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| **Group Name** | Pink Horizons |
| **Team Members** | Formiglio Angelica, Manuzzi Samuele, Monastero Simone, Moretti Sofia, Nyeko Gunther N, Zanotti Ivan |

### 0. Rationale:

### This analysis investigates fall risk in older adults during daily activities using accelerometer-derived measures from body-worn sensors. Compared to costly laboratory equipment, this approach provides a cheaper and scalable method for real-time fall risk evaluation in home environments.

### 1. Methodology:

**Lab activity analysis:**

The analysis involved a comprehensive signal processing and modeling pipeline. Accelerometry data, converted from the *PhysioNet* format into *.mat* structures for both control and faller groups, were initially corrected for spatial orientation using the Moe-Nilssen algorithm ('*tiltandnog*') across the vertical, medio-lateral, and antero-posterior axes.

Cadence (steps/s) was obtained by computing the Power Spectral Density (PSD) of the antero-posterior acceleration using the Welch method, focusing on the walking frequency band (0.5 – 3 Hz) to identify the maximum peak. For gait speed and step length estimation, the vertical acceleration was band-pass filtered with a 4th-order Butterworth filter (0.5–15 Hz), then double-integrated with intermediate filtering (*cumtrapz*) to estimate positionFinally, the Inverted Pendulum Model (IPM) was applied to the position data to derive step length and, consequently, gait speed.

**Three-day activity analysis:**

Data were imported with the WFDB toolbox and preprocessed as in the lab sessions. Activity periods were detected using SMA and energy thresholds: segments with SMA between 0.135–0.8 or energy > 0.05 were classified as walking. Walking periods longer than 60 s were defined as bouts to compute walking percentage, start, end, and duration. Initial and final contacts were identified via continuous wavelet transform on the AV acceleration signal (McCamley et al., 2012) to derive step count and stride duration. Mean and standard deviation were then calculated after outlier removal.  
  
\*\**Describe your methodology, from data loading and preprocessing to statistical analysis of the results, citing relevant papers where appropriate.*

***You may use flowcharts or similar diagrams. Clear and concise illustrations are highly encouraged, while still providing sufficient detail on the work performed.***

*Don’t forget to mention the sample size used for each analysis, and if some subjects are removed, explain the reason(s). \*\**

### 2. Results

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| **Metric (Mandatory Goals)** | **Nonfallers** | | **Fallers** | |
| **BioMotion**  **(Value ± SD)** | **Weiss et al. 2013 (Value ± SD)** | **BioMotion**  **(Value ± SD)** | **Weiss et al. 2013 (Value ± SD)** |
| **Gait Speed (Lab)** |  | 1.19 ± 0.24 m/s |  | 0.97 ± 0.30 m/s |
| **Total Walking Duration (%)** |  | 2.06 ± 1.55 % |  | 1.55 ± 1.01 % |
| **Total Number of Steps for 3 days (n)** |  | 9055.28 ± 6444.7 |  | 7842.07 ± 6135.6 |
| **Avg. Stride Duration per walking bout (s)** |  | 112.08 ± 8.53 s |  | 119.87 ± 14.81 s |

GitHub code repository can be accessed **🔗**[**here**](https://github.com/SimoneMonastero/Pink_Horizons/tree/main/CodiceCorretto)

*Perhaps include a couple of most significant figures, for example:*

* *Box plots can show variability (standard deviation).*
* *Time-Series Plot*

1. *Example: filtered vertical acceleration signal with detected step peaks marked.*
2. *Demonstrates how the algorithm identifies walking bouts in real-world data.*

* *Histogram / Distribution Plot*

1. *Example: Distribution of stride durations across participants.*
2. *Helps visualize whether most strides cluster around the mean or if there’s a wide spread.*

### 3. Discussion & Challenges:

The significant correlations between the 3-day acceleration measures and their laboratory counterparts confirm their validity in a home setting. The acceleration-derived quality measures also reflected fall risk, as indicated by moderate correlations with functional performance tests and differences between fallers and non-fallers. These results extend previous work by demonstrating the applicability of the algorithms in real-life conditions.

However, the study lacks full methodological transparency: subject height, algorithm thresholds, anthropometric parameters, and exact sensor placement on the lower back were not reported. Moreover, data processing was computationally demanding, requiring approximately 10 minutes per subject and high system specifications.

### 4. Optional Goal: Classifier:

If a classifier was developed, this section should offer a clear and concise description, including sufficient methodological detail to ensure reproducibility.

* Features used (e.g., stride variability, bout duration, frequency-domain features).
* Model type (e.g., Random Forest, SVM, or Neural Network).
* Performance metrics (accuracy, F1-score, ROC-AUC).
* Use case: e.g., distinguishing between “healthy” vs. “at-risk” gait patterns.