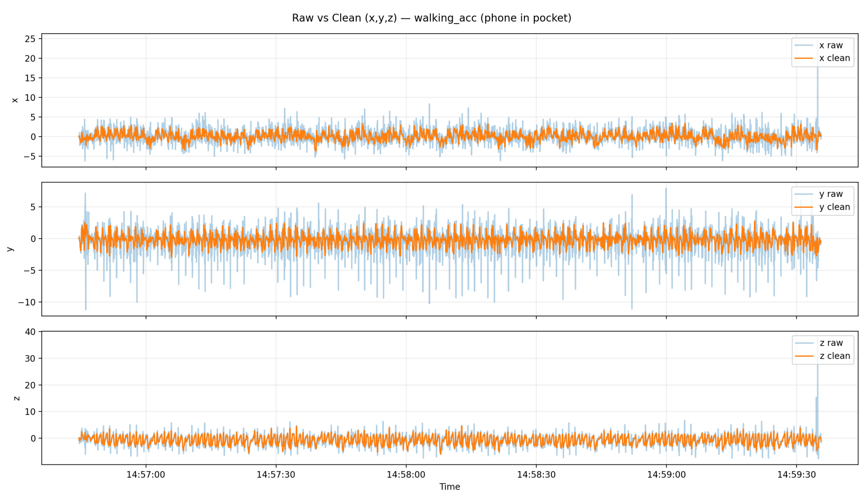

Figure 11: Raw vs. clean accelerometer signals (x, y, z) during walking (phone in pocket).

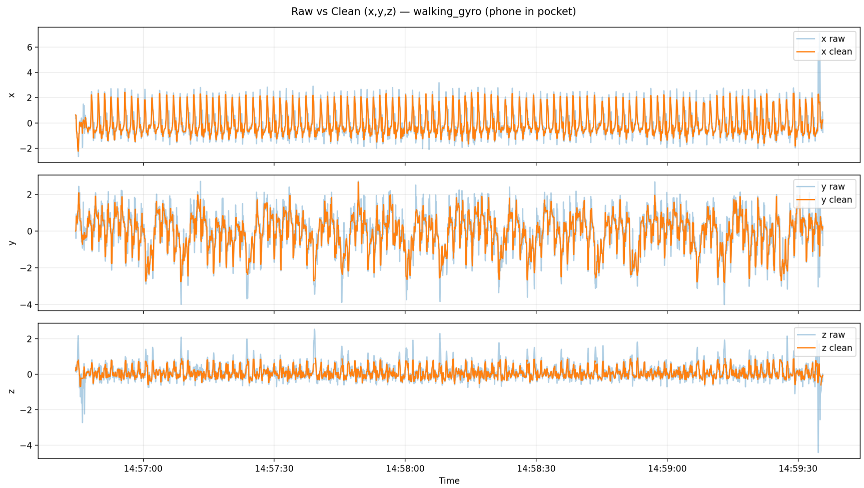

Figure 12: Raw vs. clean gyroscope signals (x, y, z) during walking (phone in pocket).

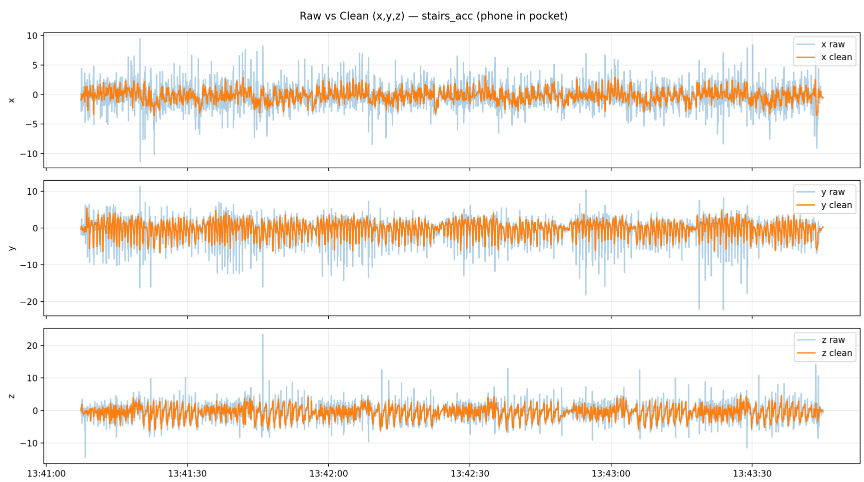

Figure 13: Raw vs. clean accelerometer signals (x, y, z) during stairs (phone in pocket).

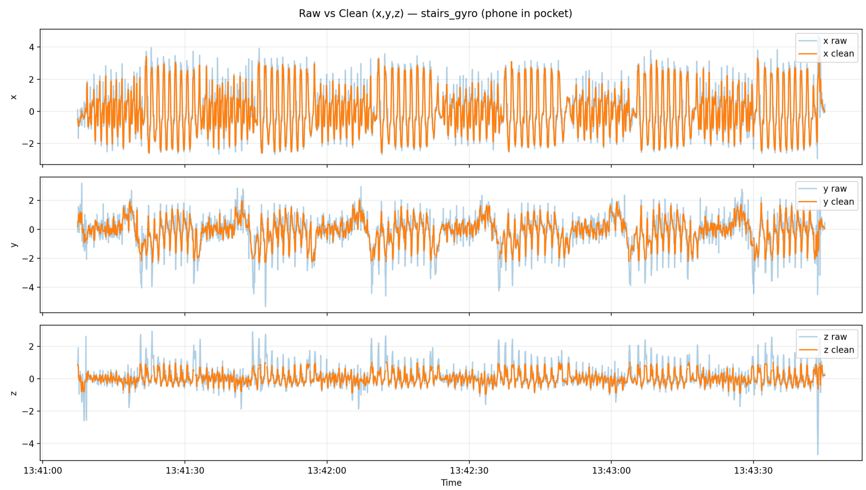

Figure 14: Raw vs. clean gyroscope signals (x, y, z) during stairs (phone in pocket).

8.2 Magnitude by Activity (raw vs. clean)

To reduce the dependence on device orientation and to enable a compact comparison across activities, magnitude signals were computed for both sensors. Figures 15 and 16 show that sitting exhibits minimal motion intensity, while walking is characterized by more regular oscillations and stairs by a more irregular profile with larger peaks and variability. Across all activities, the clean magnitude preserves the overall dynamics while reducing spurious spikes.

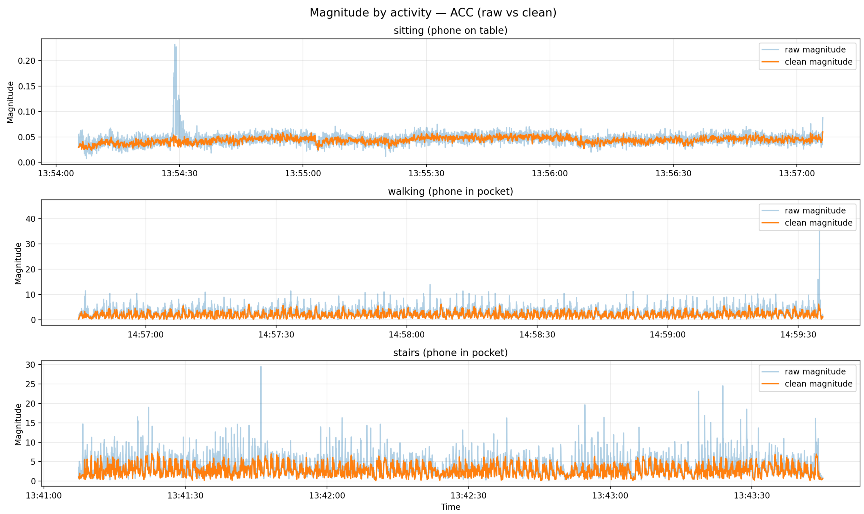

Figure 15: Accelerometer magnitude by activity (raw vs. clean).

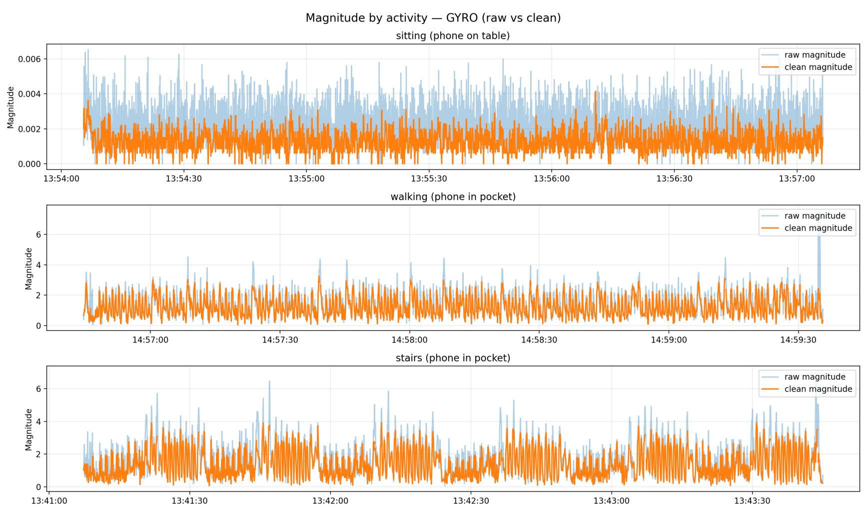

Figure 16: Gyroscope magnitude by activity (raw vs. clean).

8.3 Activity Intensity via Rolling Standard Deviation

A rolling standard deviation (STD) computed on the clean magnitude provides a simple proxy for local motion intensity. Figures 17 and 18 confirm a clear ranking: sitting produces near-zero variability, walking increases the STD with a more structured pattern, and stairs generally shows higher and more irregular fluctuations due to repeated impacts and posture changes during ascent/descent.

Although stair activity exhibits higher variability compared to walking, the observed patterns are not purely irregular. The rolling features reveal structured fluctuations associated with repeated ascent and descent cycles, as well as increased vertical motion. This indicates that stair climbing represents a more complex but still partially periodic activity rather than random motion.

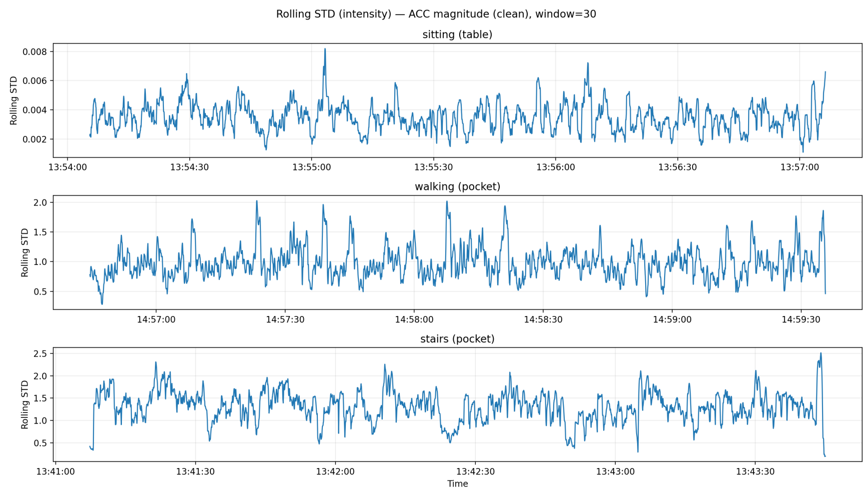

Figure 17: Rolling STD of accelerometer magnitude (clean), window = 30 samples.

Figure 18: Rolling STD of gyroscope magnitude (clean), window = 30 samples.

8.4 Rolling RMS vs. rolling STD (walking)

To compare two complementary intensity descriptors, rolling RMS and rolling STD were computed for walking. Figures 19 and 20 show that RMS captures the local energy level of the motion, while STD emphasizes local variability around the mean. As expected, the two measures follow similar trends but are not identical, since RMS is influenced by both mean level and fluctuations.

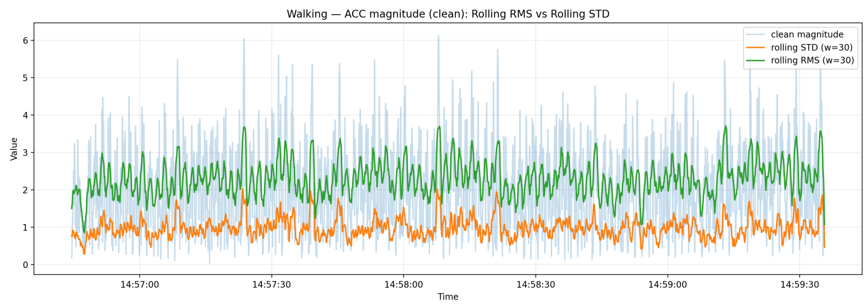

Figure 19: Walking: rolling RMS vs. rolling STD for accelerometer magnitude (clean), window = 30 samples.

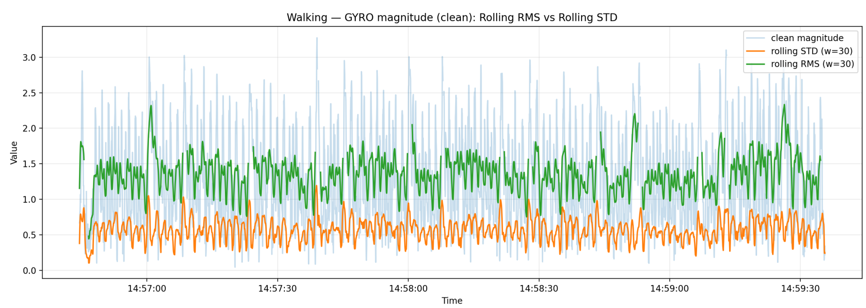

Figure 20: Walking: rolling RMS vs. rolling STD for gyroscope magnitude (clean), window = 30 samples.

8.5 Feature distributions across activities: boxplots and histograms

To evaluate how well a simple feature separates activities, the distribution of the rolling STD (magnitude) was analyzed across sitting, walking, and stairs. Figures 21–24 highlight a strong separation between the static activity (sitting) and the dynamic ones. In particular, walking and stairs show much higher median values and wider spreads; stairs tends to present broader distributions and more extreme values, consistent with less regular and more complex motion patterns.

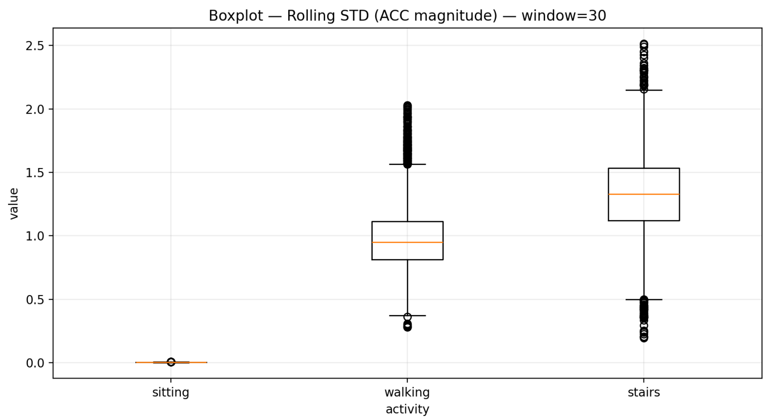

Figure 21: Boxplot of rolling STD (accelerometer magnitude), window = 30 samples.

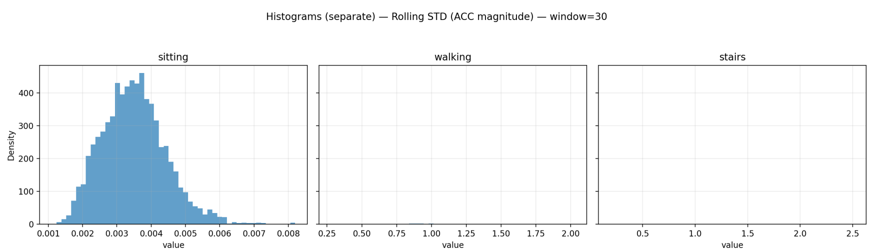

Figure 22: Separate histograms of rolling STD (accelerometer magnitude), window = 30 samples.

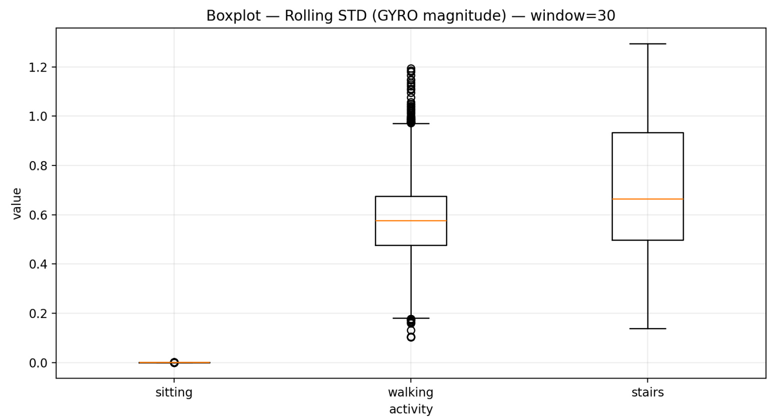

Figure 23: Boxplot of rolling STD (gyroscope magnitude), window = 30 samples.

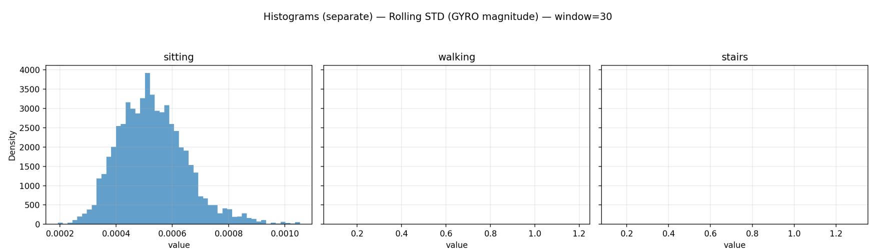

Figure 24: Separate histograms of rolling STD (gyroscope magnitude), window = 30 samples.

8.6 Normalized Histograms (z-score)

Since activities can differ greatly in absolute scale, a z-score normalization was applied to the accelerometer rolling STD before plotting the histograms. Figure 25 enables a shape-based comparison of the distributions, showing that walking and stairs still exhibit broader and more dispersed profiles compared to sitting. This indicates that variability-related features remain informative and discriminative even after removing mean and scale differences.

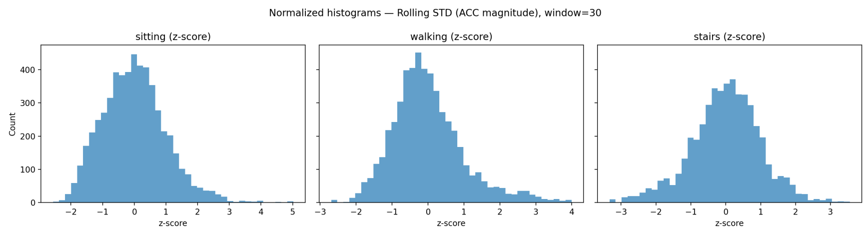

Figure 25: Z-score normalized histograms of rolling STD (accelerometer magnitude), window = 30 samples.

8.7 Correlation Heatmap (walking features)

Finally, correlations among magnitude-based features were analyzed for walking. Figure 26 reveals strong relationships between rolling mean, RMS, and magnitude-related quantities, which is expected because they are all influenced by overall motion intensity. This analysis is useful to identify redundant descriptors and to guide feature selection in downstream HAR tasks.

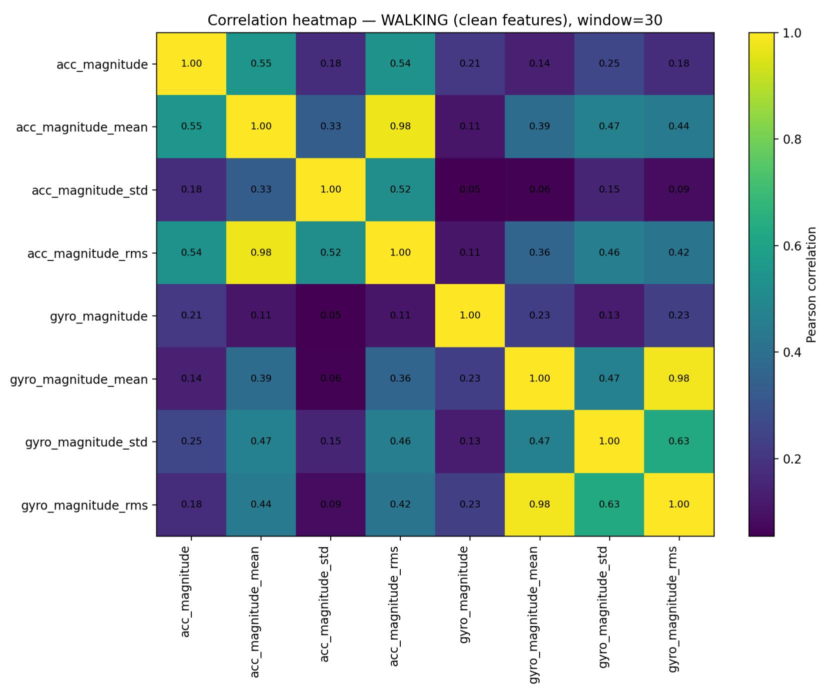

Figure 26: Correlation heatmap of walking features (Pearson), window = 30 samples.

Overall, the visual inspection confirms that preprocessing produces stable and consistent signals, and that simple magnitude-based rolling features (STD/RMS) provide clear activity-dependent patterns, enabling a qualitative discrimination between static (sitting) and dynamic (walking, stairs) behaviors.

9 Discussion and Limitations

This project investigated inertial data acquired from a smartphone-based IMU to analyze and characterize different human activities, namely sitting, walking, and stair ascent/descent. Through a structured pipeline including raw data exploration, preprocessing, feature extraction, and visualization, several meaningful patterns emerged that are consistent with both the physical nature of the activities and existing literature on Human Activity Recognition (HAR).

9.1 Discussion of Results

The raw data exploration highlighted clear differences between static and dynamic activities. Sitting was characterized by low-amplitude signals with minimal variability, reflecting the absence of intentional movement and the dominance of sensor noise. In contrast, walking and stair negotiation exhibited pronounced oscillatory patterns and higher signal amplitudes, consistent with periodic locomotion.

In particular, stair ascent and descent showed signals with higher variability and more complex dynamics compared to walking. While the motion is still structured and periodic, the combination of vertical displacement, impacts, and repeated movement cycles results in larger peaks and increased non-stationarity. These characteristics were consistently observed across accelerometer and gyroscope signals, as well as in magnitude-based representations.

The preprocessing pipeline proved effective in improving signal quality. Resampling to a uniform sampling rate enabled consistent time-based analysis, while interpolation and IQR-based outlier handling reduced artifacts without introducing unrealistic signal behavior. Rolling median smoothing further attenuated high-frequency noise, as confirmed by the reduction in signal standard deviation across all activities.

Feature extraction steps successfully summarized both time-domain and frequency-domain characteristics of the signals. Rolling statistics captured local motion intensity and variability, which clearly differentiated sitting from dynamic activities. Frequency-domain analysis via FFT revealed dominant frequencies associated with locomotion, with the accelerometer magnitude exhibiting a dominant frequency around 0.65 Hz during walking, corresponding to a typical step cadence. The gyroscope magnitude showed a dominant frequency approximately twice as large, reflecting multiple rotational events occurring within a single gait cycle.

Visualization results further supported these findings. Magnitude plots, rolling statistics, boxplots, histograms, and correlation heatmaps consistently showed activity-dependent patterns. Even after z-score normalization, feature distributions remained distinguishable, indicating that variability-related features retain discriminative power independently of absolute scale.

Overall, the results demonstrate that relatively simple preprocessing and feature extraction techniques applied to smartphone IMU data are sufficient to capture meaningful characteristics of common daily activities.

9.2 Limitations

Despite the encouraging results, several limitations should be acknowledged. First, the dataset was collected from a single device and from a single subject, which limits the generalizability of the findings. Human motion patterns can vary significantly across individuals due to differences in body morphology, walking style, and physical condition.

Second, the smartphone placement was not strictly controlled across activities. While this reflects realistic usage scenarios, it introduces additional variability related to device orientation and coupling with the body, which may affect signal consistency and feature robustness.

Third, the analysis focused on a limited set of handcrafted features and did not include classification or model-based evaluation. As a result, conclusions are primarily qualitative and exploratory, rather than quantitatively assessed in terms of recognition accuracy.

Finally, frequency-domain analysis was performed on relatively short and activity-specific segments, which may limit frequency resolution and stability of spectral estimates, especially for non-stationary signals such as stair negotiation.

9.3 Future Work

Future extensions of this work could address these limitations by including data from multiple subjects and devices, exploring additional sensor fusion strategies, and evaluating classification performance using machine learning models. More advanced time-frequency representations and adaptive windowing techniques could also be investigated to better capture non-stationary motion patterns.

Nevertheless, this project provides a solid exploratory foundation and demonstrates the effectiveness of systematic preprocessing and feature analysis for smartphone-based IMU data in Human Activity Recognition tasks.