Calisthenics Activity Analysis with Accelerometer Data

HAH913E : physical activity for health

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Introduction

Regular physical activity is one of the most effective ways to improve health, prevent chronic diseases, and enhance overall quality of life. However, many people exercise without feedback on the quality of their movements, which can limit progress or even increase the risk of injury. In this context, wearable sensors such as accelerometers offer an affordable and non-invasive solution to monitor physical activity and provide objective feedback on exercise performance.

The goal of this project is to design and implement a *physical activity analysis pipeline* based on accelerometer data collected during calisthenics exercises. We focus on three fundamental bodyweight movements : **pull-ups**, **dips**, and **push-ups**. These exercises are widely used in strength and conditioning programs and are particularly interesting because they involve controlled, repetitive motions that can be captured and analysed using inertial sensors.

The project aims to demonstrate the complete workflow required to move from raw sensor signals to meaningful, human-understandable feedback. More specifically, we address the following objectives :

— **Data acquisition** : record accelerometer measurements during the execution of selected calisthenics exercises ;

— **Preprocessing** : clean and filter the raw signals to remove noise and artefacts ;

— **Segmentation** : automatically detect individual repetitions within a continuous recording ;

— **Feature extraction** : compute relevant metrics describing the quality and consistency of the movements ;

— **Visualisation and feedback** : represent results in a way that can help users understand and improve their performance.

All the code, notebooks and data are available in our public GitHub repository.

The present report is organised as follows. In Section 1, we describe the analysis of accelerometer data for pull-ups and dips, including data collection, preprocessing, repetition detection, and basic performance metrics. In a later section, we will extend the methodology to push-ups. Finally, we discuss the overall results, limitations, and perspectives for future work, such as integrating more advanced machine learning models or deploying the solution as a real-time feedback tool.

1 Analysis of Dips and Pull-Ups

Upper-body pushing and pulling exercises such as dips and pull-ups produce clear oscillatory acceleration patterns that can be extracted using wearable sensors. In this section, we present a refined analysis pipeline applied to two maximal-effort sets of dips and pull-ups recorded consecutively during a three-minute session. The goal is to quantify performance (cadence, amplitude, mechanical load) and characterise fatigue by analysing how acceleration patterns evolve over time.

The accelerometer was worn on the torso to capture whole-body movement while minimising artefacts from limb motion. Because dips and pull-ups were executed within the same recording, their processing remains consistent and directly comparable.

1.1 Data Collection and Exercise Segmentation

The raw accelerometer data were exported from OmGui in CSV format and contained timestamps and tri-axial acceleration (`Ax`, `Ay`, `Az`). Timestamps were converted to relative time in seconds from the first sample.
Let ts_i denote the original timestamp of sample i and ts_0 the timestamp of the first sample. A relative time axis was constructed as

$$t_i = (ts_i - ts_0)_{\text{in seconds}}, \tag{1}$$

so that $t_0 = 0$ corresponds to the start of the recording.
Consecutive time differences are then given by :

$$\Delta t_i = t_i - t_{i-1}, \tag{2}$$

which are later used to estimate the sampling frequency via :

$$f_s = \frac{1}{E[\Delta t]}, \tag{3}$$

This value remained stable throughout the recording and ensured that the temporal resolution was sufficient to capture fast upper-body movements.

Two short maximal-effort sets were extracted using their annotated times :

— **Dips :** from `19:00:00` to `19:00:55` (55 seconds).

— **Pull-ups :** from `19:02:00` to `19:02:39` (39 seconds).

Each window was isolated to form two independent datasets, guaranteeing that subsequent analyses (smoothing, repetition detection, fatigue estimation) were applied exclusively to the intended exercise segment.

1.2 Preprocessing and ENMO Computation

To obtain an orientation-insensitive magnitude of body acceleration, we computed the Euclidean Norm Minus One (ENMO) :

$$\text{ENMO} = \max\left(\sqrt{a_x^2 + a_y^2 + a_z^2} - 1,\ 0\right), \tag{4}$$

where accelerations are expressed in units of gravity (g). Negative values were truncated to zero to remove gravitational bias.
The ENMO signal was then smoothed using :

1. a median filter (width 5 samples) to suppress impulsive noise, and
2. a centred moving average over a 0.2 s window to reduce high-frequency fluctuations.

The filtered ENMO for dips and pull-ups is shown in Figures 1 and 2. Dips exhibit large, regular oscillations, whereas pull-ups produce lower-amplitude cycles due to the sensor's proximity to the rotation axis of the movement.

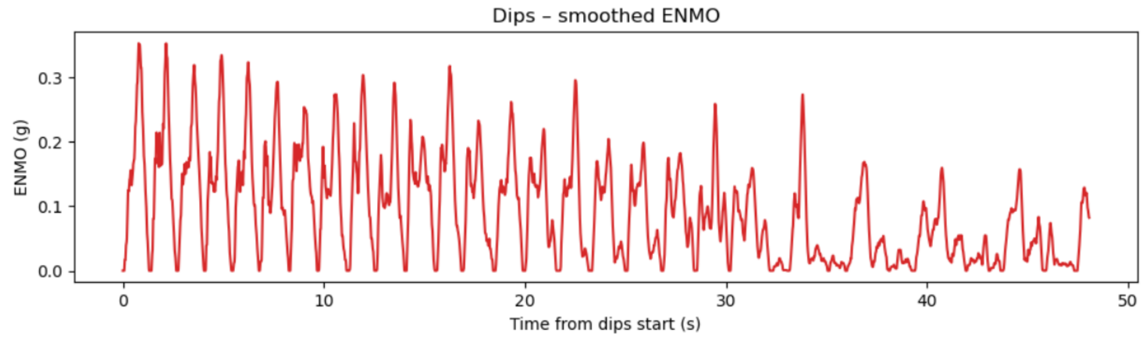

FIGURE 1 – Smoothed ENMO signal during the dip set

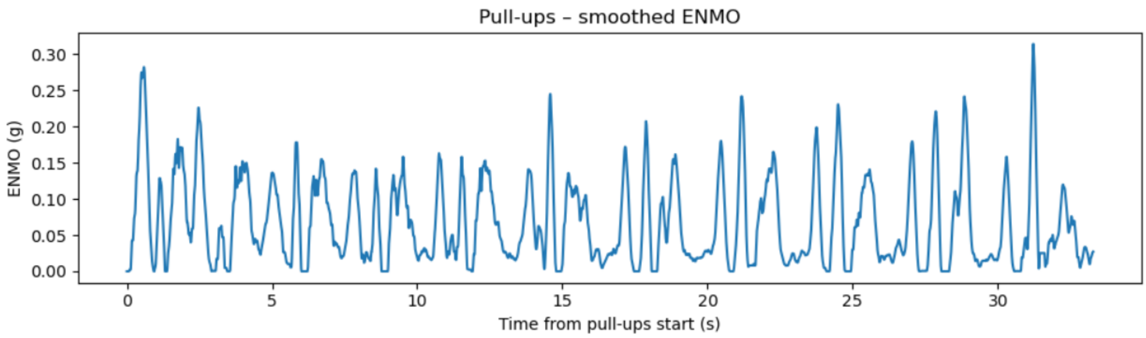

FIGURE 2 – Smoothed ENMO signal during the pull-up set

1.3 Repetition Detection

Repetitions were identified using the `find_peaks` function from `scipy`. The detection was tailored to each exercise using two parameters :

— a minimum inter-peak interval (in seconds),

— an adaptive amplitude threshold defined as a percentile of the smoothed ENMO distribution.

For this dataset :

— **Dips :** 88th-percentile threshold and a 1.3 s minimum interval ;

— **Pull-ups :** 85th-percentile threshold and a 1.6 s interval.

Only peaks above this threshold were counted as full repetitions (red markers).
To better visualize fatigue, smaller peaks in the **last third of the set** were also detected using a lower threshold and marked as **fatigue movements** (orange crosses). These represent incomplete, low-amplitude motions that no longer qualify as proper repetitions but illustrate the loss of movement quality.

Figures 3 and 4 below display the results.

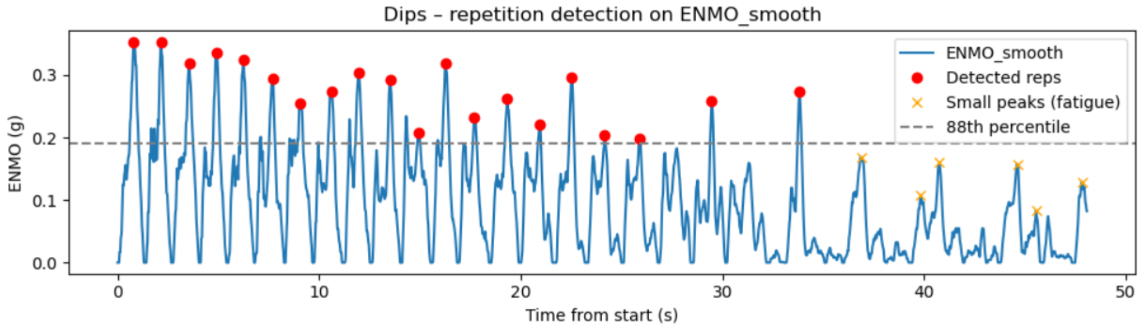

FIGURE 3 – Dip repetition detection

It should be noted that, according to this graph, 20 repetitions were identified as valid by the algorithm. Several smaller peaks, visible in the fatigued portion of the set, were not counted because their amplitude did not exceed the adaptive threshold. The actual number of repetitions performed by the practitioner was 25.

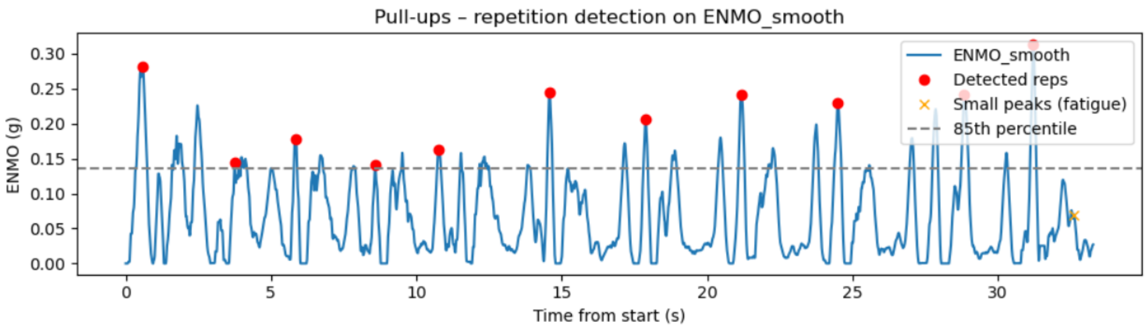

FIGURE 4 – Pull-up repetition detection

For the pull-ups exercise, the algorithm identified 11 repetitions above the detection threshold. The actual number of repetitions performed by the practitioner was 12.

1.4 Performance Metrics

From the detected repetitions, we extracted classical performance indicators :

— **total number of repetitions**,

— **repetition duration** (inter-peak interval),

— **instantaneous cadence** (repetitions/min),

— **peak ENMO amplitude**, an indicator of movement intensity.

Instantaneous cadence was computed from the inter-peak intervals using :

$$\text{Cadence}(n) = \frac{60}{t_n - t_{n-1}}, \tag{5}$$

expressed in repetitions per minute, where t_n and t_{n-1} denote the timestamps of two consecutive repetitions.

Figure 5 below illustrates how cadence evolves across successive dip repetitions for example. The first two thirds of the set show a stable cadence (≈ 40–45 reps/min), followed by a sharp drop in the final repetitions as fatigue appears, which shows a clear decline toward failure.

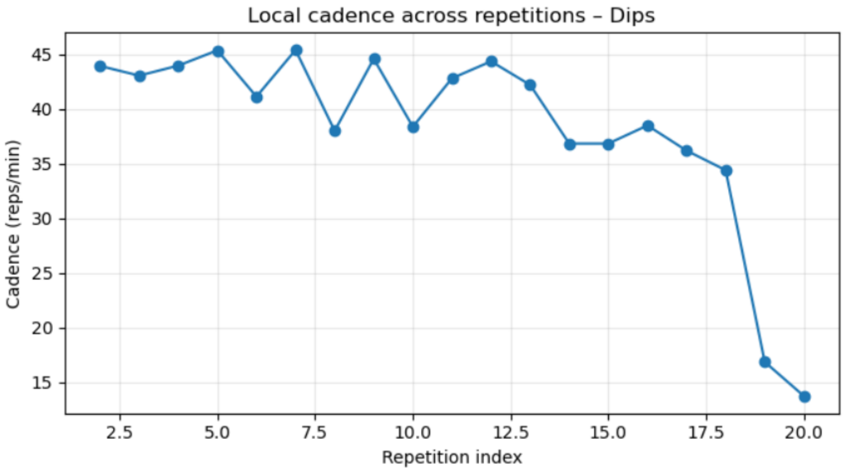

FIGURE 5 – Local cadence across dip repetitions

To further analyse fatigue, repetitions were grouped into three temporal phases : early, middle, and late. Figure 6 shows cadence and peak ENMO by phase for dips.

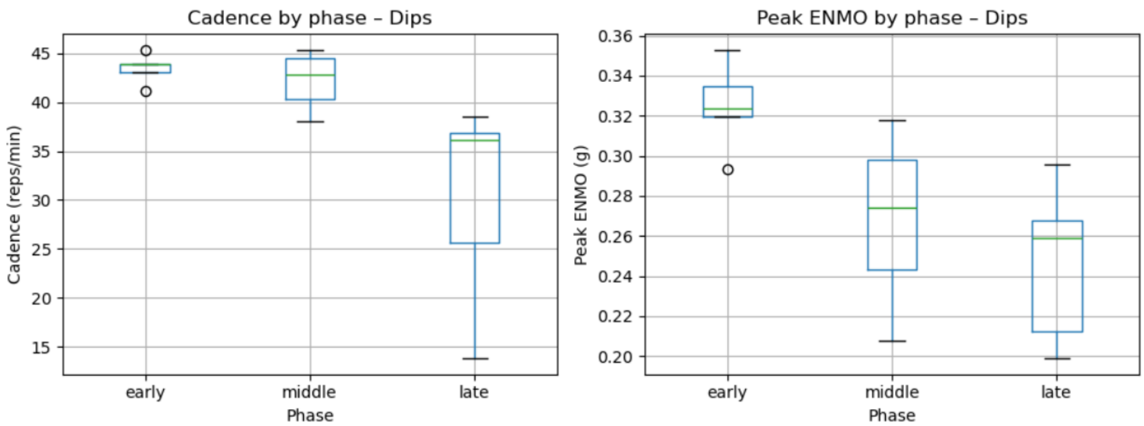

FIGURE 6 – Cadence and peak ENMO for dips across early, middle, and late phases.

Boxplots summarise the distribution of each metric by showing the median, the central 50% of the data, and possible outliers. Cadence is high and stable in the early and middle phases but drops and becomes irregular in the late phase, indicating fatigue. Peak ENMO follows the same pattern : strong, consistent movement at the beginning, then a progressive decrease in amplitude as fatigue develops. Together, the two plots clearly capture the loss of speed and power as the athlete approaches muscular failure.

1.5 Mechanical Load via Integrated ENMO

To quantify the mechanical demand of the exercises, we computed the time integral of ENMO for each repetition (in g·s). This "ENMO impulse" reflects movement intensity and duration simultaneously, providing a compact measure of repetition load.
Repetitions were then grouped into :

— **early + middle** (controlled execution),

— **late** (fatigue repetitions).

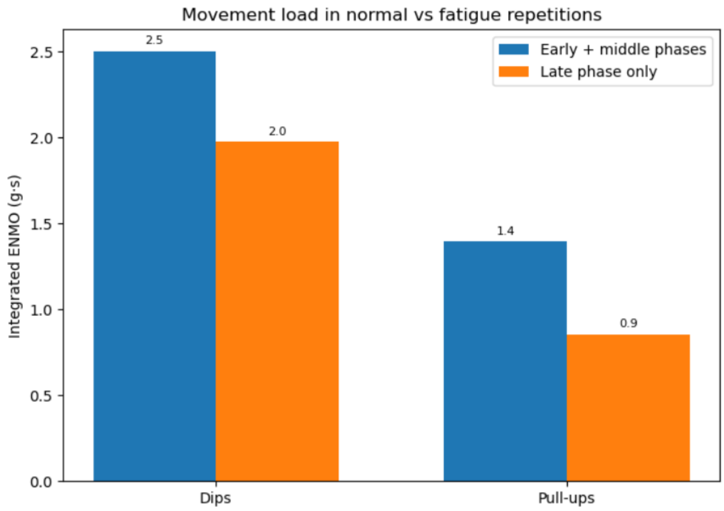

FIGURE 7 – Integrated ENMO load for early/middle vs. late repetitions

The figure 7 above summarises the total load for dips and pull-ups. Despite their lower amplitude, late-phase repetitions still contribute substantially to total load, demonstrating that a considerable portion of effort occurs under fatigue.

1.6 Discussion

This refined analysis of dips and pull-ups demonstrates how accelerometer data can capture performance and fatigue during short maximal-effort sets. Key findings include :

- A clear decrease in cadence and amplitude toward the end of each set.
- Successful detection of subthreshold end-of-set movements, characteristic of fatigue.
- Larger amplitude and higher rhythm for dips compared to pull-ups, reflecting their biomechanical characteristics.
- Integrated ENMO provides a meaningful estimate of mechanical load and highlights how much work occurs under fatigue.

Overall, this section establishes a robust processing pipeline that will be reused in the following part of the project (push-ups), ensuring consistency in data analysis and interpretation.

2 Analysis of Push-Ups

Push-ups are a fundamental calisthenics exercise involving cyclic vertical translation of the torso. Because the movement is rhythmic and primarily sagittal, the accelerometer configuration and ENMO-based analysis introduced in Section 1 are directly applicable here. In this section, we analyse a continuous push-up set performed to muscular failure, lasting approximately 90 seconds.

The sensor was positioned on a chest belt around the upper abdomen, a placement that maximises the sensitivity to the upward and downward phases of the movement. The same preprocessing pipeline as in Section 1 was used, including ENMO computation and two-step smoothing.

2.1 Data Collection and Preprocessing

The raw tri-axial accelerometer data were exported from OmGui in CSV format and loaded using `pandas`. A relative time axis (in seconds) was obtained by subtracting the initial timestamp. Although the recording lasted around three minutes, only the first 90 s contained the continuous push-up set and were retained.

The sampling frequency was estimated from the mean inter-sample interval :

$$f_s = \frac{1}{E[\Delta t]}, \quad (6)$$

which remained stable throughout the recording.

As in the previous section, ENMO was computed and smoothed through a median filter followed by a moving average. The resulting signal, shown in Figure 8, reveals a clear oscillatory structure corresponding to consecutive repetitions, with a visible decrease in amplitude toward the end of the set.

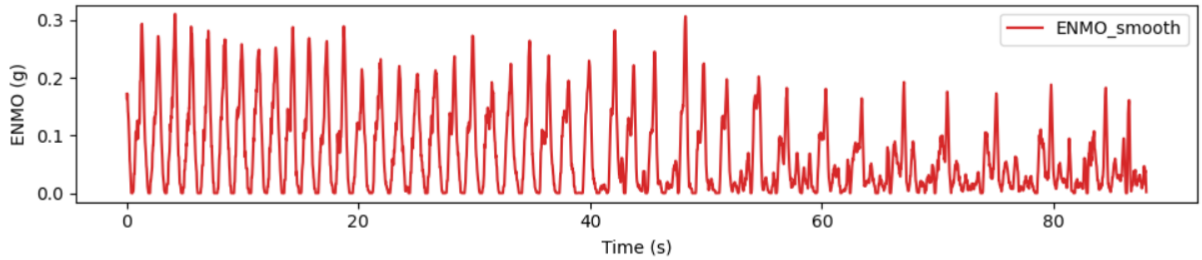

FIGURE 8 – Smoothed ENMO signal during the continuous 92-second push-up set.

2.2 Repetition Detection

Push-ups were performed as a single uninterrupted set, so repetition detection relied on identifying the peaks of `ENMO_smooth`.
Peak detection was carried out using `scipy.signal.find_peaks` with two exercise-specific constraints :

- a minimum peak-to-peak interval of about 1.0 s, corresponding to a typical push-up tempo ;
- an amplitude threshold defined adaptively as the 85th percentile of the ENMO values.

This adaptive strategy ensures that only true repetitions are detected, while smaller sub-threshold oscillations emerging under fatigue are not counted as full repetitions.
Figure 9 shows the smoothed ENMO signal with detected repetition peaks superimposed. The alignment between red markers and the maximal points of the movement confirms the reliability of the detection.

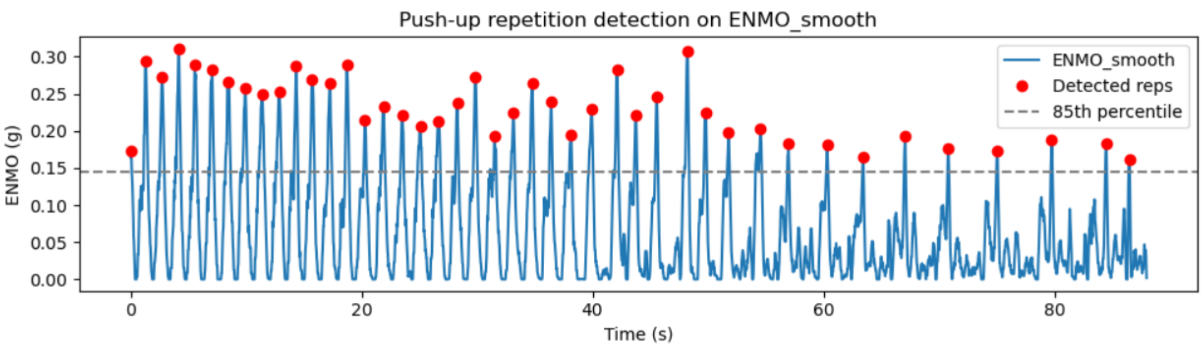

FIGURE 9 – Detected push-up repetitions (red markers) using adaptive ENMO peak detection.

For the push-up exercise, the algorithm detected 43 repetitions. The actual number of push-ups performed was 45.

2.3 Performance Metrics and Fatigue Analysis

The set contained the number of repetitions corresponding to the detected peaks in Figure 9. Using peak times, instantaneous cadence (repetitions per minute) was computed. As shown in Figure 10, cadence decreases markedly after approximately 25–30 repetitions, illustrating progressive fatigue.

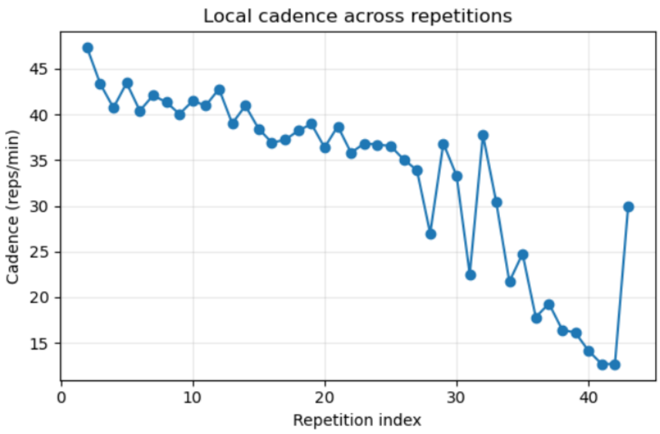

FIGURE 10 – Instantaneous cadence across the push-up set.

To analyse fatigue more formally, repetitions were divided into three equal phases (early, middle, late). For each phase, descriptive statistics were computed for :

— repetition duration,

— cadence,

— peak ENMO amplitude.

The resulting boxplots, presented in Figure 11, show a consistent decline across all metrics. Cadence drops sharply in the late phase, and peak ENMO decreases substantially, indicating reduced movement amplitude and power output. These trends mirror the fatigue patterns observed in dips and pull-ups (Section 1), but appear more gradual due to the continuous nature of the push-up set.

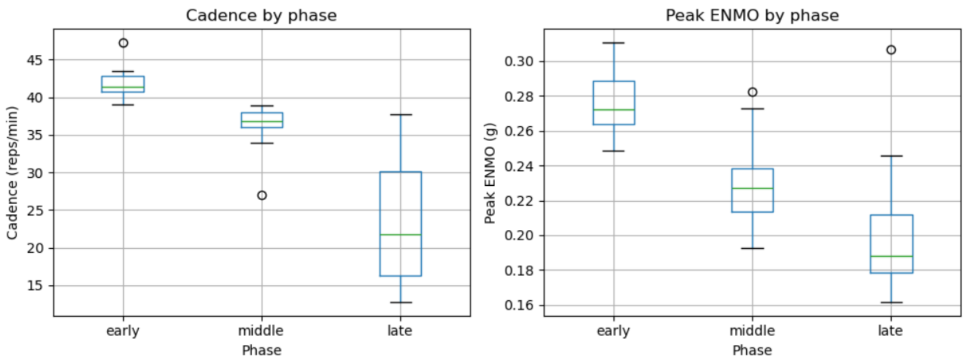

FIGURE 11 – Cadence (left) and peak ENMO amplitude (right) across early, middle, and late phases

2.4 Discussion

This analysis confirms that a single torso-mounted accelerometer provides reliable and interpretable information about push-up performance. The ENMO-based method used previously for dips and pull-ups generalises well to a continuous set, with peak detection remaining robust even as fatigue reduces amplitude.

Compared to the upper-body pulling and pushing movements analysed in Section 1, push-ups exhibit :

— a more regular rhythm, facilitating peak detection ;

— a smoother fatigue profile, reflected in gradual reductions of cadence and ENMO ;

— clearer cyclicity, due to the stable contact with the ground.

Overall, the push-up analysis demonstrates how accelerometry can quantify both repetition count and movement quality, offering objective markers of fatigue that can support personalised training feedback.

Conclusion

This project demonstrated that a single torso-mounted accelerometer, combined with a rigorous signal-processing pipeline, can provide meaningful, exercise-specific insights into calisthenics performance. Across the three analysed movements—dips, pull-ups, and push-ups—we showed that ENMO-based peak detection, cadence estimation, and phase-based fatigue analysis form a coherent and reliable framework for quantifying movement quality.

Among the exercises, push-ups produced the most stable and interpretable patterns, with clear oscillations, robust peak detection, and a smooth fatigue curve.

Dips also showed strong, regular oscillations and allowed precise measurement of cadence decline and integrated mechanical load.

In contrast, pull-ups presented more challenges, with lower amplitude, more irregular oscillations, and a smaller number of valid peaks detected. This reflects both the biomechanics of the movement and the higher sensitivity of pull-ups to fatigue and sensor placement.

Despite these differences, the overall methodology remained effective across all exercises. Repetition counts were close to the ground truth ; cadence curves accurately captured fatigue progression ; and integrated ENMO provided a compact measure of mechanical workload across phases.

From a broader perspective, this work illustrates how consumer-level wearable sensors can be repurposed into practical tools for training feedback, fatigue monitoring, and movement quality assessment. The methodology developed here is extensible to other cyclic exercises (such as biceps curls or squats) and provides a foundation for future innovations, including :

— real-time repetition counting and fatigue alerts on a mobile device ;

— automatic detection of incomplete or low-quality repetitions ;

— personalised progression tracking based on mechanical load and cadence ;

— integration of machine learning to classify exercise types or detect compensatory movements ;

— multi-sensor systems combining wrist, chest, and hip accelerometers for richer biomechanical assessment.

Overall, this study demonstrates that accelerometry can bridge the gap between raw sensor data and actionable fitness insights. With further refinement, such pipelines could form the basis of accessible digital coaching tools, supporting safe and effective strength training for a wide range of users