Atypical Gait Cycles Measured in Free-Living Conditions for Fall Prevention of Frail Subjects

(Article begins on next page)

Atypical Gait Cycles Measured in Free-Living Conditions for Fall Prevention of Frail Subjects

Nicolas Leo
Department of Electronics and Telecommunications, Polito[BIO]MedLab, Politecnico di Torino
Turin, Italy
nicolas.leo@polito.it

Marco Ghislieri
Department of Electronics and Telecommunications, Polito[BIO]MedLab, Politecnico di Torino
Torino, Italy
marco.ghislieri@polito.it

Marco Caruso
Department of Electronics and Telecommunications, Polito[BIO]MedLab, Politecnico di Torino
Torino, Italy
marco.caruso@polito.it

Andrea Cereatti
Department of Electronics and Telecommunications, Polito[BIO]MedLab, Politecnico di Torino
Torino, Italy
marco.caruso@polito.it

Valentina Agostini
Department of Electronics and Telecommunications, Polito[BIO]MedLab, Politecnico di Torino
Torino, Italy
valentina.agostini@polito.it

***Abstract*—Fall-risk assessment of frail individuals is pivotal to implement fall prevention campaigns. Within the framework of the ongoing project MOVEWISE (Mobility Observation Via Wearable Integrated Sensor Evaluation), the aim of this work is to introduce digital gait biomarkers for monitoring frail patients in an ecological (but challenging) scenario. The open database provided by the Mobilise-D consortium was used to test our algorithm. We analyzed walking bouts recorded through pressure insoles in an unsupervised setting, during free activities of daily living (lasting approximately 2.5 hours). 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)). On average, PFF patients showed a reduced number of gait cycles (PFF: 524 ± 100, HA: 1030 ± 123, *p* = 0.006), a reduced cadence (PFF: 35.5 ± 1.8 cycles/min, HA: 42.3 ± 1.3 cycles/min, *p* = 0.005), an increased percentage of atypical gait cycles (PFF: 0.90 ± 0.23 %/cycles/min, HA: 0.38 ± 0.06 %/cycles/min, *p* = 0.046), and more asymmetrical gait phases, significantly different for Flat-Foot contact (PFF: 6.5 ± 1.3 % of gait cycle, HA: 2.5 ± 0.4 % of gait cycle, *p* = 0.003) and Swing (PFF: 6.6 ± 1.6 % of gait cycle, HA: 1.7 ± 0.3 % of gait cycle, *p* = 0.002). The proposed pipeline was able to extract informative gait parameters although the recordings were performed out-of-lab in an unsupervised environment, efficiently pinpointing key factors related to fall risk.**

Keywords—foot-pressure insoles, elderly, Proximal Femur Fracture, walking

I. Introduction

Accurate fall-risk assessment is crucial to implement prevention programs in frail populations of elderly subjects, such as patients with severe osteoporosis, previous hip fractures, history of falls, or neurodegenerative diseases affecting locomotor patterns.

The ongoing project MOVEWISE (Mobility Observation Via Wearable Integrated Sensor Evaluation) is 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 [1].

Within this study, we further explored the use of data recorded using plantar Pressure Insoles (PIs) to characterize walking quality and fall risk by identifying the number and type of atypical gait cycles during activities of daily living in unsupervised, real-life conditions [2].

In previous studies carried in laboratory conditions, it was demonstrated that the Percentage of Atypical Gait Cycles (*Perc_AGC*) extracted from foot-switch signals are a valid gait biomarker for patients' follow-up in Parkinson's Disease (PD) [3],[4] and it was hypothesized to be descriptive of fall risk. However, *Perc_AGC* was never extracted from PI signals, and in particular, from PI signals collected in an unsupervised manner in frail subjects during free (outdoor and unrestricted) activities of daily living.

The specific aims of this study are: *(i)* to describe a pipeline for extracting *Perc_AGC* (and other relevant gait parameters) from PI signals acquired during a prolonged digital monitoring outside of the clinical setting, in free-living conditions and *(ii)* to test the pipeline on a population of frail elderly patients after Proximal Femur Fracture (PFF) and a reference population of older Healthy Adults (HA).

This proceeding is part of the project NODES, which has received funding from the MUR – M4C2 1.5 of PNRR funded by the European Union - NextGenerationEU (Grant agreement no. ECS00000036) – CUP E13B22000020001.

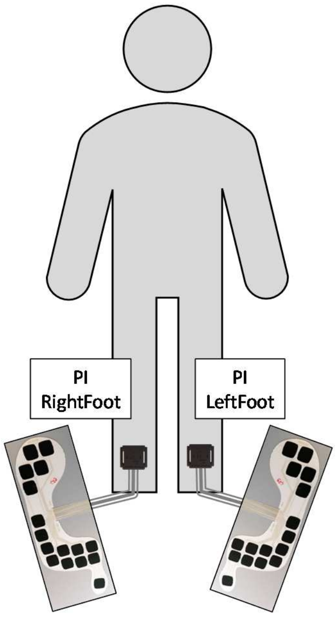

Figure 1: Schematization of the experimental set-up: a 16-channel Pressure Insole (PI) is positioned inside each subject's shoe.

II. Materials and Methods

A. Populations monitored in free-living conditions

Since data acquisition related to the MOVEWISE project is still ongoing, PI signals were extracted from the database made freely available by the Mobilise-D consortium [5], analyzing a group of 32 elderly subjects: 14 PFF patients and 18 controls (HA). All participants were asked whether they had experienced any falls in the 12 months prior to the assessment. All PFF patients had a history of fall, except 2 subjects for which this information was not available. Only 3 subjects in the HA group had a history of fall during the same retrospective period.

Figure 1 shows the acquisition system. PIs consisted of 16 force sensing resistors (thickness: 240 µm) covered with a polyester layer. Two different sizes of pressure insoles (PIs) were employed to accommodate varying foot dimensions among participants: a small size corresponding to EU shoe sizes 36–37, and a large size corresponding to EU sizes 42–43. The analog front-end enabled the connection between the PIs and the microcontroller unit, which was integrated into the main board along with other components such as a Inertial Measurement Unit (IMU), a memory, and a Bluetooth module [2]. The main board has been designed for low-power motion detection and local data storage, supporting both wired and wireless transmission. It was fixed to the shoelaces of each shoe, ensuring both the stability of the wearable system and the safety of the subject while walking. The sampling frequency was 100 Hz.

For each subject, the recording lasted about 2.5 hours, and it was conducted outside the clinical setting, in free-living conditions, as described in [6]. In this context, all participants were instructed to carry on with their usual daily activities, which included some suggested tasks such as walking outdoors, walking on an inclined path, going up and down stairs, and moving between rooms.

B. Data analysis

Out-of-lab data were standardized as described in [7] and imported in MATLAB release R2024b (The MathWorks Inc., Natick, MA, USA). The dataset was organized into individual participant folders, that included subfolders corresponding to different experimental sessions. Among these, the '*Free-living'* subfolder contained data acquired from the 2.5-hour continuous recording in real-world conditions. Specifically, pressure insole data were stored within two dedicated fields, named '*LeftFoot'* and '*RightFoot'*, which corresponded to the left and right foot, respectively. Each field contained a matrix called *'NormalizedPressure'*, structured as a N-by-M array, where N is the number of time samples recorded and M represents the number of pressure channels (or sensors) embedded.

The overall signal-processing pipeline is schematized in **Figure 2**, for a representative subject. **Figure 2a** shows signals collected along the whole recording, captured from 16 PI channels. The dataset includes the indication of Walking Bouts (WBs), containing at least two consecutive right and left strides [2]. We extracted for further analysis only the WB containing at least three consecutive right and left strides, discarding those with a smaller number of strides [2].

PI signals were grouped into three clusters, corresponding to the three anatomic contact points on the foot: the heel, the 5th, and the 1st metatarsal heads. An example of WB is displayed in **Figure 2b** (9 gait cycles are represented). PI signals within the same cluster were summed and smoothed (ΣPI) using an 11-sample moving average filter (**Figure 2c**) and their first derivative (ΣPI)' was calculated. The resulting signals underwent an additional moving average filter with a 5-sample span (**Figure 2d**).

For each cluster, the activation start times (maxima) and end times (subsequent minima) were identified as peaks exceeding a height of 0.06, with a minimum prominence of 0.15, and a minimum distance of 20 samples (200 ms) between consecutive peaks.

In cases where two consecutive minima occurred within a 500 ms interval, the second minimum was selected as the deactivation point. Gait cycle phases were then determined based on the clusters' activation/deactivation windows, as illustrated in **Figure 2f**:

- Heel contact-phase (H): only the heel cluster is active
- Flat foot contact-phase (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 inactive, while at least one forefoot cluster remains active
- Swing-phase (S): all clusters are inactive.

Anti-bouncing filter was applied to remove short and spurious phases shorter or equal to 50 ms surrounded by the same phase before and after them. Gait cycle segmentation and post-processing followed the pipeline as in [8], with some modifications. In particular, thresholds were set based on the median Gait Cycle (GC) duration, using α = 0.8 and β = 1.6.

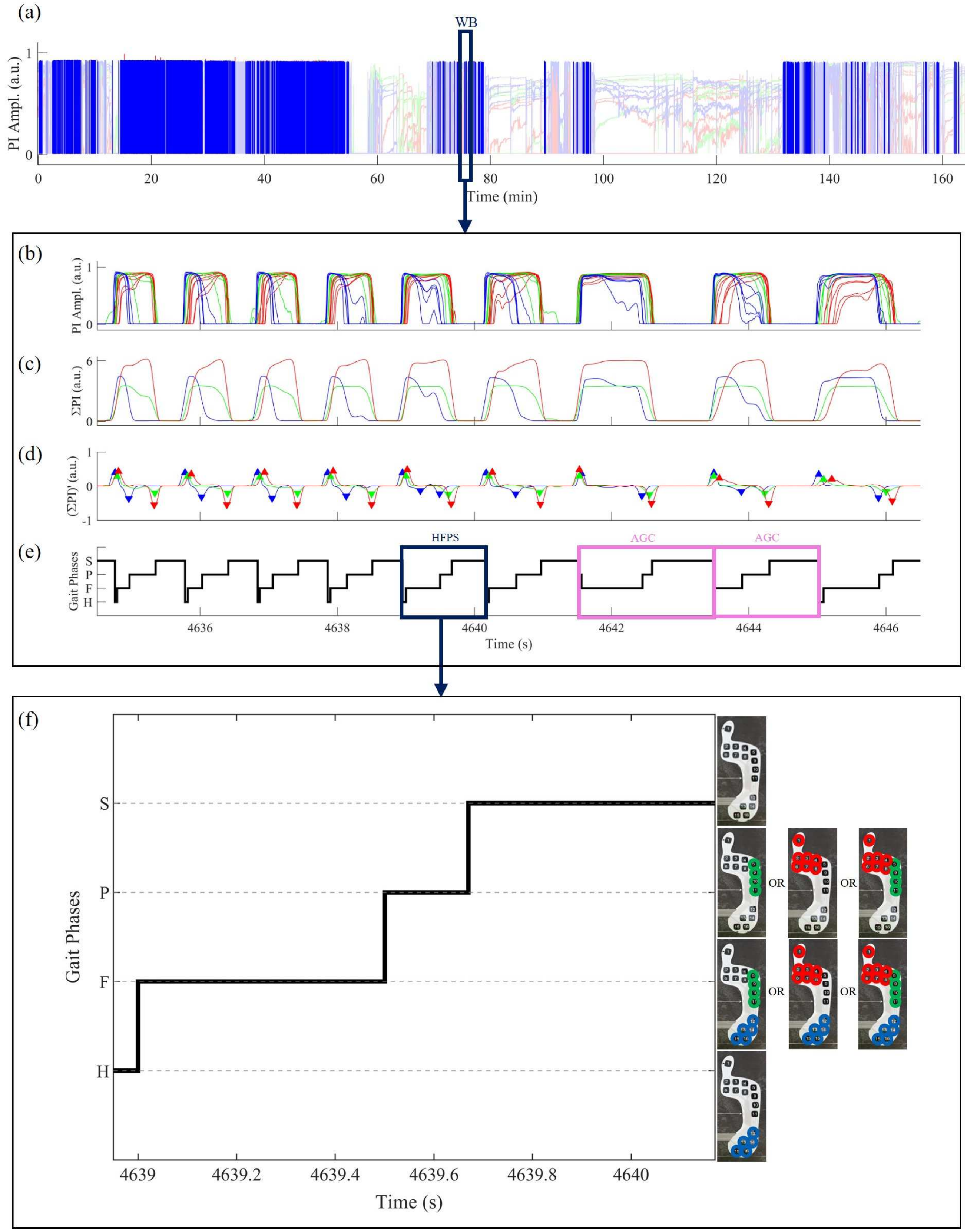

Figure 2: Pipeline for the detection of gait phases on a representative subject. (a) Normalized Pressure Insole (PI) signals (right foot, 16 channels) during a long recording (~ 2.5 h) of real-world unsupervised activity: walking bouts (WB) are highlighted with deeper colors; (b) Zoom of a WB (containing 9 gait cycles) extracted from the recording, with PI channels 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); (c) Sum of signals belonging to each cluster; (d) After calculating the first derivative of the sum-signals represented in (c), the activation and deactivation of each cluster are identified finding the local maxima (▲) and local minima (▼) of each signal (blue, green and red). (e) 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). Examples of AGCs are highlighted through magenta rectangles (PFPS and FPS gait cycles are present). (f) 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 inactive, while at least one forefoot cluster remains active. Swing (S): all clusters are inactive.

A GC is defined as the interval between successive initial contacts of the same foot with the ground.

C. Gait parameters

For each subject of Proximal Femur Fracture and older Healthy Adults populations, the following parameters were extracted:

- *Total number of GCs*, averaging left and right cycles
- *Cadence*, expressed as cycles per minute
- *Perc_AGC_norm (*for *worst side)*: the *Perc_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 [6]. Then, it was extracted the maximum value between left and right *Perc_AGC* (subject-specific "worst side"). Finally, *Perc_AGC_norm* was computed normalizing *Perc_AGC* with respect to individual cadence
- *Gait-phase asymmetry*: for all the cycles showing the standard sequence of gait phases (HFPS), it was calculated the asymmetry of each gait-phase duration (Heel contact, Flat foot contact, Push off, Swing), as the absolute value of the difference between the left and right duration of each gait phase (expressed in %GC).

D. Statistical analysis

For each gait parameter, the mean value and Standard Error (SE) were estimated, separately 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 α =0.05). Statistical analyses were performed using the Statistical and Machine Learning Toolbox of MATLAB release R2024b (The MathWorks Inc., Natick, MA, USA).

III. Results

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

On average, PFF patients showed a decreased number of gait cycles (almost half of that observed in HA), and a decreased cadence. The percentage of atypical gait cycles was doubled. Furthermore, the interlimb asymmetry of gait phaseswas consistently increased. In particular, considering the gait cycles showing a standard foot-floor contact sequence, significant differences were found between PFF and HA in flat-foot-contact and swing phases, while these differences were at the limit of significance for push-off.

TABLE I. Analysis of Gait Cycles in Proximal Femure Fracture (PFF) Patients and Elderly Healthy Adults (HA)

Gait parameter	Comparison of PFF and HA gait cycles and statistical analysis		
	PFF	***HA***	***p-value***
Total number of gait cycles extracted	**524 ± 100**	**1030 ± 123**	**0.006**
Cadence (cycles/min)	**35.5 ± 1.8**	**42.3 ± 1.3**	**0.005**
Normalized percentage of Atypical Gait Cycles, worst side (%/cycles/min)	**0.90 ± 0.23**	**0.38 ± 0.06**	**0.046**
Standard gait cycles (HFPS)			
Heel contact asymmetry (%GC)	3.8 ± 1.4	1.2 ± 0.2	0.4
Flat Foot contact asymmetry (%GC)	**6.5 ± 1.3**	**2.5 ± 0.4**	**0.003**
Push-off asymmetry (%GC)	4.7 ± 0.8	2.8 ± 0.5	0.052
Swing asymmetry (%GC)	**6.6 ± 1.6**	**1.7 ± 0.3**	**0.002**

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.

IV. Discussion

This work proposed a pipeline to extract digital gait biomarkers (i.e., percentage of atypical gait cycles) related to fall risk, from pressure-insole signals. The average number of gait cycles analyzed was remarkable: one thousand gait cycles were studied in healthy elderly and about the half in patients after Proximal Femur Fracture (PFF). It is also remarkable that the described algorithm was able to extract informative gait parameters in spite of the fact that the recordings were performed out-of-lab in an unsupervised real-life setting.

As one could expect, PFF patients showed a reduced (halved) number of gait cycles. They walked consistently less than healthy elderly, and with a reduced cadence (probably for the fear of falling and/or a sense of imbalance). On the other hand, PFF patients increased (doubled) the percentage of atypical gait cycles. This is in agreement with previous literature reporting an augmented percentage of atypical gait cycles in patients after total hip arthroplasty [9]. The presence of a higher percentage of atypical cycles can increase the fall risk, in particular when the initial foot-strike is characterized by a forefoot-strike instead of a (standard) heel-strike. Furthermore, the asymmetry in gait phases was evidently increased in PFF with respect to healthy elderly. It should be noted that the proposed method represents a step further with respect to traditional methods focusing on stance and swing parameters only, and that neglect studying the sub-phases of stance (heel contact, flat-foot contact, and push-off). In other words, the detailed study of gait phases (including the sub-phases of stance) is what allows to unravel otherwise covert information related to abnormal gait patterns that make frail patients more prone to an increased fall risk.

References

[1] M. Caruso *et al.*, "MOVEWISE (mobility observation via wearable integrated sensor evaluation): a multicentric, prospective, observational, and longitudinal study," in *Proceedings XXIV Congresso SIAMOC*, Stresa, 2024, pp. 42–42.

[2] F. Salis *et al.*, "A multi-sensor wearable system for the assessment of diseased gait in real-world conditions," *Front Bioeng Biotechnol*, vol. 11, 2023, doi: 10.3389/fbioe.2023.1143248.

[3] M. Ghislieri, V. Agostini, L. Rizzi, M. Knaflitz, and M. Lanotte, "Atypical gait cycles in parkinson's disease," *Sensors*, vol. 21, no. 15, Aug. 2021, doi: 10.3390/s21155079.

[4] M. Ghislieri, V. Agostini, L. Rizzi, C. Fronda, M. Knaflitz, and M. Lanotte, “Foot–Floor Contact Sequences: A Metric for Gait Assessment in Parkinson’s Disease after Deep Brain Stimulation,” *Sensors*, vol. 24, no. 20, p. 6593, Oct. 2024, doi: 10.3390/s24206593.

[5] A. Küderle, “Mobilise-D Technical Validation Study (TVS) dataset [Data set],” Zenodo. [Online]. Available: http://doi.org/10.5281/zenodo.13899385

[6] C. Mazzà *et al.*, “Technical validation of real-world monitoring of gait: A multicentric observational study,” *BMJ Open*, vol. 11, no. 12, Dec. 2021, doi: 10.1136/bmjopen-2021-050785.

[7] L. Palmerini *et al.*, “Mobility recorded by wearable devices and gold standards: the Mobilise-D procedure for data standardization,” *Sci Data*, vol. 10, no. 1, Dec. 2023, doi: 10.1038/s41597-023-01930-9.

[8] V. Agostini, G. Balestra, and M. Knaflitz, “Segmentation and classification of gait cycles,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 5, pp. 946–952, Sep. 2014, doi: 10.1109/TNSRE.2013.2291907.

[9] V. Agostini, D. Ganio, K. Facchin, L. Cane, S. Moreira Carneiro, and M. Knaflitz, “Gait parameters and muscle activation patterns at 3, 6 and 12 months after total hip arthroplasty,” *Journal of Arthroplasty*, vol. 29, no. 6, pp. 1265–1272, 2014, doi: 10.1016/j.arth.2013.12.018.