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Semiogram: a Visual Tool for Gait Quantification in Routine Neurological Follow-Up

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Abstract

In this work, we present an innovative multidimensional tool developed for gait evaluation and monitoring in patients with neurological disorders in routine clinical practice using Inertial Sensors, named semiogram. It has previously been published and validated by Voisard et al. [C. Voisard, N. de l'Escalopier, A. Vienne-Jumeau, A. Moreau, F. Quijoux, F. Bompaire, M. Sallansonnet, M-L. Brechemier, I. Taifas, C. Tafani, E. Drouard, N. Vayatis, D. Ricard and L. Oudre, Innovative Multidimensional Gait Evaluation using IMU in Multiple Sclerosis: introducing the Semiogram, Frontiers in Neurology, 2023]. This tool offers a quantitative semiological analysis based on average speed and 16 other gait parameters, grouped into 7 criteria recognized in the literature: sturdiness, springiness, steadiness, stability, smoothness, synchronization, and symmetry. The provided visualization aims to facilitate easy interpretation by the clinician.

Source Code

The source code (written in Python 3) and documentation for this algorithm have been made available on the web page associated with the article[1]. The web page also provides an online demo for testing the algorithm. The code is extensively commented on, and usage instructions can be found in the README.md file within the archive.

Keywords: gait quantification; gait disorders; clinical follow-up; wearable inertial sensors; inertial measurement unit

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1 Introduction

The assessment and monitoring of gait in neurological pathologies pose significant challenges in clinical practice. Indeed, pathologies such as Parkinson's disease, stroke, multiple sclerosis, and spinal cord injuries often result in gait abnormalities, which can have a major impact on the patient's quality of life [1]. Accurate and objective measurement of gait parameters is crucial for assessing the progression of these conditions, evaluating treatment interventions, and making informed clinical decisions. In recent years, there has been a growing interest in developing gait quantification tools as a valuable resource in the clinical evaluation of gait disorders. By providing objective and precise measurements, gait quantification tools offer substantial advantages over subjective clinical evaluations, which are prone to inter-observer variability and imprecise manual measurements [10, 13].

One of the key benefits of gait quantification tools is their ability to capture and analyze subtle changes in gait characteristics over time. Neurological pathologies often exhibit progressive degenerative patterns, where gait parameters gradually deteriorate as the disease advances. On the other hand, patient management can lead to an improvement in motor function, which can be reflected in objective gait progression. By incorporating gait quantification tools into routine clinical practice, healthcare professionals can obtain precise measurements at regular intervals, enabling them to monitor disease progression, evaluate treatment effectiveness, and make timely adjustments to therapeutic interventions [6, 7]. More generally, knowing the evolution of walking quality in the general population as a function of age is important to decipher more precisely the physiology of this complex function.

Another significant advantage of gait quantification tools is their potential to enhance communication and collaboration among healthcare professionals. By generating standardized and easily interpretable gait reports, these tools facilitate information sharing between different specialists involved in the care of patients with neurological pathologies. This interdisciplinary approach promotes comprehensive evaluations, fosters evidence-based decision-making, and improves the overall management of these complex conditions.

Among the measurement techniques employed to construct these tools, Inertial Measurement Units (IMUs) have emerged as a popular technology. These sensors provide real-time measurements of accelerations, angular velocities, and orientations, allowing for precise characterization of kinematic parameters associated with gait [12, 5, 4]. The key advantages of IMUs are their low cost and their ease of use, as they do not require complex laboratory setups and can be conveniently employed in various clinical settings. These sensors are placed at different locations on the body, and the testing protocols in which they are deployed can vary. From these IMUs, a significant number of parameters can also be calculated using different methods [12]. Some of these parameters can be more challenging to compute in cases of severely impaired gait, particularly those that require precise segmentation of walking events. Indeed, gait abnormalities often result in altered temporal and spatial characteristics. These factors make it difficult to establish consistent and reliable event segmentation using traditional manual or rule-based approaches. Hence, the development and validation of automated segmentation algorithms specifically tailored for impaired walks are of paramount importance [14].

This article presents the algorithmic description of a graphical tool, known as a semiogram, for the semiotic quantification of gait represented as a radar plot. The semiogram serves as an example of an easily deployable reference tool for gait assessment. Firstly, we describe the algorithmic principle of the semiogram and the mathematical and physical formulas used in its development (Section 2). Secondly, we provide details about the data format and expected input content for the tool (Section 3). Finally, we provide some application examples to illustrate its usage (Section 4).

2 Semiogram Algorithm

In this section, we summarize with a pseudo-code (Algorithm 2) the semiogram computation algorithm, which has been previously described in detail by Voisard et al. [14].

2.1 Overall Principle

The semiogram is a graphical representation, akin to a radar plot, used to depict the walking abilities of patients during routine clinical examinations. Within this distinctive radar plot, the intricate process of gait is broken down into 7 semiological criteria, derived from 17 parameters. Each criterion is symbolized by a radiant spoke, emanating from a central point and extending outward. These semiological criteria for gait, drawn from existing literature, encompass springiness, smoothness, steadiness, sturdiness, stability, symmetry, and synchronization [12]. Each line on the radar plot embodies one of these criteria, with its distance from the chart's center indicating the level of the respective criterion in comparison to the healthy population, by means of a z-score. Overall, the resulting color of the chart is influenced by the widely recognized global gait parameter: average speed [12].

The radar plot serves as a relevant tool for visually comparing a patient's walking abilities across two separate visits by seamlessly superimposing multiple charts. Such a visualization not only facilitates tracking the quantitative evolution of walking but also allows for the detection of subtle, subclinical variations.

2.2 Input Data and Sensors Axes

The input data consists in time series derived from the raw sensor signals of the trunk, potentially pre-processed. The sensor is placed on the lower back, in front of the fifth lumbar vertebra. The XZ plane corresponds to the sagittal plane and the YZ plane to the axial plane, as shown in Figure 1.

Missing data are completed by linear interpolation. To remove the effect of gravity from the acceleration signals, its influence on the sensors is estimated during the initial 6 seconds of immobility. This estimation allows obtaining gravity-independent time series. To limit noise, a low-pass Butterworth filter of 8th order with a cut-off frequency of 14 Hz is applied to all the signals [11].

In addition to the raw data, segmentation data of the U-turn and gait events are required. An example of gait event segmentation algorithm has previously been described in detail and validated [14]. An example of U-turn boundaries detection algorithm has also been described [3].

Overall, 6 time series and 3 events lists are relevant. They can be obtained automatically from dedicated algorithms, or manually, and are detailed below:

- Trunk accelerations free from gravity time series: $\mathbf{acc^x}$, $\mathbf{acc^y}$ and $\mathbf{acc^z}$;
- Trunk gyration time series: $\mathbf{gyr^x}$, $\mathbf{gyr^y}$ and $\mathbf{gyr^z}$;
- U-turn boundaries. List $[u_{start}, u_{end}]$ which corresponds to the time estimations of the start and the end of the U-turn phase.
- Left foot gait events. List $\left[\left[t_1^{left}, h_1^{left}\right], \left[t_2^{left}, h_2^{left}\right], \ldots\right]$ of final ground contact (Toe-Off, TO) and initial ground contact (Heel-Strike, HS) indexes of the gait events of the left foot, excluding the U-turn period. We define N_left as the number of couples in the list.
- Right foot gait events. List $\left[\left[t_1^{right}, h_1^{right}\right], \left[t_2^{right}, h_2^{right}\right], \ldots\right]$ of final ground contact (TO) and initial ground contact (HS) indexes of the gait events of the right foot, excluding the U-turn period. We define N_right as the number of couples in the list.

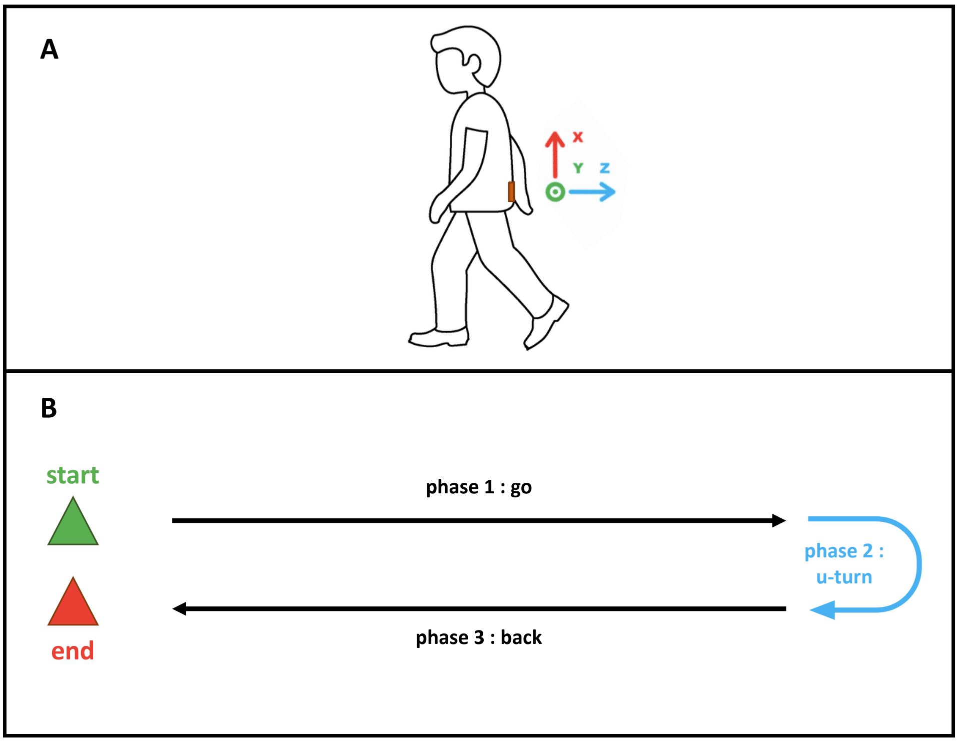


Figure 1: A - Lower back sensor position and orientation; B - Gait protocol.

Two other features concerning the protocol are required for further processing: the walked distance D and the sampling frequency F_s.

2.3 Criteria and Parameters

The list and calculation methods for each parameter were based on existing literature and are described in detail in Voisard et al. [15]. The parameters were grouped into 7 semiological criteria based on proposals in the literature. To these semiological criteria, we have added average walking speed, a criterion recognized as more global by the literature. The list can be summarized as follows:

- **Average speed**
- **Springiness**: stride time, U-turn time.
- **Smoothness**: spectral arc length, log dimensionless jerk.
- **Steadiness**: variation coefficient of step time, variation coefficient of double stance time, craniocaudal step autocorrelation coefficient, craniocaudal stride autocorrelation coefficient.
- **Sturdiness**: step length.
- **Stability**: mediolateral root mean square.
- **Symmetry**: ratio of the step to the stride peak of the craniocaudal correlation coefficient, ratio of left and right mean swing times, three improved harmonic ratios (anteroposterior, mediolateral, craniocaudal).
- **Synchronization**: double stance time.

The calculations are provided in the following section for good reproducibility.

2.3.1 Introducing Functions and Notations

Function - In the following, the following function is introduced:

– remove_outliers: this function uses the z-score to identify and remove outliers from a dataset. In indicators that use averages, this notably limits the impact of potential errors. Hereafter, the default z-score threshold is set at 2. Algorithm 1 is the corresponding pseudocode.

Algorithm 1: Remove outliers function

Input $\mathbf{v_{in}}$ vector
Parameter outliers limit z_{lim} (default value: 2)
Output $\mathbf{v_{out}}$ vector
$z_v \leftarrow \text{zscore}(v)$ /* *Compute z score of each value in* v_{in}, *relative to its mean and standard deviation.*
$\mathbf{v_{out}} \leftarrow \{v_{in}[i] \text{ if } z_v[i] \leq z_{lim}\}$

Notations - In the following, some notations are introduced:

– $\mathbf{x}^{go}$ and $\mathbf{x}^{back}$: for a time-series or vector $\mathbf{x}$, the index corresponds to the forward ($\mathbf{x}^{go}$) and backward ($\mathbf{x}^{back}$) phases of the test. $\mathbf{x}^{phase}$ is used to refer to either of the two phases.

– **stride_durations**: vector representing the durations of each individual stride (left and right). We apply the remove_outliers function as well as a check for the alternation of left and right steps to exclude aberrant values.

$$\begin{aligned}\textbf{stride\_durations} = \text{remove\_outliers}([&h_2^{left} - h_1^{left}, h_3^{left} - h_2^{left}, \ldots, h_{N_{left}}^{left} - h_{N_{left}-1}^{left}, \\ &h_2^{right} - h_1^{right}, h_3^{right} - h_2^{right}, \ldots, h_{N_{right}}^{right} - h_{N_{right}-1}^{right}]). \end{aligned} \quad (1)$$

– **double_stance**: vector representing the proportion of double stance phases in gait cycles (Figure 2), with the same exclusion of aberrant values. For example, for the gait cycle from h_i^{right} to h_{i+1}^{right}, considering that the jth left swing phase completes the gait cycle, we have

$$dstT_i = \frac{(t_{i+1}^{right} - h_j^{left}) + (t_j^{left} - h_i^{right})}{h_{i+1}^{right} - h_i^{right}}. \quad (2)$$

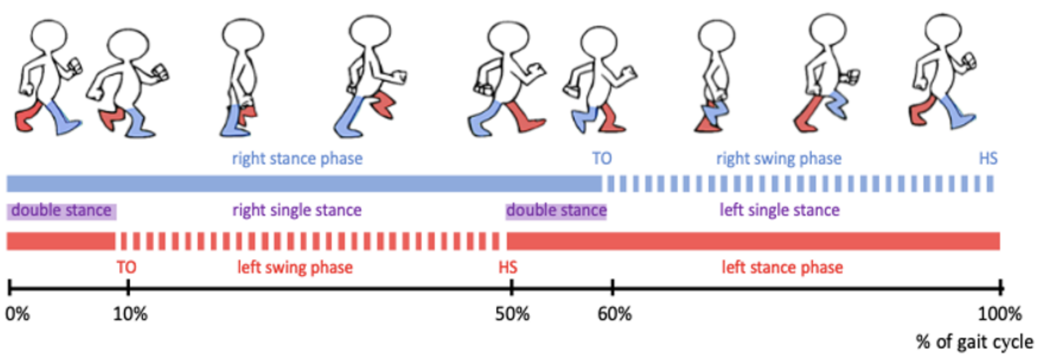


Figure 2: Double stance definition. For each gait cycle, the double stance time is the ratio of the time during which both feet are on the ground (highlighted in violet) to the total duration.

2.3.2 Computation of Parameters

The calculation methods for each parameter included in the semiogram are provided below with the previously detailed notations.

- **Average speed:** quantifies gait velocity with 1 parameter:
  - *Velocity (V):* walked distance D divided by the total duration of the walking test (from the first to the last gait event) after the exclusion of the U-turn.

$$V = F_s \times \frac{D}{\max(h_{N_{left}}^{left}, h_{N_{right}}^{right}) - \min(t_1^{left}, t_1^{right},) - u_{end} + u_{start}}. \tag{3}$$

- **Springiness:** quantifies gait rhythmicity with 2 parameters:
  - *Stride time ($StrT$):* average stride time duration after excluding the initiation step.

$$StrT = \text{mean}(\textbf{stride\_durations}). \tag{4}$$

  - *U-turn time ($UtrT$).*

$$UtrT = \frac{1}{F_s} \times (u_{end} - u_{start}). \tag{5}$$

- **Smoothness:** quantifies gait continuousness or non-intermittency with 2 parameters:
  - *Spectral arc length ($SPARC_{rot}$):* measures the arc length of the Fourier magnitude spectrum of the trunk gyration signal within an adaptive frequency range. We considered the method described by Melendez-Calderon et al. [9]. According to these recommendations, we use the gyration norm during the walking period, which is calculated as follows

$$\mathbf{gyr} = \sqrt{\mathbf{gyr_x}^2 + \mathbf{gyr_y}^2 + \mathbf{gyr_z}^2}.$$

    We then plot the normalized magnitude spectrum (from Fast Fourier transform with N^{FFT} points, see Appendix A) and set the spectral arc selection limit as a function of an amplitude threshold (threshold = 0.05) and a frequency threshold (10 Hz according to the literature) [9]. It leads to a spectral arc with N_{sel}^{FFT} points. An illustration is provided in Figure 3.
    Finally, the arc length is calculated using the following formula

$$SPARC_{rot} = \text{SAL}_{\text{uturn}} = -\sum_{i=1}^{N_{sel}^{FFT}-1} \sqrt{\left(\frac{f_{\text{sel},i+1} - f_{\text{sel},i}}{f_{\text{sel},N_{sel}^{FFT}} - f_{\text{sel},1}}\right)^2 + (\text{Mf}_{\text{sel},i+1} - \text{Mf}_{\text{sel},i})^2}. \tag{6}$$

    where :

    * SAL is know as the Spectral Arc Length for the smoothness of the movement.
    * N_{sel}^{FFT} is the total number of frequencies in the selected frequency range.
    * $\mathbf{Mf_{sel}}$ represents the normalized magnitude spectrum for the selected frequency range, defined as the normalized Fast Fourier Transform (FFT) of the gyration norm.
    * $\mathbf{f_{sel}}$ corresponds to the selected frequency range for calculating the SAL, defined as the frequency range corresponding to $\mathbf{Mf_{sel}}$.

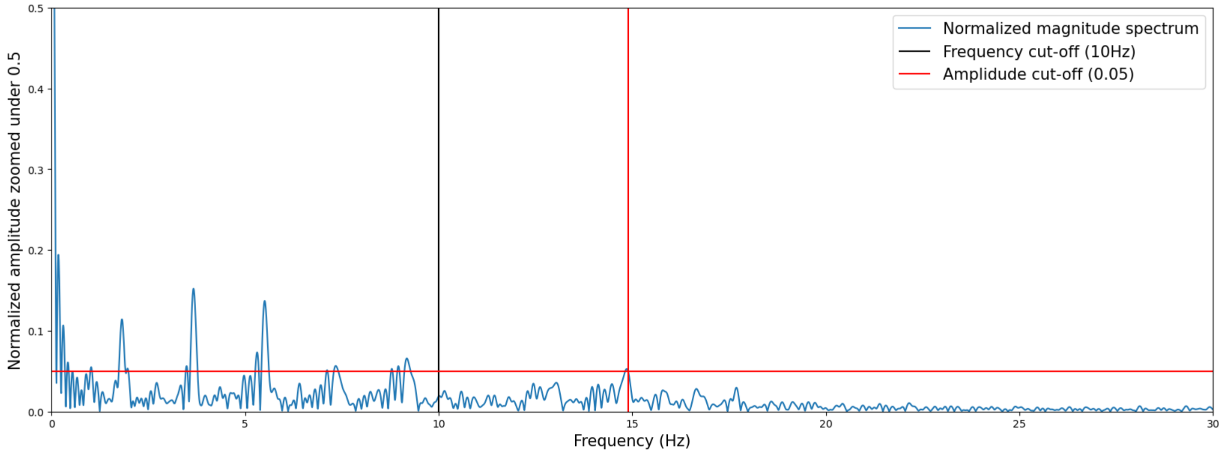


Figure 3: Spectral arc length construction with power spectrum for positive frequencies and cut-offs.

- *Log dimensionless jerk ($LDLJ_A$):* quantifies the rate at which the total acceleration of the trunk signal is changing over time, considering both its amplitude and duration. We compute the procedure described in [9].

$$LDLJ_A^{phase} = -\log\left(\text{abs}\left(-s \times \frac{1}{F_s} \times \sum_{i=1}^{M-1} (\mathbf{jerk^{phase}}_i)^2\right)\right), \tag{7}$$

where :

  - M is the number of time samples in the considered phase.
  - $\mathbf{jerk^{phase}}$ is the discrete derivative of $\mathbf{acc^{phase}}$, which corresponds to the vector of the acceleration magnitude measured by the IMUs

$$\mathbf{jerk} = \frac{\text{d}\mathbf{acc}}{\text{d}t} = F_s \times (\mathbf{acc}_{t+1} - \mathbf{acc}_t), \text{ with } \mathbf{acc} = \sqrt{\mathbf{acc_x}^2 + \mathbf{acc_y}^2 + \mathbf{acc_z}^2}.$$

  - s is the scaling factor used to adjust the smoothing measurement calculation in order to normalize the smoothing measurement based on the unit and dynamics of the acquired motion data (in this case, acceleration). We calculate it as follows

$$s = \frac{N}{F_s \times \max(\mathbf{acc^{phase}})^2}.$$

We then have

$$LDLJ_A = \frac{1}{2} \times (LDLJ_A^{go} + LDLJ_A^{back}).$$

- **Steadiness:** quantifies gait regularity with 4 parameters:
  - *Variation coefficient of step time (CV_{StrT}):* standard deviation of the vector of stride times (outliers excluded) divided by its average.

$$CV_{StrT} = 100 \times \frac{\text{sd}(\mathbf{stride\_durations})}{\text{mean}(\mathbf{stride\_durations})}. \tag{8}$$

  - *Variation coefficient of double stance time (CV_{dstT}):* standard deviation of the vector of double stance times (outliers excluded) divided by its average.

$$CV_{dsT} = 100 \times \frac{\text{sd}(\mathbf{double\_stance})}{\text{mean}(\mathbf{double\_stance})}. \tag{9}$$

– *Craniocaudal step autocorrelation coefficient ($P1_{aCC}$):* first peak of the craniocaudal autocorrelation coefficient of the lower back, to assess for step to stride similarity (Figure 4). The theoretical autocorrelation formula is given in (10), and the code application is provided in Appendix B.
For t in $\{0, 1, \dots, N/2\}$,

$$\text{autocorr}_{CC}(t) = \frac{\sum_{i=1}^{N-t}(acc_i^x - \mu)(acc_{i+t}^x - \mu)}{\sum_{i=1}^{N}(acc_i^x - \mu)^2}, \tag{10}$$

$$P1_{aCC} = \max_{\frac{StrT}{3} \leq t \leq \frac{2*StrT}{3}}(\text{autocorr}_{CC}(t)),$$

where:

* N is the total number of samples.
* acc_i^x is the craniocaudal acceleration value at time i.
* μ is the mean of the acceleration values.
* $StrT$ is defined previously in Equation (4).
* t is the time shift.

– *Craniocaudal stride autocorrelation coefficient ($P2_{aCC}$):* second peak of the craniocaudal autocorrelation of the lower back, to assess for stride to stride similarity (Figure 4).

$$P2_{aCC} = \max_{\frac{5\times StrT}{6} \leq t \leq \frac{7\times StrT}{6}}(\text{autocorr}_{CC}(t)). \tag{11}$$

where autocorr_{CC}, $StrT$ and t are defined previously in Equation (10).

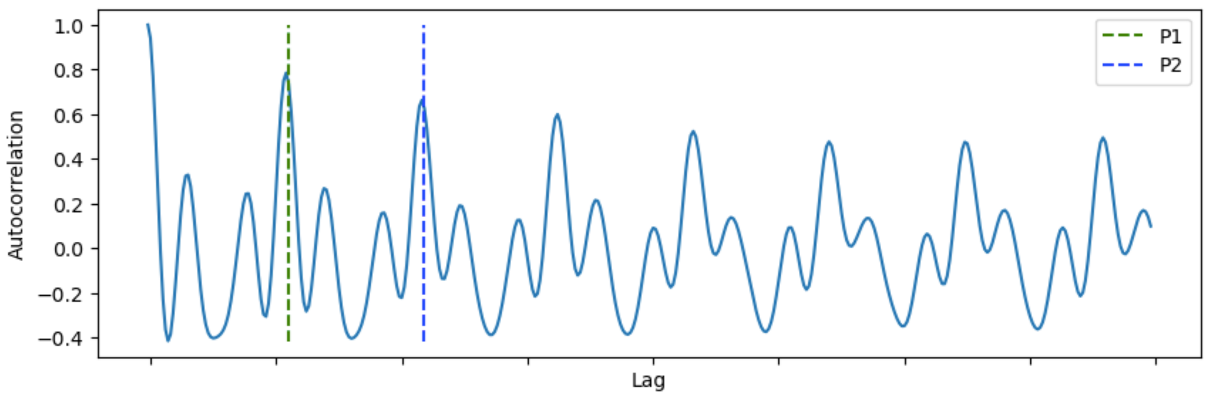


Figure 4: Craniocaudal step (first peak, P1) and stride (second peak, P2) autocorrelation coefficient (X-axis acceleration). Autocorrelation is estimated from FFT.

- **Sturdiness:** quantifies gait amplitude with 1 parameter:

  – *Step length (SteL):* total length (20 m) divided by the total number of steps after the exclusion of the U-turn.

$$SteL = \frac{20}{N_{right} + N_{left}}. \tag{12}$$

- **Stability:** quantifies gait balance with 1 parameter:
  - *Mediolateral root mean square (RMS_{aML}):* dispersion of the mediolateral acceleration of the lower back relative to zero during straight-walking phases. We take the best (lower) result between the forward and the backward phases.

$$\begin{aligned} RMS_{aML}^{phase} &= \sqrt{(\text{mean}(\mathbf{acc}^{\mathbf{y,phase}})^2)}, \\ RMS_{aML} &= \min(RMS_{aML}^{go}, RMS_{aML}^{back}). \end{aligned} \tag{13}$$

- **Symmetry:** quantifies right/left concordance during gait with 5 parameters:
  - *Ratio of the step to the stride peak of the craniocaudal correlation coefficient ($P1P2_{aCC}$):* ratio of P1 to P2, P1 and P2 previously defined (Figure 4).

$$P1P2_{aCC} = 1 - \min\left(\text{abs}\left(1 - \frac{P1_{aCC}^{go}}{P2_{aCC}^{go}}\right), \text{abs}\left(1 - \frac{P1_{aCC}^{back}}{P2_{aCC}^{back}}\right)\right). \tag{14}$$

  - *Ratio of left and right mean swing times ($swTr$):* ratio of the minimum (right or left) of averaged swing time divided by the maximum (right or left) of averaged swing time.

$$\begin{aligned} swT^{left} &= \frac{1}{N_{left} - 2} \times \sum_{i=2}^{N_{left}-1} \left(h_i^{left} - t_i^{left}\right), \\ swTr &= \frac{\min(swT^{left}, swT^{right})}{\max(swT^{left}, swT^{right})}. \end{aligned} \tag{15}$$

  - *Three improved harmonic ratios: anteroposterior (iHR_{aAP}), mediolateral (iHR_{aML}), craniocaudal (iHR_{aCC})*: evaluate the similarity of the trunk energy distribution as a function of frequency between the left and right limbs. The computation procedure was previously described [8]. First, for each part of the signal corresponding to a stride, we decompose the filtered acceleration signals into harmonics using a discrete Fourier transform as shown in Figure 5. We consider the Fourier coefficients for the multiple harmonics of the approximate fundamental frequency, taken as $\frac{F_s}{n_{sample}}$, where F_s represents the sampling frequency and n_{sample} denotes the number of samples in the stride.
    The improved harmonic ratio is calculated as the ratio between the power of the even harmonics (for anteroposterior and craniocaudal) or odd harmonics (for mediolateral) over the total power of the signal. Indeed, the craniocaudal and anteroposterior accelerations have two periods every stride, resulting in dominance of the second (and subsequent even) harmonic, whereas mediolateral accelerations have only one period per stride, resulting in dominance of the first (and subsequent odd) harmonic.

$$\begin{aligned} iHR_{aAP}^{\vartheta} &= 100 \times \frac{\sum_{j=1}^{10}(A_{aAP,E}^{j})^2}{\sum_{j=1}^{10}(A_{aAP,E}^{j})^2 + \sum_{j=1}^{10}(A_{aAP,O}^{j})^2}, \\ iHR_{aML}^{\vartheta} &= 100 \times \frac{\sum_{j=1}^{10}(A_{aML,O}^{j})^2}{\sum_{j=1}^{10}(A_{aML,E}^{j})^2 + \sum_{j=1}^{10}(A_{aML,O}^{j})^2}, \\ iHR_{aCC}^{\vartheta} &= 100 \times \frac{\sum_{j=1}^{10}(A_{aCC,E}^{j})^2}{\sum_{j=1}^{10}(A_{aCC,E}^{j})^2 + \sum_{j=1}^{10}(A_{aCC,O}^{j})^2}, \end{aligned}$$

    where:

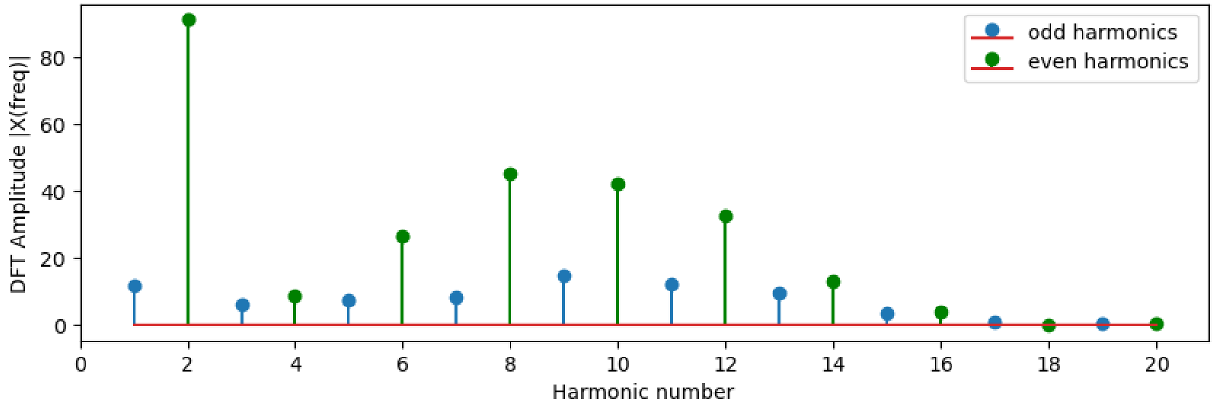


Figure 5: Discrete Fourier Transform (DFT) for the anteroposterior acceleration time-series. The power of even harmonics estimates the improved Harmonic Ratio of anteroposterior acceleration.

* $A^j_{aCC,O}$, $A^j_{aML,O}$, $A^j_{aAP,O}$ are respectively the amplitudes of the jth odd harmonics of the discrete Fourier Transform of $\mathbf{acc^x}$, $\mathbf{acc^y}$, $\mathbf{acc^z}$, taken in the interval ϑ.
* $A^j_{aCC,E}$, $A^j_{aML,E}$, $A^j_{aAP,E}$ are respectively the amplitudes of the jth even harmonics of the discrete Fourier Transform of $\mathbf{acc^x}$, $\mathbf{acc^y}$, $\mathbf{acc^z}$, taken in the interval ϑ.

For each step k bounded by h_k and h_{k+1}, excluding the first and the last ones, we define the improved harmonic ratio of neighborhood maxima

$$iHR^k_{aAP} = \max_{\vartheta \in V([h_k;h_{k+1}])} \left(iHR^\vartheta_{aAP}\right),$$

$$iHR^k_{aML} = \max_{\vartheta \in V([h_k;h_{k+1}])} \left(iHR^\vartheta_{aML}\right),$$

$$iHR^k_{aCC} = \max_{\vartheta \in V([h_k;h_{k+1}])} \left(iHR^\vartheta_{aCC}\right),$$

where:

* $V([h_k; h_{k+1}])$ is the neighborhood of step k, defined as the set of time intervals whose start is within 15 time intervals of h_k and whose end is within 15 time intervals of h_{k+1}, with an additional duration variability of 5 time intervals.

Finally, we define our 3 parameters as the average iHR of each step

$$iHR_{aAP} = \text{mean}(iHR^k_{aAP})_k, \tag{16}$$

$$iHR_{aML} = \text{mean}(iHR^k_{aML})_k, \tag{17}$$

$$iHR_{aCC} = \text{mean}(iHR^k_{aCC})_k. \tag{18}$$

- **Synchronization:** quantifies inter-limb coordination during gait with 1 parameter:
  - *Double stance time (dstT):* time between the HS of one foot and the TO of the contralateral foot divided by the total time of the cycle time (Figure 2). We represent this ratio as a percentage.

$$dstT = 100 \times \text{mean}(\textbf{double\_stance}). \tag{19}$$

2.3.3 Parameters Reference

The semiogram is a comparative tool that utilizes z-score calculation. A sample of data from the healthy population is necessary to compute the mean values and standard deviations for each parameter. The dataset and its characteristics are available here[2].

Characteristics of the reference population - Nineteen individuals who did not have any reported medical impairments or health conditions performed a series of 4 to 6 recordings of the 10-meter round-trip walking test. The characteristics of the population are summarized in Table 1.

Sex (M/F)	12/7
Age (years)	51 (17)
Height (m)	1.71 (0.06)
Weight (kg)	71.7 (14.3)
Body mass index (kg/m^2)	24.3 (4.3)

Table 1: Baseline characteristics of healthy subjects. Mean and SD are given.

Parameter Values - The mean and standard deviation (SD) for each of the 17 selected qualitative parameters were computed using the entire set of trials from the reference group (Table 2). A Z-coefficient of 1 (+) or -1 (-) was assigned to each parameter to indicate whether an increase in the parameter was considered beneficial or pathological, respectively.

Criteria	Parameter	Mean	SD	Z-coefficient
Average speed	V (m/s)	1.22	0.20	+
Springiness	StrT (s)	1.10	0.09	-
	UtrT (s)	2.62	0.75	-
Smoothness	LDLJ$_A$ (-)	-8.07	0.35	+
	SPARC$_{rot}$ (-)	-4.18	0.89	-
Steadiness	CVStrT (%)	2.34	0.97	-
	CVdstT (%)	5.63	2.07	-
	P1$_{aCC}$ (-)	0.82	0.10	+
	P2$_{aCC}$ (-)	0.82	0.10	+
Sturdiness	SteL (m)	0.68	0.08	+
Stability	RMS$_{aML}$ (m/s^2)	1.28	0.33	-
Symmetry	iHR$_{aAP}$ (%)	95.48	2.13	+
	iHR$_{aCC}$ (%)	94.88	3.10	+
	iHR$_{aML}$ (%)	86.77	6.32	+
	P1P2$_{aCC}$ (-)	0.96	0.04	+
	swT$_r$ (-)	0.96	0.03	+
Synchronization	dstT (%)	23.34	3.50	-

Table 2: Mean, SD, and Z-coefficient for included gait features for the reference group. V: velocity; SteL: step length; StrT: stride time; UtrT: U-turn time; LDLJ$_A$: log-dimensionless jerk computed from the trunk acceleration; SPARC$_{rot}$: spectral arc length computed from the trunk gyration; CVStrT: coefficient of variation of the stride time; CVdstT: coefficient of variation of the double stance time; P1$_{aCC}$: step autocorrelation coefficient of the trunk craniocaudal acceleration; P2$_{aCC}$: stride autocorrelation coefficient of the trunk craniocaudal acceleration; RMS$_{aML}$: root mean square of the trunk mediolateral acceleration; iHR$_{aAP}$: improved harmonic ratio of the trunk anteroposterior acceleration; iHR$_{aML}$: improved harmonic ratio of the trunk mediolateral acceleration; iHR$_{aCC}$: improved harmonic ratio of the trunk craniocaudal acceleration; P1P2$_{aCC}$: ratio P1 to P2; swT$_r$: ratio of left and right swing times; dstT: double stance time ratio.

[2] https://www.ipol.im/pub/art/2023/497/

2.3.4 Semiogram Algorithm Description

Algorithm 2: Semiogram computation

Input Trunk sensor pre-processed time series: $\mathbf{acc^x}$, $\mathbf{acc^y}$, $\mathbf{acc^z}$, $\mathbf{gyr^x}$, $\mathbf{gyr^y}$, $\mathbf{gyr^z}$;
U-turn limits list $[u_{start}, u_{end}]$;
Gait event detection $\mathbf{e^{IC}_{right}}$, $\mathbf{e^{IC}_{left}}$ for initial contact and $\mathbf{e^{FC}_{right}}$, $\mathbf{e^{FC}_{left}}$ for final contact.

Parameter sampling frequency F_s, distance D, reference values.

Output semiogram image

Step 1. Criteria computation

for *criterion* ***in*** *criteria* **do**
- $n \leftarrow$ number of parameters in the criterion
- **for** $i \leftarrow 0$ **to** n **do**
  - $p_i \leftarrow$ parameter i value
  - $m_i \leftarrow$ average parameter i value in general population
  - $sd_i \leftarrow$ standard deviation for parameter i value in general population
  - $k_i \leftarrow$ Z-coefficient (-1 or 1) for parameter i
  - $z_i = k_i \times \dfrac{p_i - m_i}{sd_i}$
- $Z_{criterion} = \dfrac{1}{n} \times \displaystyle\sum_{i=1}^{n} z_i$

Step 2. Semiogram representation

Build a 7 axes radar plot with polar axes.

for *criterion* ***in*** *criteria (except average speed)* **do**
- Place $Z_{criterion}$ on the corresponding axis.

Connect the points.
Polygon color $\leftarrow Z_{average\_speed}$.

3 Data Description for Demo

The semiogram described in this article requires precise data acquisition within a specific gait testing context. The code for the demo will work on datasets acquired in the correct format and under the conditions specified in this section.

3.1 Protocol and Experiment

3.1.1 Sensor Placement

The subject is equipped with at least 1 inertial sensor on the lower back at the level of the fifth lumbar vertebra. The placement of the sensor and the orientation of the axes in space are indicated in Figure 1A. For optimal use of the demo, data sampling at a frequency of 60 to 100 Hz is highly recommended.

3.1.2 Gait Evaluation Test

The conducted gait test consists of a 10-meter round trip with a U-turn. The testing location must be sufficiently wide to allow the patient to walk without obstacles and perform the turnaround. Ideally, the boundaries, particularly the turnaround area, should be marked. The objective is to record the patient under the same conditions as in their daily life: if they are accustomed to using walking aids (cane, orthosis, etc.), the test should be performed with those aids. If the patient is unable to complete the entire test, the semiogram analysis cannot be conducted.

3.1.3 Test Protocol Instructions

The instructions given to the patient should be as follows, whenever possible:

- Wait for approximately 6 seconds in a static standing position after starting the recording, facing the walking test location, until the operator's signal;
- Walk 10 meters at a comfortable and habitual pace;
- Perform a U-turn within the designated area, without being concerned about slightly stepping outside of it;
- Return to the starting point at a comfortable and habitual pace;
- Wait on the finish line for 2 seconds before the operator's signal and the sensors stop.

3.2 Data Format

3.2.1 Demo Parameters

For the demo, 5 parameters relating to data acquisition and final visualization are required to establish the semiogram:

- Sampling frequency in Hertz;
- Walked distance of the trial in meters;
- Minimum and maximum z-score for representation.

3.2.2 Required Files

To run the demo, you need to provide 2 files in the specified formats corresponding to the lower back inertial sensor signal, and the gait events metadata. To properly identify them, the suffixes of each file can be as follows:

- For the trunk sensor: **[filename]_lb.txt**.
- For the gait events metadata: **[filename]_ge.json**.

3.2.3 Format for Each File

The data format needs to be compatible with the demo. In addition to being in .txt format, the sensor data file should have at least 7 columns, following the same naming format as shown below:

- **PacketCounter**: this column contains the count of acquisition times, where the time interval between two time units depends on the sampling frequency;
- **Acc_X, Acc_Y, Acc_Z**: these three columns contain the values of acceleration or gravity-free acceleration along each of the three axes in the sensor's reference frame;
- **Gyr_X, Gyr_Y, Gyr_Z**: these three columns contain the values of angular velocity along each of the three axes in the sensor's reference frame.

An example of a sensor data mask is provided in Figure 6. Please note that there can be as many lines of context as desired before the data, as long as the first column begins with "PacketCounter".

PacketCounter	Acc_X	Acc_Y	Acc_Z	Gyr_X	Gyr_Y	Gyr_Z	Mag_X	Mag_Y	Mag_Z
0.0	3.552714e-14	2.220446e-16	1.154632e-14	-0.003527	0.005281	0.000665	-0.289795	0.073486	-0.801758
1.0	3.552714e-14	2.220446e-16	1.154632e-14	-0.003527	0.005281	0.000665	-0.289795	0.073486	-0.801758
2.0	3.552714e-14	2.220446e-16	1.154632e-14	-0.003527	0.005281	0.000665	-0.289795	0.073486	-0.801758
3.0	3.552714e-14	2.220446e-16	1.154632e-14	-0.003527	0.005281	0.000665	-0.289795	0.073486	-0.801758
4.0	3.552714e-14	2.220446e-16	1.154632e-14	-0.003527	0.005281	0.000665	-0.289795	0.073486	-0.801758
...	...	...	...	...	...	...	...	...	...

Figure 6: Data mask for each file. This example file corresponding to a trunk sensor contains 10 columns. Among these 10 columns, 7 of them correspond to the expected format for the demo: PacketCounter, Acc_X, Acc_Y, Acc_Z, Gyr_X, Gyr_Y, Gyr_Z. The additional 3 columns (Mag_X, Mag_Y, Mag_Z) correspond to the magnetometer and do not affect the algorithm.

As for the .json file, which contains the timestamped gait events, it should be a dictionary containing at least 3 keys:

- *UTurnBoundaries*. List $[u_{start}, u_{end}]$ which corresponds to the time estimations of the start and the end of the U-turn phase.
- *LeftFootEvents*. List $\left[\left[t_1^{left}, h_1^{left}\right], \left[t_2^{left}, h_2^{left}\right], \ldots\right]$ of final ground contact (Toe-Off, TO) and initial ground contact (Heel-Strike, HS) indexes of the gait events of the left foot, excluding the U-turn period.
- *RightFootEvents*. List $\left[\left[t_1^{right}, h_1^{right}\right], \left[t_2^{right}, h_2^{right}\right], \ldots\right]$ of final ground contact (TO) and initial ground contact (HS) indexes of the gait events of the right foot, excluding the U-turn period.

4 Application

4.1 Output Analysis Report Format

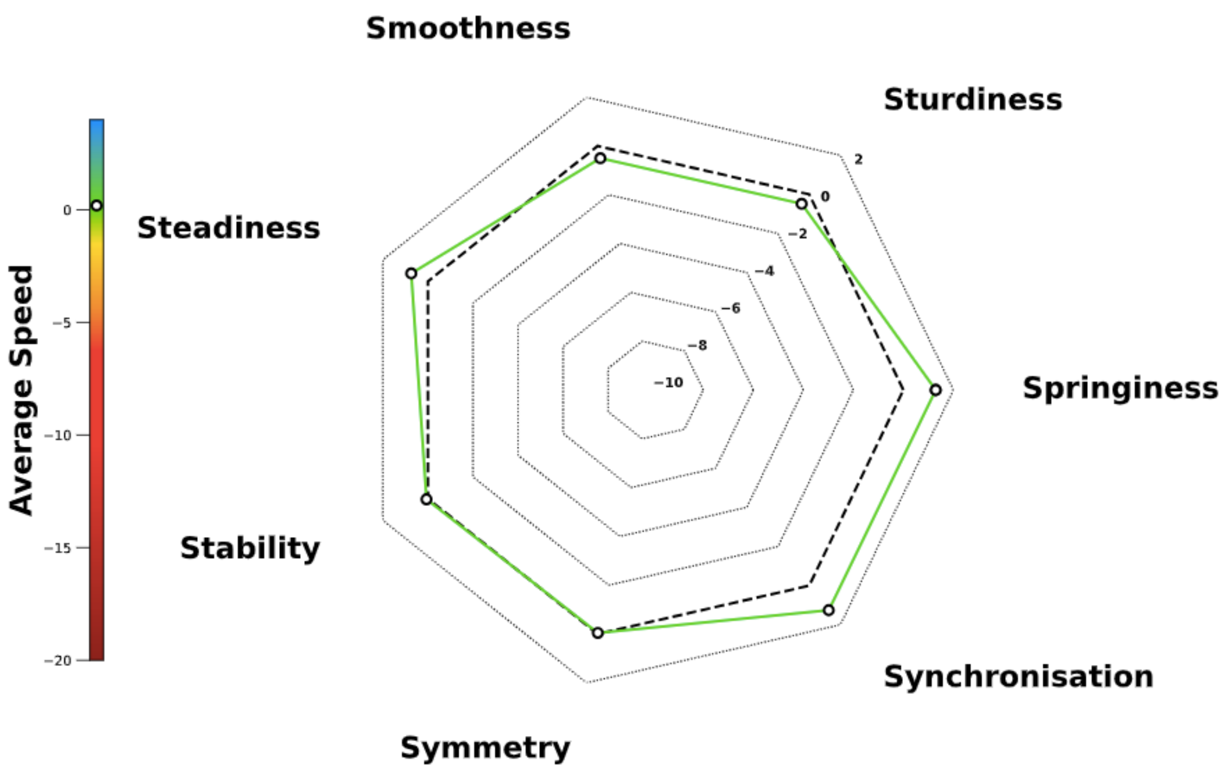
The algorithm generates a visually interpretable report for the clinician, consisting of one figure. Arrays containing parameter values and the z-scores resulting from the criteria are provided for reference. An example is given in Figure 7.

It is possible to focus solely on the figure, which represents the final output of the semiogram analysis (Figure 7A). Each branch within the chart corresponds to one of the seven semiological criteria: springiness, smoothness, steadiness, sturdiness, stability, symmetry, and synchronization. The color of the chart is determined by the average walking speed, providing an indication of the overall quality of the analysis.

4.2 Overlay for the Follow-Up

As for follow-up, in order for the clinician to easily compare the semiogram with a reference semiogram previously conducted, overlaying them on the same graph is possible (Figure 8). To achieve this,

A



B

Criteria computed from the trial

```
Z-Scores
--------------------------------------------------+--------------------------------------------------
Average Speed: 0.19249122174006436                | Steadiness: 0.7375875141023236
Springiness: 1.2941407316364795                   | Stability: 0.06268470959212703
Sturdiness: -0.482214030670318                    | Symmetry: -0.04290042977470039
Smoothness: -0.4982135740361504                   | Synchronisation: 1.2539463266163626
```

C

Parameters computed from the trial

```
Values                         | Z-Scores
-------------------------------+------------------------------
V: 1.2554927809165097          | 0.19249122174006436
StrT: 1.008695652173913        | 0.9352991150973057
UTurn: 1.38                    | 1.6529823481756531
SteL: 0.6451612903225806       | -0.482214030670318
SteL: 0.6451612903225806       | -0.482214030670318
LDLJAcc: -8.083830562238358    | -0.044606113011339356
CVStrT: 1.250742942116113      | 1.1262577321402119
CVdsT: 5.162990570712865       | 0.22662526289309082
P1_aCC: 0.8636886471477262     | 0.48297117068341366
P2_aCC: 0.9301819739958057     | 1.1144958906925782
ML_RMS: 1.263644187598376      | 0.06268470959212703
P1P2: 0.9285157864730033       | -0.8530499448306148
MSwTR: 0.9770471464019851      | 0.42926384273612234
AP_iHR: 94.3091246960241       | -0.5507855433001577
ML_iHR: 92.6570654357186       | -0.7175253984633283
CC_iHR: 96.11246123845746      | 1.4775948949844766
```

Figure 7: Example for a demo report with a semiogram. A - semiogram. B - criteria z-scores. C - parameters values and z-scores.

both sets of data may be uploaded to the demo, using the formats specified earlier. The two polygons are represented differently, and the area of progression is colored to facilitate clear visualization.

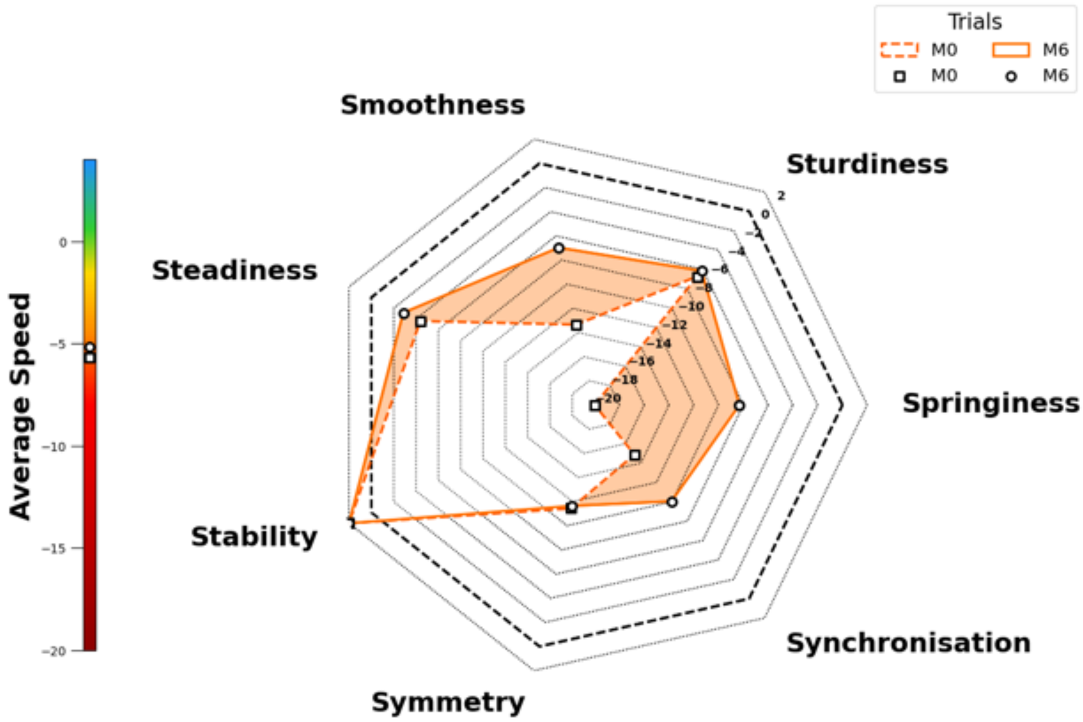


Figure 8: Example of the evolution of the semiogram at a 6-month interval in a patient with post-stroke equinovarus foot. The recording at M0 corresponds to the pre-operative trial, and at M6 to the post-operative trial.

5 Conclusion

The incorporation of visual gait quantification tools in clinical practice shows great potential for assessing and monitoring gait abnormalities associated with neurological conditions. These tools offer objective measurements, facilitate longitudinal tracking, and encourage interdisciplinary collaboration, thereby improving the accuracy and efficiency of clinical evaluations and ultimately enhancing patient outcomes. As technology continues to progress, it is crucial for researchers and healthcare professionals to establish standards that allow for the implementation and widespread adoption of these tools in clinical practice. In this context, the semiogram provides a multidimensional and visual approach to gait quantification. It encompasses all the desired features of an easily interpretable, quantitative, and precise tool for monitoring the semiological evolution of gait in neurological pathologies.

A Fast Fourier Transform and Normalized Magnitude Spectrum for SPARC Calculation

In the SPARC calculation (see Equation (6)), we employ the Fast Fourier Transform (FFT) to convert time-domain signals into the frequency domain. This complex output is then transformed into a magnitude spectrum, which is normalized to allow comparison.

A.1 FFT with Zero-Padding

When applying an FFT to convert a signal into the frequency domain, it is important to carefully choose the size of the FFT. In our code, this corresponds to the variable *nfft*, calculated as follows

$$\text{nfft} = 2^{\lceil \log_2(\text{len}(\mathbf{gyr})) \rceil + \text{padlevel}}. \tag{20}$$

The length of the input gyration signal is first computed, and its base-2 logarithm is taken to determine the next highest power of 2. An additional padlevel parameter is then added to increase the length, determining the amount of zero-padding applied to the signal before performing the FFT. A higher padlevel increases the length of the padded signal, which improves the frequency resolution of the resulting spectrum. However, excessive padding may also introduce artificial peaks or noise. The value of padlevel is fixed to 4 in our demo, following the recommendations from [2]. Thus, it does not alter the original signal but increases the frequency resolution, leading to a more refined frequency spectrum. It leads to a spectral arc with N^{FFT} points (in the code, from 0 to N^{FFT} excluded).

A.2 Normalized Magnitude Spectrum

The FFT output is complex, so we compute the magnitude of the spectrum, calculated by taking its absolute value. This magnitude spectrum is then normalized by dividing it by its maximum value

$$M_f = \frac{|\text{FFT}(\mathbf{gyr})|}{\max(|\text{FFT}(\mathbf{gyr})|)}. \tag{21}$$

The normalization process allows for easier comparison between different signals or experiments, which is the basic principle of the semiogram.

B Autocorrelation and Peak Detection

B.1 FFT-based Method to Calculate Autocorrelation

The exact mathematical formulation for autocorrelation is provided in Equation (10). In the Python code, autocorrelation is efficiently computed using FFT, which leverages the convolution theorem. It first computes the FFT of the signal and then performs an inverse FFT on the product of the signal's FFT and its conjugate. We computed a non biased estimator, with a normalization. The equivalence of these two formulas is based on an assumption of periodicity, which is a reliable assumption in the analysis of gait signals. It ensures that our computational approach faithfully represents the theoretical analysis.

B.2 Autocorrelation Peak Detection Methods for P1 and P2

The first and second peaks of the autocorrelation function for craniocaudal acceleration data respectively correspond to the step (P1) and stride (P2) phases of gait. The search for the amplitude of the P1 and P2 peaks is conducted during each of the two straight-line phases, the 'go' and 'back' phases, ignoring the U-turn phase. It evaluates the P1 and P2 values for both the 'go' and 'back' phases. Finally, the best amplitude is retained as the reference value.

To estimate the peak amplitude, the algorithm selects the most appropriate peak detection technique by comparing two different methods (function peak_1 and peak_2 in code), ensuring robust detection of the step and stride phases. This limits the risk of incorrect detection.

- Method 1 (function peak_1 in code): This method first detects all autocorrelation maxima greater than 0.3 and then selects the peaks closest to the average stride duration for P2 and half the average stride duration P1.

- Method 2 (function peak_1 in code): This method focuses on a defined frame around the mean stride duration for P2 (between 85% and 115% of the mean stride duration) and half the mean stride duration for P1 (between 35% and 65% of the mean stride duration). These ranges are based on the assumption that the step and stride phases will exhibit strong periodicity around these time intervals. The function thus detects maximum autocorrelation values greater than 0.3 within each interval.

Peaks are detected by analyzing the first-order difference. It allows for control over peak selection through thresholding and minimum distance constraints, ensuring that only the most significant peaks are identified.

References

[1] S. D. Alster, S. Menascu, A. Achiron, A. Kalron, M. Dolev, and U. Givon, *Longitudinal Relationships Between Disability and Gait Characteristics in People with MS*, Scientific Reports, (2022), pp. 1–10, https://doi.org/10.1038/s41598-022-07734-y.

[2] S. Balasubramanian, A. Melendez-Calderon, A. Roby-Brami, and E. Burdet, *On the Analysis of Movement Smoothness*, Journal of NeuroEngineering and Rehabilitation, 12 (2015), pp. 1–11, https://doi.org/10.1186/s12984-015-0090-9.

[3] R. P. M. Barrois, D. Ricard, L. Oudre, L. Tlili, C. Provost, A. Vienne, P. P. Vidal, S. Buffat, and A. P. Yelnik, *Observational Study of* 180^o *Turning Strategies Using Inertial Measurement Units and Fall Risk in Poststroke Hemiparetic Patients*, Frontiers in Neurology, 8 (2017), pp. 1–11, https://doi.org/10.3389/fneur.2017.00194.

[4] Y. Beck, T. Herman, M. Brozgol, N. Giladi, A. Mirelman, and J. M. Hausdorff, *SPARC: A New Approach to Quantifying Gait Smoothness in Patients with Parkinson's Disease*, Journal of NeuroEngineering and Rehabilitation, 15 (2018), pp. 1–9, https://doi.org/10.1186/s12984-018-0398-3.

[5] F. do Vale Garcia, M. J. da Cunha, C. P. Schuch, G. P. Schifino, G. Balbinot, and A. S. Pagnussat, *Movement Smoothness in Chronic Post-Stroke Individuals Walking in an Outdoor Environment-A Cross-Sectional Study Using IMU Sensors*, PLoS ONE, 16 (2021), pp. 1–18, https://doi.org/10.1371/journal.pone.0250100.

[6] N. E. Fritz, S. D. Newsome, A. Eloyan, R. E. R. Marasigan, P. A. Calabresi, and K. M. Zackowski, *Longitudinal Relationships Among Posturography and Gait Measures in Multiple Sclerosis*, Neurology, 84 (2015), pp. 2048–2056, https://doi.org/10.1212/WNL.0000000000001580.

[7] A. A. Ibrahim, A. Küderle, H. Gassner, J. Klucken, B. M. Eskofier, and F. Kluge, *Inertial Sensor-Based Gait Parameters Reflect Patient-Reported Fatigue in Multiple Sclerosis*, Journal of NeuroEngineering and Rehabilitation, 17 (2020), https://doi.org/10.1186/S12984-020-00798-9.

[8] H. Iijima, R. Eguchi, T. Aoyama, and M. Takahashi, *Trunk Movement Asymmetry Associated with Pain, Disability, and Quadriceps Strength Asymmetry in Individuals with Knee Osteoarthritis: a Cross-Sectional Study*, Osteoarthritis and Cartilage, 27 (2019), pp. 248–256, https://doi.org/10.1016/J.JOCA.2018.10.012.

[9] A. Melendez-Calderon, C. Shirota, and S. Balasubramanian, *Estimating Movement Smoothness From Inertial Measurement Units*, Frontiers in Bioengineering and Biotechnology, 8 (2021), pp. 1–16, https://doi.org/10.3389/fbioe.2020.558771.

[10] M. Pau, S. Mandaresu, G. Pilloni, M. Porta, G. Coghe, M. G. Marrosu, and E. Cocco, *Smoothness of Gait Detects Early Alterations of Walking in Persons with Multiple Sclerosis Without Disability*, Gait and Posture, 58 (2017), pp. 307–309, https://doi.org/10.1016/J.GAITPOST.2017.08.023.

[11] F. A. Storm, A. Cesareo, G. Reni, and E. Biffi, *Wearable Inertial Sensors to Assess Gait During the 6-Minute Walk Test: A Systematic Review*, Sensors, 20 (2020), p. 2660, https://doi.org/10.3390/S20092660.

[12] A. Vienne, R. P. Barrois, S. Buffat, D. Ricard, and P. P. Vidal, *Inertial Sensors to Assess Gait Quality in Patients with Neurological Disorders: A Systematic Review of Technical and Analytical Challenges*, Frontiers in Psychology, 8 (2017), pp. 1–12, https://doi.org/10.3389/fpsyg.2017.00817.

[13] A. Vienne-Jumeau, F. Quijoux, P.-P. Vidal, and D. Ricard, *Wearable Inertial Sensors Provide Reliable Biomarkers of Disease Severity in Multiple Sclerosis: A Systematic Review and Meta-Analysis*, Annals of Physical and Rehabilitation Medicine, 63 (2020), pp. 138–147, https://doi.org/10.1016/j.rehab.2019.07.004.

[14] C. Voisard, N. De l'Escalopier, D. Ricard, and L. Oudre, *Automatic Gait Events Detection with Inertial Measurement Units: Healthy Subjects and Moderate to Severe Impaired Patients*, Journal of NeuroEngineering and Rehabilitation, (2024), https://doi.org/10.1186/s12984-024-01405-x.

[15] C. Voisard, N. De l'Escalopier, A. Vienne-Jumeau, A. Moreau, F. Quijoux, F. Bompaire, M. Sallansonnet, M.-L. Brechemier, I. Taifas, C. Tafani, E. Drouard, N. Vayatis, D. Ricard, and L. Oudre, *Innovative Multidimensional Gait Evaluation Using IMU in Multiple Sclerosis: Introducing the Semiogram*, Frontiers in Neurology, (2024), https://doi.org/10.3389/fneur.2023.1237162.