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A toolbox for the identification of foot-floor contact sequences to analyze atypical gait cycles in a real-life scenario: application on patients after proximal femur fracture and healthy elderly

Marco Ghislieri[1*], Nicolas Leo[1], Marco Caruso[1], Clemens Becker[2], Andrea Cereatti[1] and Valentina Agostini[1]

Abstract

Background The detection of gait subphases is pivotal for a comprehensive assessment of gait quality, playing a key role in different applications such as rehabilitation programs, movement disorder diagnostics, and fall prevention strategies. However, few methods provide dynamic subphase segmentation relying solely on plantar pressure signals in real-life, unsupervised conditions. This work aims to present an open-source, flexible toolbox for the automatic detection of gait subphases, and to introduce novel digital gait biomarkers derived from subphase analysis, enabling effective monitoring of frail patients in real-world, challenging environments.

Methods A novel MATLAB toolbox for decoding gait subphases from plantar pressure signals (PIN2GPI – from Pressure INsoles to Gait Phase Identification) is described and made publicly available. To test our algorithm, the open database provided by the Mobilise-D consortium is used, focusing on walking bouts recorded through pressure insoles in an unsupervised setting during free activities of daily living (lasting approximately 2.5 h). We extracted relevant gait parameters from a population of 32 elderly subjects: 14 frail patients after Proximal Femur Fracture (PFF) and 18 older Healthy Adults (HA).

Results On average, PFF patients showed, with respect to HA, a reduced number of gait cycles (1059 ± 201 vs. 2076 ± 246; $p = 0.006$), percentage of time spent walking (9.1 ± 1.7% vs. 15.0 ± 1.9%; $p = 0.04$), and cadence (39.2 ± 2.0 cycles/min vs. 45.7 ± 1.2 cycles/min; $p = 0.007$), as well as an increased percentage of atypical gait cycles on the worst side (8.8 ± 4.1%/min vs. 0.8 ± 0.1%/min; $p = 0.007$), interlimb gait asymmetries in flat-foot contact (6.9 ± 1.2% of the Gait Cycle (%GC) vs. 2.5 ± 0.4%GC; $p = 0.007$) and swing subphase durations (6.5 ± 1.6%GC vs. 1.6 ± 0.3%GC; $p = 0.0003$).

Conclusion These findings highlight the potential of gait subphase analysis as a valuable tool for pinpointing key factors related to walking quality from real-life measurements collected during unsupervised monitoring of frail subjects, paving the way to more precise and objective gait assessment in real-life scenarios.

*Correspondence:
Marco Ghislieri
marco.ghislieri@polito.it

Full list of author information is available at the end of the article

Keywords Foot-pressure insoles, Gait phases, Hip fracture, Walking, Rehabilitation, Fall prevention

Introduction

Assessing gait quality is crucial to monitor and implement prevention and rehabilitation programs in patients and in frail populations of elderly subjects, such as patients with severe osteoporosis, previous hip fractures, history of falls, and/or neurodegenerative diseases affecting locomotor patterns [1]. To this purpose, the adoption of digital gait biomarkers is increasingly gaining recognition in the scientific community [2, 3]. In particular, the detection of foot-floor contact sequences plays a key role in estimating spatio-temporal gait parameters, and variability in gait phase sequence can serve as early indicators of gait disturbances, frailty, or neurological disorders [4, 5].

While walking, the same individual can express a variety of different foot-floor contact sequences. In fact, although the typical sequence of gait phases is the succession of Heel contact, Flat-foot contact, Push-off, and Swing (i.e., standard HFPS gait cycles), other sequences can be segmented and classified (i.e., "atypical" gait cycles), both in physiological and pathological gait [4]. In previous studies, the percentage of Atypical Gait Cycles ($AGC\%$) was extracted from foot-switch signals using a 4-level coding [4–6]. It was found that patients after Total Hip Arthroplasty (THA) have an increased $AGC\%$ with respect to age- and gender-matched controls [6]. An increased $AGC\%$ was also found in Parkinson's Disease (PD) patients with respect to age-matched controls [5, 7]. As an example, FPS cycles (i.e. the sequence of Flat-Foot Contact, Push-Off, and Swing) were observed, with a missing heel strike phase, as well as cycles with a forefoot strike (PFPS and PS) [7]. However, to the best of the authors' knowledge, all previous studies focusing on the analyses of gait phases (including also the subphases of stance) and atypical gait cycles have been performed in laboratory or clinical settings under supervised conditions. This typically requires that the subject is constrained to move within a specific walking path. No information is available on frail subjects during prolonged digital monitoring in real-life conditions.

The identification and classification of gait subphases are pivotal, as atypical gait sequences are associated with increased instability and reduced efficiency in locomotion. There are various ways for detecting gait events, including footswitches [4, 5], Pressure Insoles (PIs) [8, 9], Inertial Measurement Units (IMUs), and, more recently, human electrostatic field detection systems [10–13]. One of the most simple and accurate ways to identify gait subphases is through Pressure Insoles (PIs), which are wearable sensors (worn inside the shoes) that provide direct, real-time measurements of foot pressure during ground contact. As such, they are considered the gold standard in gait subphase detection, unlike Inertial Measurement Units (IMUs) that alone cannot provide detailed information about foot-floor interactions [14]. Consequently, their application span a wide range of fields from the control of exoskeletons [9, 15] and lower-limb active prostheses [16] to the fall-risk assessment and prediction [17–19]. Many existing gait analysis algorithms focus primarily on distinguishing between stance and swing phases [8, 9, 20–22]. However, the complexity of human walking can require a more refined classification of gait phases (including the subphases of stance) to address specific challenges, such as analyzing non-standard sequences of foot-floor contact (e.g., with initial forefoot strike), as well as their frequency of occurrence during walking.

In literature, PI-based gait-phase identification approaches incorporating three to six phases have been proposed [23–25]. From the computational perspective, the approaches that employ input PI data to detect gait phases can be broadly classified into two main categories: threshold-based methods and machine learning-based algorithms. The first ones typically comprise an automatic pipeline that involves specific cutoff values to identify relevant events within the pressure measurements [8, 20, 25]. The second category includes more sophisticated computational techniques, such as supervised and unsupervised learning, to recognize complex patterns, make predictions, or classify different gait characteristics based on pressure data [19, 23, 24].

Adopting a threshold-based approach, the specific aims of this study are: (*i*) to provide an open-source and flexible toolbox (PIN2GPI), designed for the automatic detection of gait subphases, easily configurable to work with other types of PIs regardless of the number of sensors, and (*ii*) to test the algorithmic pipeline on PI signals collected during prolonged unrestricted digital monitoring of a population of frail elderly patients after Proximal Femur Fracture (PFF) and a reference population of older Healthy Adults (HA), for extracting $AGC\%$ and other relevant gait parameters. We hypothesize that PFF patients are characterized by augmented $AGC\%$, with respect to HA, and more asymmetric gait-phase durations between lower limbs. To test this hypothesis, the open source Mobilise-D Technical Validation Study (TVS) dataset (https://zenodo.org/records/13987963; accessed on 19 June 2025) [26–29] was used. This includes a comprehensive set of standardized laboratory-based tests as well as free-living recordings. In addition to PI data, these recordings also comprise measurements from inertial sensors placed on the pelvis, head, and feet, as detailed in the dataset description. For the purpose of this study, we deliberately focused on PI data collected under free-living conditions, as this is where we believe our contribution can offer a novel and valuable perspective. This specific context is still relatively underrepresented in the scientific literature, especially when it comes to the detection of gait subphases [30].

Materials and methods

The PIN2GPI toolbox (from Pressure INsoles to Gait Phases Identification), developed in MATLAB release R2024b, is introduced and made publicly available through a GitHub repository (https://github.com/Biolab-PoliTO/PIN2GPI; accessed on 19 June 2025). This open-source toolbox is designed for the automatic identification and classification of gait subphases using the temporal and spatial information provided by PIs. The algorithmic pipeline is described step-by-step in the following and is then applied to analyze PFF and HA data made publicly available in the Mobilise-D Technical Validation Study (TVS) dataset (https://zenodo.org/records/13987963; accessed on 19 June 2025) [26–29]. Afterward s, specific gait parameters related to fall risk are extracted and compared between the populations.

PIN2GPI toolbox for gait-phase identification

This toolbox is specifically designed to process and analyze PI signals, requiring no additional sensors, such as IMUs. PI data, amplitude-normalized with respect to the global maximum between 0 and 1, serve as the required input for the algorithm and should be organized in a single structure containing two matrices: '$LeftFoot$' (N-by-M matrix) and '$RightFoot$' (N-by-M matrix), where N is the number of time samples and M is the number of channels. The overall signal-processing pipeline is schematized in Fig. 1, showing signals captured from 16 PI channels of one foot of a representative participant (Fig. 1a):

- PI signals are grouped into three distinct clusters, corresponding to the three anatomically relevant contact points on the foot during the gait cycle: the heel, the 5th metatarsal head (lateral forefoot), and the 1st metatarsal head (medial forefoot) (Fig. 1b);
- PI signals within the same cluster are summed and normalized with respect to the number of channels inside each cluster, ensuring that the amplitude of the aggregated signal remains comparable across different foot regions. Subsequently, the normalized signals are smoothed using an 11-sample moving average filter ($\sum PI$ in Fig. 1c);
- The first derivative is calculated ($\sum PI$)', representing the rate of pressure change over time within each cluster and an additional moving average filter with a 5-sample span is applied to reduce local fluctuations (Fig. 1d);
- For each cluster (corresponding to a specific portion of the foot), activation windows of foot-floor contact are identified using the derivative signal ($\sum PI$)', as described in the following. Candidate start-times and end-times are determined by detecting *maxima* and *minima* peaks exceeding an absolute amplitude threshold of 0.01 arbitrary units (a.u.). An activation window is defined as the time interval between the current maximum and the lowest minimum before the subsequent maximum. In cases where two maxima occur consecutively, the higher one marks the activation onset, and the next occurring minimum represents activation offset (deactivation of the PI channels in the specific cluster);
- The gait cycle subphases are then determined based on the activation/deactivation status of each cluster, as illustrated in Fig. 1e:
  - Heel contact phase (H): only the heel cluster is active;
  - Flat-foot contact phase (F): the heel cluster is active, with at least one cluster under the forefoot also active;
  - Push-off phase (P): the heel cluster becomes inactive, while at least one forefoot cluster is active;
  - Swing phase (S): all clusters are inactive.
  - Finally, the left and right (4-level) signals are graphically represented and can be exported in.csv format.

Dataset: toolbox validation in real-life conditions

From the open database made available by the Mobilise-D consortium [26–28], the dataset analyzed consists of bilateral PI signals recorded from a total of 32 volunteers: 14 PFF and 18 HA. The subjects were monitored during free activities of daily living lasting approximately 2.5 h, in an unsupervised manner [27].

Figure 2 shows the acquisition system. PIs consisted of 16 force sensing resistors (thickness: 240 μm) covered with a polyester layer. Two different PI sizes were used (small size: EU 36–37; large size: EU 42–43). An IMU was attached to the shoelaces of each shoe, serving as the central unit for data collection. The sampling frequency was 100 Hz.

The original dataset comprised a higher number of subjects: 19 PFF patients and 20 HA. Inclusion criteria for PFF patients were: age 65 years or older and surgical treatment (fixation or arthroplasty) for a low-energy proximal femur fracture (ICD-10 codes S72.0, S72.1, S72.2) confirmed by X-ray within the previous 12 months.

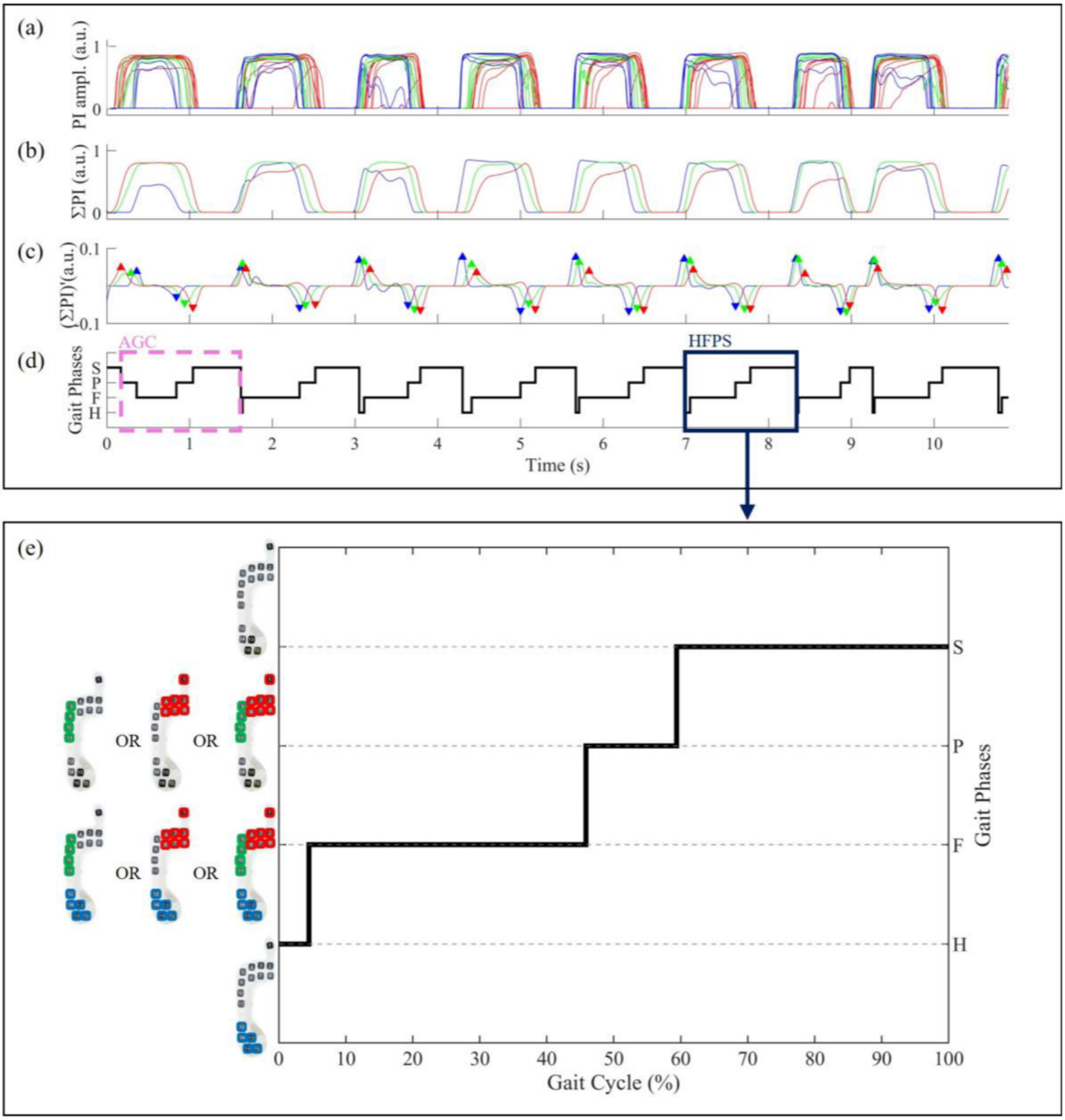

Fig. 1 Pipeline for the identification of gait phases on a representative subject. (**a**) Normalized Pressure Insole (PI) signals (16 channels, left foot) color-coded based on (spatial) cluster membership: heel (blue signals), 5th metatarsal head/anterior-lateral aspect (green signals), and 1st metatarsal head/hallux (red signals); (**b**) Sum of signals belonging to each cluster, normalized with respect to number of channels within each cluster; (**c**) After calculating the first derivative of the sum-signals represented in (**b**), the activations and deactivations of each cluster are identified finding local maxima (▲) and minima (▼) of each signal (blue, green, and red). (**d**) Four-level foot-floor contact signal (black line) is obtained from which it is possible to distinguish typical gait cycles (displaying the standard sequence of gait phases: HFPS) from Atypical Gait Cycles (AGC). An example of AGC (sequence of gait phases: PFPS) is highlighted by a magenta dashed-line rectangle. (**e**) Zoom of a standard HFPS sequence. Heel contact (H): only the heel cluster is active. Flat-foot contact (F): the heel cluster is active, and at least one cluster under the forefoot is also active. Push-off-phase (P): the heel cluster is non active, while at least one forefoot cluster is active. Swing (S): all clusters are non-active

Fig. 2 Schematization of the experimental set-up: a 16-channel Pressure Insole (PI) is positioned inside each subject's shoe

Patients with impaired mobility due to non-PFF causes were excluded. Healthy adults were included based solely on being 65 years of age or older [27]. However, after a visual check of PI signals, 1 PFF patient was excluded due to partial data missing, while 6 participants were discarded due to deteriorated PI signal quality (2 HA and 4 PFF participants). Therefore, the subsequent analysis is conducted on a dataset of 32 individuals: 14 PFF (Age: 79.2 ± 1.8 years; Gender: 7 females, 6 males, and 1 not declared or not available; Height: 169.4 ± 2.1 cm; Weight: 70.0 ± 4.2 kg; Body Mass Index: 24.2 ± 1.1 kg/m^2) and 18 HA (Age: 72.4 ± 1.3 years; Gender: 8 females, 10 males; Height: 165.7 ± 2.3 cm; Weight: 74.7 ± 2.8 kg; Body Mass Index: 27.2 ± 0.8 kg/m^2). The demographic and clinical characteristics of every participant are reported in the Supplementary Table (S1). Most recordings reached the target duration of 2.5 h (29 out of 32), but 3 recordings lasted less than two hours (2 PFF and 1 HA). All PFF patients had a history of fall in the 12 months prior to the assessment, except 2 subjects for which this information was not available. Only 3 subjects in the HA group had a history of fall. This information was retrieved directly from the open database documentation. Moreover, the dataset includes the indication of Walking Bouts (WBs), containing at least two consecutive right and left strides [26].

Gait cycle identification

Gait cycle segmentation is performed based on the output provided by the PIN2GPI toolbox, following the algorithm proposed by Agostini et al. in [4] with some modifications. Specifically, the gait cycle is defined as the interval between two consecutive initial contacts of the same foot with the ground, after the swing phase. The algorithm is based on two thresholds for the gait-cycle duration. The Gait-Cycle (GC) duration cannot be shorter than $\alpha * M$ or longer than $\beta * M$, where $\alpha = 0.8$, $\beta = 1.2$, and M is the *median* value of the GC durations. In this work, α and β were set at the same values defined in the previous algorithm [4], but here M represents the *median* value instead of the *mode*, as it was in the previous work. Firstly, cycles with only two subphases and a duration shorter than $\alpha * M$ are merged, provided that the total duration does not exceed $\beta * M$. Afterwards, any cycle shorter than $\alpha * M$, regardless of the number of subphases, is merged with the next one under the same condition.

Gait parameters

To consider only walking epochs extracted from the 2.5-hour recordings, the gait cycles identified within the previously defined WBs were included in the subsequent analyses. For each subject of PFF and HA populations, the following gait parameters were then extracted:

- Total number of GCs (sum of left and right cycles);
- Percentage of time spent walking during the recording, computed as the sum of all the WB durations (gait epochs) performed by the subject,

divided by the overall duration of the signal acquisition;

- Cadence, expressed as cycles per minute;
- $AGC\%\_norm($ worst side): $AGC\%$ was calculated for each side as the number of cycles that did not match the standard HFPS sequence, divided by the total number of segmented cycles [7]. Then, it was extracted the maximum value between left and right $AGC($ subject-specific "worst side"). Finally, $AGC\%\_norm$ was computed normalizing $AGC\%$ with respect to the gait epochs duration (expressed in min);
- Gait-phase interlimb asymmetry (for Heel strike, Flat-foot contact, Push-off, and Swing): for each of the 4 gait subphases of typical cycles (showing the standard sequence HFPS), it was calculated the asymmetry between the two lower-limb subphase durations, as the absolute value of the difference between the left and right phase durations, expressed as %GC:

$$GaitPhase\ interlimb\ asym. = |Left\ phase\ dur.\ (\%GC) - Right\ phase\ dur.\ (\%GC)| \quad (1)$$

Statistical analysis

For each gait parameter, the mean value and Standard Error (SE) were estimated for PFF and HA populations. To assess the normality of data distributions, the Lilliefors test was employed. Depending on the outcome of the normality test, either a two-sample Student's t-test (for normally distributed data) or Wilcoxon rank-sum test (for non-normally distributed data) was performed to compare results between PFF and HA populations (setting the significance level $\alpha = 0.05$). For statistically significant differences only, the absolute effect sizes were computed using the Hedges' g statistic. According to [31], an absolute g value of 0.2, 0.5, and 0.8 indicate a small, medium, and large effect size, respectively. Statistical analyses were performed using the Statistical and Machine Learning Toolbox of MATLAB release R2024b (The MathWorks Inc., Natick, MA, USA).

Results

A comparison between gait parameters extracted in PFF and HA populations is shown in Table 1; Figure 3.

On average, PFF showed fewer gait cycles (1059 ± 201, almost half of those observed in HA, i.e., 2076 ± 246, $p = 0.006$, $g = 1.0$), a reduced time spent walking (9.1 ± 1.7% vs. 15.0 ± 1.9%, $p = 0.04$, $g = 0.8$), and a reduced cadence (39.2 ± 2.0 cycles/min vs. 45.7 ± 1.2 cycles/min, $p = 0.007$, $g = 1.0$). Furthermore, the normalized percentage of atypical gait cycles (worst side) is markedly higher in PFF with respect to HA (8.8 ± 4.1%/min vs. 0.8 ± 0.1%/min, $p = 0.007$, $g = 0.7$). In addition, when considering the gait cycles showing the standard sequence of gait phases (HFPS), the interlimb asymmetry of gait phases was also higher in PFF with respect to HA population: statistically significant differences were found between PFF and HA in Flat-foot contact (6.9 ± 1.2%GC vs. 2.5 ± 0.4%GC, $p = 0.007$, $g = 1.3$) and Swing phase (6.5 ± 1.6%GC vs. 1.6 ± 0.3%GC, $p = 0.0003$, $g = 1.1$).

Discussion

This work proposes a pipeline for identifying gait subphases for the extraction of digital gait biomarkers that are hypothesized to be linked to walking quality and fall risk (e.g., the percentage of atypical gait cycles). The newly proposed pipeline uses pressure-insole signals only and translates a potentially noisy 16-channel pressure-insole signal into a 4-level signal, ready for gait-phase identification. In fact, when wearing and tightening the shoes, some pressure channels may remain active and need to be removed as a pre-processing step. Although the PIN2GPI was currently validated on the single PI configuration previously described, the toolbox is easily adaptable in the number and compositions of the spatial clusters (recording channels under each portion of foot) to best fit the user specific requirements.

Table 1 Values of parameters are reported as mean ± Standard Error (SE) across the population. Statistically significant differences ($p < 0.05$) are represented in bold. %GC: Percentage of Gait Cycle; PFF: Proximal Femur Fracture; HA: Healthy Adults; [a]: Student's t-test; [b]: Wilcoxon rank-sum test

Gait parameters	Comparison of PFF and HA gait cycles and statistical analysis		
	PFF	HA	p-value
Total number of gait cycles extracted	**1059 ± 201**	**2076 ± 246**	**0.006**[a]
Percentage of time spent walking (%)	**9.1 ± 1.7**	**15.0 ± 1.9**	**0.04**[b]
Cadence (cycles/min)	**39.2 ± 2.0**	**45.7 ± 1.2**	**0.007**[a]
Normalized percentage of Atypical Gait Cycles, worst side (%/min)	**8.8 ± 4.1**	**0.8 ± 0.1**	**0.007**[b]
Standard gait cycles (HFPS)			
Heel contact interlimb asymmetry (%GC)	3.3 ± 1.4	1.3 ± 0.2	0.9[b]
Flat-foot contact interlimb asymmetry (%GC)	**6.9 ± 1.2**	**2.5 ± 0.4**	**0.007**[b]
Push-off interlimb asymmetry (%GC)	4.4 ± 0.8	2.8 ± 0.5	0.09[a]
Swing interlimb asymmetry (%GC)	**6.5 ± 1.6**	**1.6 ± 0.3**	**0.0003**[b]

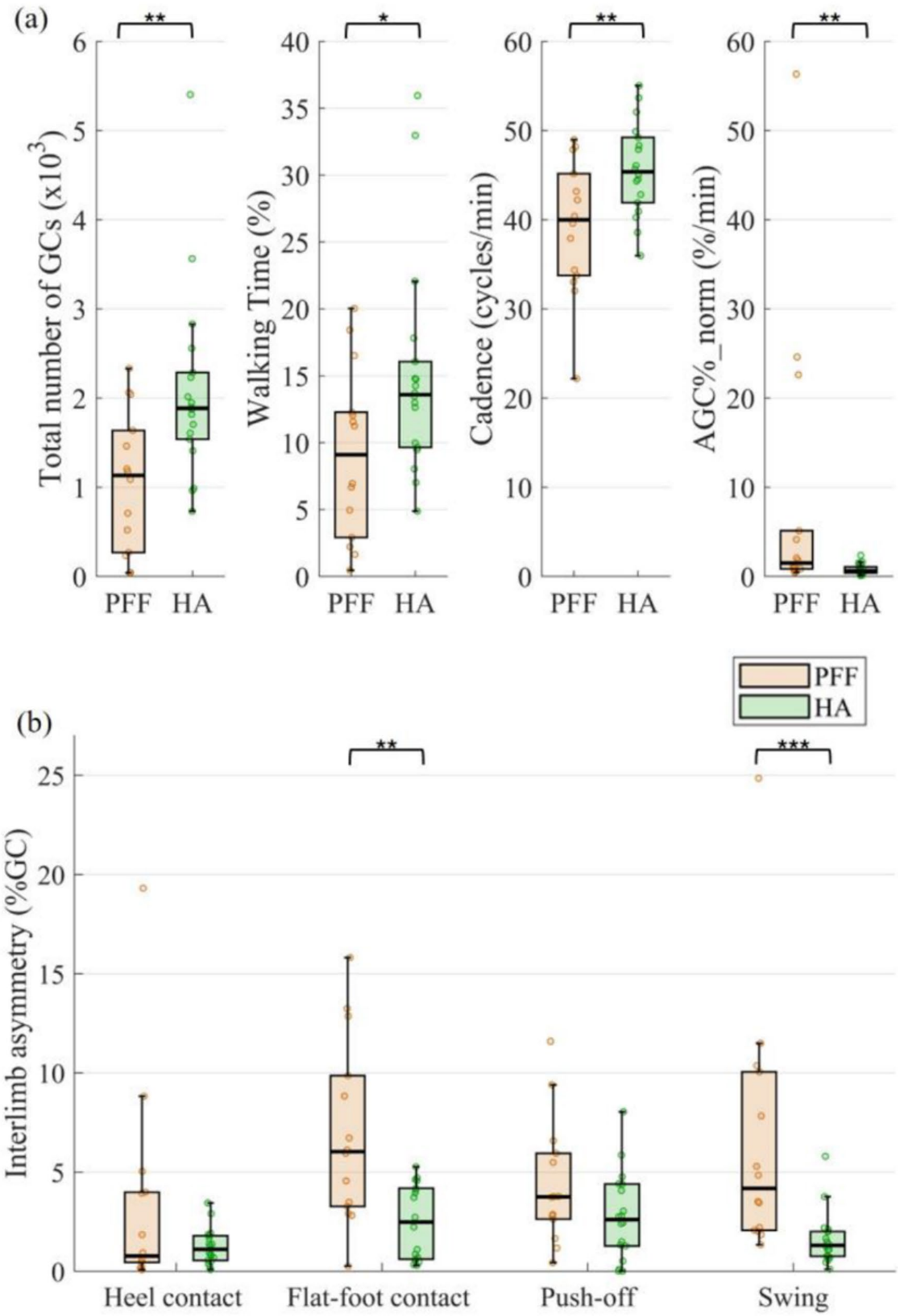

Fig. 3 Boxplot of the gait parameters extracted from Proximal Femur Fracture (PFF) and Healthy Adults (HA) populations. Panel (**a**) shows the total number of Gait Cycles (GCs), percentage of time spent walking (%), cadence (cycles/min), and normalized percentage of atypical gait cycles for worst side (%/min). Panel (**b**) shows the gait-phase interlimb asymmetry (%GC) for Heel contact, Flat-foot contact, Push-off, and Swing in the standard cycles (HFPS). Outliers are indicated by circles. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

PIN2GPI is made available to the scientific community through a GitHub repository (https://github.com/Biolab-PoliTO/PIN2GPI; accessed on 19 June 2025). Starting from the foot-floor contact sequences obtained through the PIN2GPI toolbox, informative gait parameters (i.e., digital gait biomarkers) can be derived even when the recordings are performed in an out-of-lab, unsupervised, real-life setting. The average number of gait cycles per subject analyzed in this study is remarkable: more than 1000 gait cycles in patients after Proximal Femur Fracture (PFF) and more than 2000 gait cycles in Healthy Adults (HA) were segmented, classified in "standard" and "atypical" gait cycles, and further characterized. In this study, gait parameters were extracted exclusively from gait cycles belonging to predefined WBs in order to consider walking epochs only [26]. However, other methods for selecting movement epochs could also be applicable, independent from the dataset and the WB definition. In fact, simple post-processing of the 4-level foot-floor contact signal allows the identification of walking cycles [4]. Notice that movement epoch segmentation is not necessary to apply the PIN2GPI toolbox.

As one could expect, PFF patients showed a reduced (halved) number of gait cycles: they walked consistently less than healthy elderly, also in terms of percentage of time spent walking (amount) and reduced walking cadence (rhythm), probably affected by the fear of falling and/or a perceived sense of imbalance. Results regarding the number of gait cycles and cadence align with those reported in the dataset by the Mobilise-D consortium [28], although in this study, these parameters were extracted using only PI recordings.

In healthy individuals, the most common gait cycle is HFPS, defined as the physiological sequence of Heel Contact (H), Flat-foot Contact (F), Push-Off (P), and Swing (H), with H, F, and P being the sub-phases of stance. By contrast, it is atypical any other gait cycle showing a foot-floor contact sequence different from HFPS. Focusing on the worst side, PFF patients remarkably increased the percentage of atypical gait cycles per minute with respect to HA. This agrees with previous literature reporting an augmented percentage of atypical gait cycles on the prosthetic side of patients at 12 months after total hip arthroplasty with respect to controls [6]. This is also in accordance with the clinical information available from the two populations analyzed in this study, since PFF were characterized by a history of fall, differently from HA. Furthermore, 36% of PFF patients (5 out of 14) showed $AGC\%\_norm > 3\%$, while none of the controls showed it. This suggests a higher risk of falls, due to altered ground clearance [32]. The most frequently observed atypical cycles in PFF patients are the foot-floor sequence "PFPS" (i.e., push-off, flat-foot contact, push-off, and swing), "PS" (i.e., push-off and swing), and "FPS" (i.e., flat-foot contact, push-off, and swing). The presence of a higher percentage of atypical cycles can increase the future recurrent fall risk, especially when the initial foot-strike is characterized by a forefoot-strike instead of a (standard) heel-strike. In fact, first contact with the floor with the forefoot instead of the rearfoot, in an augmented percentage of strides, can indeed be indicative of a compromised foot-ground clearance due to a reduced hip flexion and/or ankle dorsiflexion weakness or other motor control alterations, and are known key factors in the tendency to trip, slip, and fall while walking [32, 33]. In neurological populations, the presence of an increased percentage of atypical gait cycles was already addressed and correlated with clinical findings and severity of the locomotor patterns' alterations (e.g., in cerebral palsy [34] and in Parkinson's disease [5, 7] populations). In this work, we decided to focus on the "worst side", defined as the maximum (interlimb) percentage of atypical gait cycles produced in every minute of walk. This was chosen for a practical reason, since in the Mobilise-D database [27, 28] the information about the side of those that suffered proximal femur fracture could not be retrieved from the freely available dataset. This serendipity occasion allowed us to define a gait parameter that is robust and independent from the availability about the more affected-limb side, a situation that might frequently happen in studies carried out in unsupervised non-clinical settings. Analogous reasoning was adopted in the introduction of interlimb asymmetry of gait phases, since these outcome variables are independent from the knowledge of the more-/less-affected side of patients (and dominant/non-dominant side of healthy controls), although asymmetric patterns can be quantified. The strategy of focusing on interlimb asymmetry of gait outcome measures is also supported by literature [35, 36]. The interlimb asymmetry in the duration of flat-foot contact and swing was increased in PFF with respect to healthy elderly. In particular, the higher swing-phase asymmetry may be linked to the single-support duration asymmetry, which was already identified as one of the key gait variables in hip fracture patients [37]. It is interesting to notice that 43% of PFF patients (6 out of 14) showed a swing phase asymmetry > 5% GC, while only 5.5% of controls (1 out of 18) showed it. It should be noted that the proposed method represents a step further with respect to traditional methods focusing on stance and swing phases only, and that neglect studying the sub-phases of stance (heel contact, flat-foot contact, and push-off). The detailed study of gait phases (including the sub-phases of stance) unravels otherwise covert information related to abnormal gait patterns, although differences between populations are clearly highlighted also by simple (traditional) gait parameters, such as cadence, estimated in real-life conditions. For example, our threshold-based approach revealed that the interlimb asymmetry is mainly driven by the Flat-foot contact subphase with the largest effect size ($g = 1.3$), suggesting altered foot placement strategies, possibly as a compensatory mechanism to reduce load on the affected limb or due to impaired motor control. Furthermore, limiting the analysis to stance and swing phases prevents the possibility of recognising how the foot strikes the floor at the beginning of a gait cycle (e.g., physiological heel strike, flatfoot contact, or forefoot contact). Consequently, also the analysis of the percentage of atypical gait cycles (variability in the sequence of gait subphases) would not be possible.

The findings have several clinical implications. The recovery trajectories of PFF patients can be severely affected by femoral nerve palsy caused by the operative procedure [38]. This needs to be detected early on to inform the patient, physiotherapist, and surgeon. Implant failure such as cutting out or fracturing of the implant can occur during the first months after an operation and is often recognized with considerable delay [39]. Again, this complication needs to be diagnosed and is likely to lead to a revision of the implant. Finally, secondary avascular or vascular femoral head necrosis might occur after months or later. Again, this might lead to a re-operative procedure [40]. All of these events can occur in a single-digit percentage and not considered very rare. The presented approach might therefore have a relevant place in the management of these vulnerable patients.

In the ongoing project MOVEWISE (Mobility Observation Via Wearable Integrated Sensor Evaluation), we are focusing on the identification and quantification of key indicators of (in)stability for fall-risk prediction by providing continuous and ecological monitoring of people's mobility, through the recording of multicentric, prospective, observational, and longitudinal measurements using a wearable multi-sensor inertial system [41]. Within this study, we further explored the use of data recorded using plantar Pressure Insoles (PIs) during free activities of daily living in unsupervised conditions to study and characterize walking quality. Validation experiments across various insole types (and resolutions) and performance comparison with machine learning-/deep learning-based methods, whose lacks represent the limits in the current work, might be addressed by future studies.

In conclusion, the present study provides an original and practical operational tool for an accurate analysis of the sub-phases of real-world gait. It is therefore complementary information. This has clinical implications in the post-operative phase and rehabilitation period. Key features derived, such as the percentage of atypical gait cycles and interlimb asymmetry in the duration of specific subphases (Swing and especially Flat-foot Contact), have shown significant discriminatory power between patients after proximal femur fracture (PFF) and healthy adults (HA). Furthermore, this methodology allows the identification of high risk subjects for imminent falls for preventive purposes. This provides a novel framework that can be integrated and studied into future fall prevention approaches and clinical protocols.

Abbreviations

AGC	Atypical Gait Cycle
GC	Gait Cycle
HA	Healthy Adult
HFPS	Heel contact, Flat-foot contact, Push-off, and Swing sequence
IMU	Inertial Measurement Unit
PD	Parkinson's Disease
PFPS	Push-off, Flat-foot contact, Push-off, and Swing sequence
PI	Pressure Insole
PIN2GPI	from Pressure INsoles to Gait Phase Identification
PFF	Proximal Femur Fracture
PS	Push-off, and Swing sequence
SE	Standard Error
THA	Total Hip Arthroplasty
WB	Walking Bout

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12984-025-01683-z.

Supplementary Material 1

Author contributions

Marco Ghislieri: Conceptualization, Methodology, Software, Formal Analysis, Writing – Review & Editing. Nicolas Leo: Data Curation, Methodology, Software, Formal Analysis, Writing – Original Draft, Writing – Review & Editing, Visualization. Marco Caruso: Conceptualization, Writing – Review & Editing. Clemens Becker: Validation, Writing – Review & Editing. Andrea Cereatti: Conceptualization, Writing – Review & Editing. Valentina Agostini: Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing, Supervision, Funding acquisition. All the authors have read and agreed on the submitted version of the manuscript.

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Data availability

To validate the newly proposed algorithm, the Mobilise-D Technical Validation Study (TVS) dataset was used (https://doi.org/10.5281/zenodo.13987963; accessed on 19 June 2025). The PIN2GPI toolbox presented in this study is freely available on GitHub (https://github.com/Biolab-PoliTO/PIN2GPI/tree/main; accessed on 19 June 2025).

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Author details
[1]Department of Electronics and Telecommunications, PolitoBIOMed Lab, Politecnico di Torino, Torino 10129, Italy
[2]Unit Digital Geriatrie, Geriatrisches Zentrum, Universitätsklinikum, University of Heidelberg, Heidelberg, Germany

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