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Validation of an Accelerometer to Quantify a Comprehensive Battery of Gait Characteristics in Healthy Older Adults and Parkinson's Disease: Toward Clinical and at Home Use

Silvia Del Din, *Member, IEEE*, Alan Godfrey, *Member, IEEE*, and Lynn Rochester

Abstract—Measurement of gait is becoming important as a tool to identify disease and disease progression, yet to date its application is limited largely to specialist centers. Wearable devices enables gait to be measured in naturalistic environments, however questions remain regarding validity. Previous research suggests that when compared with a laboratory reference, measurement accuracy is acceptable for mean but not variability or asymmetry gait characteristics. Some fundamental reasons for this have been presented, (e.g., synchronization, different sampling frequencies) but to date this has not been systematically examined. The aims of this study were to: 1) quantify a comprehensive range of gait characteristics measured using a single triaxial accelerometer-based monitor; 2) examine outcomes and monitor performance in measuring gait in older adults and those with Parkinson's disease (PD); and 3) carry out a detailed comparison with those derived from an instrumented walkway to account for any discrepancies. Fourteen gait characteristics were quantified in 30 people with incident PD and 30 healthy age-matched controls. Of the 14 gait characteristics compared, agreement between instruments was excellent for four (ICCs 0.913–0.983); moderate for four (ICCs 0.508–0.766); and poor for six characteristics (ICCs 0.637–0.370). Further analysis revealed that differences reflect an increased sensitivity of accelerometry to detect motion, rather than measurement error. This is most likely because accelerometry measures gait as a continuous activity rather than discrete footfall events, per instrumented tools. The increased sensitivity shown for these characteristics will be of particular interest to researchers keen to interpret “real-world” gait data. In conclusion, use of a body-worn monitor is recommended for the measurement of gait but is likely to yield more sensitive data for asymmetry and variability features.

Index Terms—Accelerometer, algorithm, body-worn monitor, instrumented gait, instrumented walkway.

I. INTRODUCTION

GAIT is emerging as a powerful tool in neurodegenerative disease to identify surrogate markers of incipient disease manifestation or disease progression [1]–[5].

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The authors are with the Clinical Ageing Research Unit, Institute of Neuroscience, Newcastle University, Newcastle upon Tyne NE4 5PL, U.K. (e-mail: silvia.del-din@ncl.ac.uk; alan.godfrey@ncl.ac.uk; lynn.rochester@ncl.ac.uk).

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However, its widespread adoption for clinical and research purposes has been limited to date. This is largely because the majority of studies have been carried out using specialized gait analysis equipment (most commonly instrumented walkways, such as pressure-sensor activated, e.g., GaitRite) [6]–[9] which limits the work to specialized centers and a sparse number of gait cycles [10]. In order to develop the use of quantitative gait analysis for clinical screening and research, low-cost tools are required that facilitate measurement in the clinic and home. This has driven an interest in the use of accelerometer-based body-worn monitors (BWM) for measuring gait.

BWM can provide a continuous sampling of whole body movement in controlled or habitual environments [11]. A BWM worn on the lower back implementing single/numerous algorithm(s) can provide a simple method to quantify gait; the adoption of the inverted pendulum model to evaluate step length and the use of appropriate filtering procedures to identify initial/final (IC/FC) contact events within the gait cycle [12]–[14]. However, it is essential to validate the combination of BWM and implemented algorithms to accurately capture gait outcomes before widespread adoption. Evidence suggests suitable validity and reliability of estimated mean values of gait outcomes to a trusted laboratory reference (GaitRite) [12], [13], [15]–[19]. Yet moderate to poor agreement has been reported for step-to-step fluctuations (variability) and bilateral coordination (asymmetry) [12], [14], [15], [17], [20]–[22]. This leaves the role of BWM to comprehensively quantify gait in ageing and pathology unclear.

A comprehensive examination of systems is lacking within the literature, which is critical to further understand and explain the poor agreement for asymmetry and variability gait characteristics. Previous studies have tried to provide a rationale for the poor agreement, such as difference in sampling rates, misalignment due to device orientation/placement, and poor synchronization [12], [13], [15], [23]. However, questions still remain. Furthermore, weaknesses of previous studies [12]–[15], [21] include: 1) limited and inconsistent reporting of gait characteristics [12]–[15]; 2) introduction of newly derived variables [23]–[25], which are difficult to interpret making mainstream use problematic; 3) restricted testing on a single (small) cohort (ranging on average from 10 to 23 participants [12], [13], [15], [20], [23]), often with a lack of consideration for the effects of pathology on BWM performance; and 4) lack of BWM signal examination compared to video recordings. Evaluation of a comprehensive set of gait characteristics is, therefore, needed

while undertaking a systematic examination of all data acquired during a validation-based study of a BWM.

The purpose of this study was, therefore, to take a systematic approach to address gaps in the literature. First, we aimed to characterize a broad range of gait characteristics using a low-cost BWM in a large cohort of participants. While multiple characteristics can describe gait, studies helped us to provide a simplified framework for selection of important gait characteristics [5], [26], [27]. In this study, characteristics were selected based on our previous work [27], [28], which identified a comprehensive range of 16-core gait characteristics (using GaitRite) recognized as an indicative of healthy ageing and pathology (Parkinson’s disease, PD). Here, we used a BWM and adopted a novel combination of two algorithms to quantify gait grouped by the properties they measure, such as summary mean values, variability and asymmetry, and including phases of the gait cycle. Second, we wanted to compare results in PD and older adults to see if the performance of the BWM remained stable in pathology. The adoption of two cohorts is a key feature of this paper, providing contrasting features of gait, where asymmetric and variability characteristics are known to differ. Finally, we compared the findings from the BWM to a common laboratory reference for comparability with previous work and where possible carried out a detailed evaluation, where differences were found between systems in order to characterize the source of error. In adopting this process, we wished to determine the ability of a low-cost BWM to accurately measure a comprehensive set of core gait characteristics in normal and pathological conditions for confidence in more widespread adoption. This forms a part of our ongoing work to quantify gait simply and effectively within laboratory-based instrumented testing sessions, with a view to quantifying gait in real-world environments.

II. METHODS

A. Participants

Thirty PD patients within four months of diagnosis and 30 healthy aged matched control subjects (HC) were recruited from the incidence of cognitive impairment in cohorts with longitudinal evaluation-gait (ICICLE-GAIT) study. This is a collaborative study with the incidence of cognitive impairment in cohorts with longitudinal evaluation-PD (ICICLE-PD), an incident cohort study conducted between June 2009 and December 2011 [29]. This study was conducted according to the declaration of Helsinki and had ethical approval from the Newcastle and North Tyneside research ethics committee. All participants signed an informed consent form prior to testing.

B. Demographic and Clinical Measures

Age, gender, and body mass index (BMI) were recorded for each participant. Cognition was assessed with the Montreal cognitive assessment (MoCA) [30]. Balance confidence was measured using the self-rated activities balance self-confidence scale [31]. The severity of PD motor symptoms in the PD participants was measured using the Hoehn and Yahr scale [32], which ranges from 0 (no symptoms) to 5 (wheelchair bound or

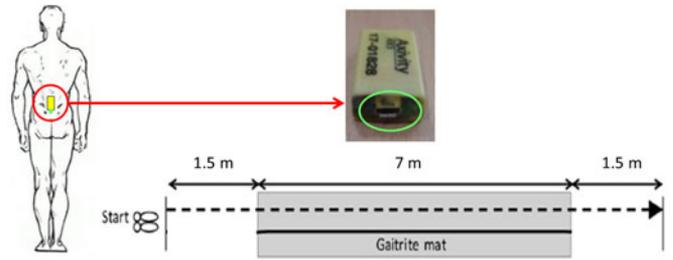


Fig. 1. Triaxial accelerometer-based device and site of attachment on the lower back (L5) and laboratory set up for testing intermittent walks.

bedridden if unaided), and Section III of the modified movement disorder society version of the unified Parkinson’s disease rating scale (MDS-UPDRS [33]), which ranges from 0 (no motor symptoms) to 132 (severe motor symptoms). The postural instability and gait disorder (PIGD) and Tremor phenotype subscales were also calculated from the MDS-UPDRS [34]. Levodopa equivalent daily doses were calculated according to established methods [35].

C. Equipment

Each participant was asked to wear a low-cost (<£100) tri-axial accelerometer-based device (Axivity AX3, dimensions: $23.0 \times 32.5 \times 7.6$ mm, weight: 9 g) located on the fifth lumbar vertebrae (L5) (see Fig. 1). It is a generic movement monitor that is nonspecific for gait or ambulatory assessment and was held in place by double-sided tape (Wig Tape, Natural Image, U.K.) and Hypafix (BSN Medical Limited, Hull, U.K.). The device measures vertical (a_v), anteroposterior (a_a), and mediolateral (a_m) accelerations and was programmed to capture data at 50 and 100 Hz (16-bit resolution) and at a range of ± 8 g. The change in sampling frequency was due to upgrading of the device during the longitudinal ICICLE-PD gait study, where updated versions had increased memory and sampling capabilities. However, for consistency of analysis, all data were downsampled, where necessary, to 50 Hz.

Gait assessment was conducted concurrently as a part of the ICICLE-GAIT study using a 7.0-m long \times 0.6-m wide instrumented walkway (Platinum model GaitRite, software version 4.5, CIR systems, NJ, USA), which was synchronized with a video camera (Logitech, Webcam Pro 9000, CA, USA) recording at 25 Hz. The instrumented walkway had a spatial accuracy of 1.27 cm and temporal accuracy of one sample (240 Hz, ~ 4.17 ms).

The quartz-stabilized real-time clock of the accelerometer (accuracy: 20 ppm) was synchronized with the computer used for the walkway recordings, and for each walking trial, the start and stop time were recorded by the assessor. Start and stop times were subsequently input to a bespoke MATLAB[®] program that automatically segmented and analyzed the accelerometer data. Digital synchronization to identify exact steps (left/right steps) between systems was not used due to the short distance traversed and lack of gyroscope within the BWM. However, the variability and asymmetry equations adopted in this

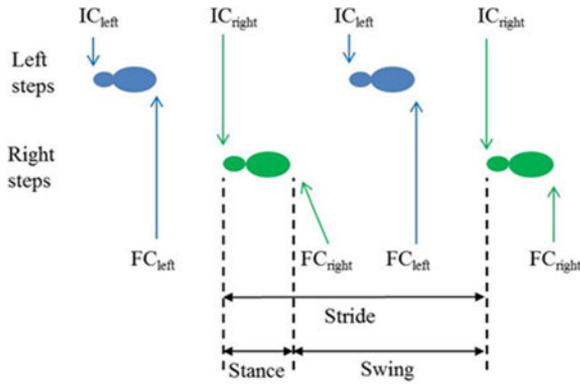


Fig. 2. Identification of stride, stance, and swing times from the double support phase of the IC and FC algorithm.

study accounted for all steps to be used interchangeably (see Section II-E2).

D. Protocol and Data Collection

Participants were asked to walk at their preferred speed, performing four intermittent straight line walking trials over 10.0 m. The 7.0-m instrumented walkway was placed in the center of the 10.0 m (see Fig. 1) to ensure that gait was captured at a steady speed. In addition, synchronized video of frontal plane motion was recorded during each walk. PD participants who were on medication were tested approximately 1 h after medication intake.

E. Data Analysis

1) *BWM (Accelerometer) Data Processing*: The BWM data were downloaded to a computer, segmented into the four different straight line passes using time stamps and analyzed by the MATLAB program. Accelerometer signals were transformed to a horizontal-vertical coordinate system [36], and filtered with a fourth-order Butterworth filter at 20 Hz [12], [14] using the MATLAB functions: *detrend*, *butter*, and *filtfilt*. For the purposes of this study, the program utilized the novel application of a combination of gait algorithms that have been previously developed for a single sensor attached to L5 on a cohort of healthy older adults.

a) *Gait algorithm #1*: The first algorithm estimated the IC and FC events within the gait cycle (see Fig. 2), and is described in detail elsewhere [12]. In brief, the algorithm consisted of the following:

- 1) The IC and FC events are estimated from a continuous wavelet transform (CWT, using the *cwt* MATLAB function) of a_v which was first integrated (*cumtrapz*) and then differentiated using a Gaussian CWT; the IC events were detected as the local minima of the CWT (*findpeaks*) [see Fig. 3(a)]. A further differentiation resulted in the local maxima being defined as the FC events [see Figs. 3(a) and 4].

Previously, the algorithm has been used to estimate step and stride times only [12]. However, in order to fully replicate the

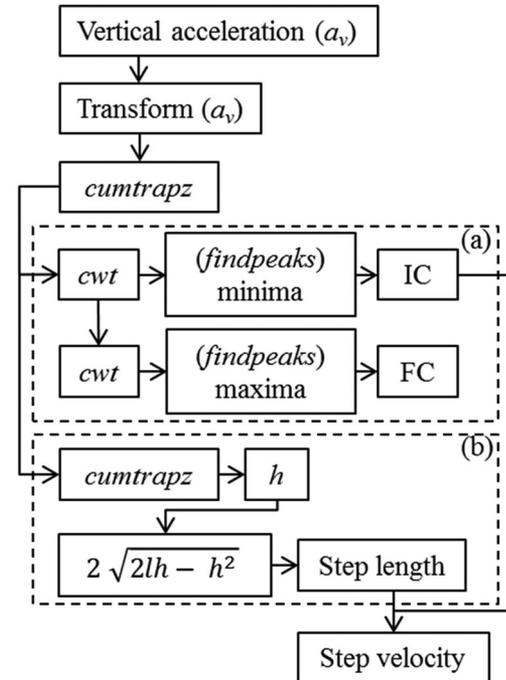


Fig. 3. Flowchart of MATLAB analysis: Algorithm #1 (a), algorithm #2 (b), and algorithm #3 (step velocity).

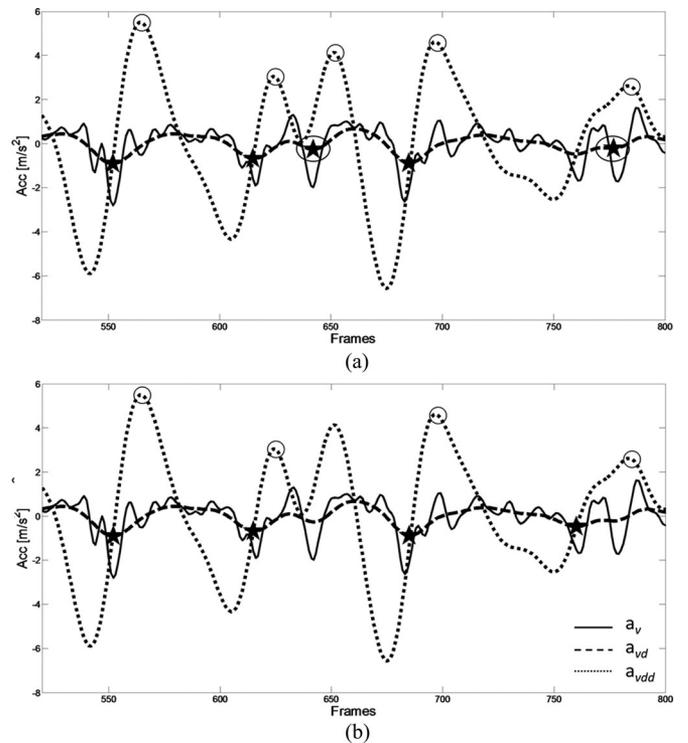


Fig. 4. Example of ICs (squares) and FCs (circles) detection during a single pass on the walkway. The black solid line represents a_v , the dashed line the differentiated with Gaussian CWT of a_v (a_{vd}), and the dotted line the differentiated with Gaussian CWT of a_{vd} (a_{vdd}). Panel (a) shows the IC/FC algorithm with spuriously detected IC events (circled squares). Panel (b) shows the correct detection of the ICs and FCs with the optimized technique.

core characteristics of gait, we needed to derive stance and swing time. This was achieved through the sequence of IC and FC events in relation to the double support phase of the gait cycle (see Fig. 2). From the sequence (i) of IC and FC events, both left and right (opposite) events were identified where stride and subsequently stance and swing time were estimated (see (1)–(3)). For direct comparison to the steps quantified by the instrumented walkway, the initial and final four steps (walk to/from the walkway) of the accelerometer data (as determined by the IC/FC algorithm) were excluded from analysis

$$\text{Stance time} = \text{FC}(i+1) - \text{IC}(i) \quad (1)$$

$$\text{Stride time} = \text{IC}(i+2) - \text{IC}(i) \quad (2)$$

$$\text{Swing Time} = \text{Stride time} - \text{Stance time.} \quad (3)$$

b) Gait algorithm #1: Optimization: Upon initial inspection of the signal traces, spurious IC events [i.e., non-IC events, see Fig. 4(a)] were detected in 37% and 58% of the HC and PD groups, respectively. As a result, the algorithm to detect IC and FC events was refined to include a previous methodology for improved step detection: The updated algorithm only included IC peaks within a predetermined timed interval similar to Najafi *et al.* [17]. The optimization procedure required IC events to be identified during a predefined interval (0.25–2.25 s) from a previous IC event. Fig. 4(b) shows an example of the updated algorithm with the correct estimation of IC and FC events.

c) Gait algorithm #2: The second gait algorithm estimated step length using the inverted pendulum model described by Zijlstra and Hof [14] [see(4), Fig. 3(b)], where h represents the change in height (vertical position) of the center of mass (CoM) derived using the double integration (*cumtrapz*) of a_v and l is the pendulum length (sensor height from ground)

$$\text{Step Length} = 2\sqrt{2lh - h^2}. \quad (4)$$

d) Gait algorithm #2: Optimization: We evaluated the step length using two methods: 1) l is estimated using leg length \times correction factor [14], and 2) l is estimated from the height of the BWM located at L5, i.e., the ratio of the participants' height ($l = \text{height} \times 0.53$) [37]. Preliminary analysis revealed better agreement between systems for the second method compared with using the correction factor and as a result was adopted in this study.

e) Gait algorithm #3: To estimate a value for step velocity, we utilized algorithm #1 and #2 and the simple ratio between distance (length) and time

$$\text{Step Velocity} = \text{Step Length}/\text{Step Time.} \quad (5)$$

We replicated 14/16 [27] clinically relevant gait characteristics (step width and step-width variability could not be measured due to the adoption of a single triaxial accelerometer). The mean, variability, and asymmetry values of the gait characteristics were then calculated for direct comparison to gait characteristics determined by the instrumented walkway (see following section for details). Right and left IC's were previously identified by the sign of the filtered vertical angular velocity at the instant of IC with the use of a gyroscope [12]. In this study, right and left IC's in the accelerometer signal were automatically selected from

the MATLAB program consistently assigning right steps to the first detected step and alternating with left step assignment.

2) Laboratory Reference: Instrumented Walkway: Data for individual steps for each walk were extracted from the instrumented walkway database using Microsoft Access 2007 (Microsoft Corp., Redmond, WA, USA). Mean gait values were calculated for step time, stance time (duration the stance foot was in contact with the ground for a given stride), swing time (duration a foot was not in contact with the ground for a given stride), step length, and step velocity. To calculate step variability, the standard deviation (SD) from all steps (left and right combined) was calculated (see (6)). SD was selected as a measure of variability due to its robustness and dual use with both the BWM and walkway. Other measures of variability (harmonic ratio, coefficient of variation) have been suggested but have shown low to moderate agreement between systems [23], [24], [38], [39] and are not all quantifiable by an instrumented walkway.

We considered each walking pass separately, and as a result, right and left steps were interchangeable. This method has no impact on the evaluation of variability values, which were described as the SD of all steps within walking trials (see (6)). Asymmetry was determined as the absolute difference between left and right steps (alternating) for each walking pass, averaged across all passes (see (7)). As asymmetry represents the absolute mean difference between right and left steps, it does not depend on the detection of the "true" right and left steps

$$\text{Variability} = \text{SD}(\text{Steps}) \quad (6)$$

$$\text{Asymmetry} = |\text{Average}_{\text{Left}} - \text{Average}_{\text{Right}}|. \quad (7)$$

F. Statistical Analysis

Statistical analysis was carried out using SPSS v19 (IBM). Descriptive statistics (means and SD) were calculated for all gait characteristics, in PD and HC pooled across the four passes. Normality of data was tested with a Shapiro–Wilk test. Bland–Altman plots were used to visually check for nonlinear or heteroscedastic distributions of error between the two systems (instrumented walkway versus BWM) as a function of the participants' mean gait performance.

Absolute agreement between the two systems was formally tested using intraclass correlation coefficients ($\text{ICC}_{2,1}$) and limits of agreement (LoA) expressed both as absolute values and as a percentage of the mean. Relative agreement between the two systems was also established using Pearson's correlations (r). Independent t -tests were used to examine the difference between groups for demographical data and systems' outcomes (p value <0.05 was considered as significant).

III. RESULTS

A. Demographic Data

Participants' demographic, clinical, and cognitive descriptors are shown in Table I. Compared to HC, PD participants were aged matched; included proportionally less women (CL: 50%, PD: 33%), presented with lower confidence in their balance

TABLE I
CLINICAL AND DEMOGRAPHIC CHARACTERISTICS

Characteristic	HC ($n = 30$) Mean \pm SD	PD ($n = 30$) Mean \pm SD	p
M/F (n)	15/15	20/10	0.197
Age (years)	66.6 \pm 7.7	66.9 \pm 9.4	0.891
Height (m)	1.7 \pm 0.1	1.7 \pm 0.1	0.795
BMI (Kg/m ²)	28.0 \pm 4.6	28.7 \pm 5.4	0.585
MoCA (0–30)	27.9 \pm 1.7	24.7 \pm 3.1	< 0.001
ABCs (0–100%)	91.3 \pm 12.7	81.7 \pm 20.0	0.031
Hoehn and Yahr (n)	-	HY I—8 HY II—20 HY III—2	-
Levodopa	-	163.3 \pm 137.2	-
Equivalent Daily Dose (mg/day)	-	HYI — 137 \pm 112.9 HYII — 177 \pm 153.1 HYIII — 130 \pm 14.1	-
MDS-UPDRS III	-	29.5 \pm 10.7 HYI — 17.5 \pm 5.7 HYII — 32.9 \pm 8.2 HYIII — 43.5 \pm 3.5	-
Motor Phenotype (n)	-	PIGD 10 ID 4 TD 16	-

BMI: Body mass index; MoCA: Montreal cognitive assessment; ABC: Activities specific balance confidence scale; UPDRS: Unified Parkinson's disease rating scale; PIGD: Postural instability and gait disorder phenotype; ID: Indeterminate phenotype; TD: Tremor dominant phenotype. p difference between HC and people with PD.

(ABCs), and poorer cognition (MoCA). No differences were found between HC and PD participants for both height and BMI. Participants with PD were in the early stages of the disease with mild motor symptoms.

B. BWM and Instrumented Walkway: Agreement

Table II shows the agreement between the two systems for ICC, r values and LoA (%). There was an excellent agreement between the systems for all the mean gait variables (step velocity, step time, stance time, and step length) except for swing time. In contrast, asymmetry of steps (bilateral coordination) and variability (step to step fluctuations) showed poor agreement.

Table III shows the results obtained from the derived gait parameters for both the BWM and instrumented walkway. Results show that the BWM had systematic longer/greater gait characteristics and this is significant for 10 of the 14 and 9 of the 14 variables for HC and PD, respectively.

1) *BWM and Instrumented Walkway: Examination #1:* To explore the differences between systems for variability and asymmetry, an analysis was conducted to check the potential impact of the quality of the measured filtered acceleration a_v on the differences observed. For exploratory purposes, we decided to examine the step-time variability obtained by both systems.

TABLE II
AGREEMENT BETWEEN INSTRUMENTED WALKWAY AND BWM

Variable	HC			PD		
	ICC _{2,1}	r	LoA	ICC _{2,1}	r	LoA
Mean gait characteristics						
Step time (s)	0.983	0.998	1.2	0.981	0.997	1.4
Stance time (s)	0.927	0.912	9.5	0.913	0.854	1.4
Swing time (s)	0.766	0.708	18.0	0.511	0.618	19.5
Step length (m)	0.913	0.867	13.9	0.869	0.850	15.6
Step vel. (m/s)	0.952	0.906	14.7	0.928	0.890	16.7
Variability (var) gait characteristics						
Step time var (s)	0.508	0.429	100.9	0.627	0.633	132.6
Stance time var (s)	0.645	0.747	159.9	0.529	0.576	164.2
Swing time var (s)	0.307	0.302	206.7	0.366	0.512	171.1
Step length var (m)	0.060	0.102	126.3	0.216	0.254	83.3
Step vel. var (m/s)	-0.143	-0.086	110.2	0.225	0.229	107.5
Asymmetry (asy) gait characteristics						
Step time asy (s)	-0.637	-0.349	268.2	0.811	0.757	130.2
Stance time asy (s)	0.370	0.249	177.2	0.318	0.473	362.3
Swing time asy (s)	-0.229	-0.111	316.1	0.448	0.304	259.7
Step length asy (m)	0.132	0.078	243.5	-0.223	-0.120	225.4

LoA expressed as a percentage (%) of the Mean; Step vel.: Step velocity.

A range of features based on the filtered a_v were calculated and averaged across the four passes: mean, SD, root-mean-square values (RMS), number of peaks (maxima of a_v) and valleys (minima of a_v), number of zero crossing (ZC), and frequency below which is the 95% of the signal power spectrum (f95%). Pearson's correlations explored the association between each of these features and the differences in step-time variability of the two systems. None of the extracted features showed a strong positive correlation in either group ($r < 0.353$, Table IV), demonstrating that the poor agreement for the variability results could not be explained by the nature of the acceleration signal.

2) *BWM and Instrumented Walkway: Examination #2:* As no correlations were found between a_v and the mean differences between the systems, further analyses of the filtered a_v signal, estimated step times, and instrumented walkway data were carried out to explore the source of discrepancy for asymmetry and variability.

In first instance, we explored the impact of the height of the participants on the evaluation of the gait characteristics. Pearson's correlations revealed that only the HC stance time asymmetry ($r = 0.435$, $p = 0.016$) and the PD swing time variability ($r = -0.362$, $p = 0.049$) showed a poor correlation with height. Subsequently, our analysis uncovered two key findings:

- 1) Inspection of the filtered signal confirmed that the BWM identified each step, but with a greater range of step-time values (see Figs. 5 and 6). This is accounted for higher variability and low agreement; moreover, variability is evaluated considering all the steps (left and right combined).
- 2) Where gait was clearly asymmetrical (e.g., PD), asymmetry results were comparable [see Fig 6(a)], while more subtle asymmetric gait patterns (e.g., HC) were detected by the BWM but not instrumented walkway [see

TABLE III
MEAN \pm SD VALUES AND MEAN DIFFERENCES OF 14 GAIT PARAMETERS EVALUATED WITH AN INSTRUMENTED WALKWAY AND BWM

Characteristic	HC				PD			
	Instrumented walkway	BWM	Mean Difference, %	p	Instrumented walkway	BWM	Mean Difference, %	P
Mean gait characteristics								
Step time (s)	0.554 \pm 0.051	0.567 \pm 0.054	0.013, 2.4%	< 0.001	0.543 \pm 0.045	0.555 \pm 0.047	0.012, 2.2%	< 0.001
Stance time (s)	0.715 \pm 0.080	0.731 \pm 0.062	0.016, 2.2%	0.018	0.706 \pm 0.072	0.717 \pm 0.063	0.011, 1.6%	0.119
Swing time (s)	0.393 \pm 0.031	0.404 \pm 0.051	0.011, 2.7%	0.116	0.380 \pm 0.029	0.394 \pm 0.044	0.014, 3.7%	0.052
Step length (m)	0.692 \pm 0.094	0.718 \pm 0.099	0.026, 3.7%	0.009	0.638 \pm 0.100	0.681 \pm 0.089	0.043, 6.7%	< 0.001
Step vel. (m/s)	1.266 \pm 0.219	1.275 \pm 0.220	0.009, 0.7%	0.606	1.187 \pm 0.223	1.242 \pm 0.218	0.055, 4.6%	0.007
Variability (var) gait characteristics								
Step time var (s)	0.017 \pm 0.008	0.024 \pm 0.011	0.007, 32.8%	0.002	0.022 \pm 0.012	0.031 \pm 0.023	0.009, 41.8%	0.009
Stance time var (s)	0.022 \pm 0.012	0.026 \pm 0.015	0.005, 21.8%	0.039	0.023 \pm 0.010	0.033 \pm 0.022	0.011, 46.3%	0.003
Swing time var (s)	0.016 \pm 0.009	0.027 \pm 0.024	0.011, 66.3%	0.015	0.019 \pm 0.007	0.031 \pm 0.025	0.013, 65.9%	0.004
Step length var (m)	0.023 \pm 0.007	0.043 \pm 0.021	0.021, 92.6%	< 0.001	0.025 \pm 0.008	0.040 \pm 0.015	0.015, 57.6%	< 0.001
Step vel. var (m/s)	0.058 \pm 0.017	0.043 \pm 0.021	-0.015, 25.4%	0.008	0.062 \pm 0.023	0.040 \pm 0.015	-0.022, 35.8%	< 0.001
Asymmetry (asy) gait characteristics								
Step-time asy (s)	0.010 \pm 0.006	0.015 \pm 0.014	0.005, 38.2%	0.151	0.023 \pm 0.027	0.023 \pm 0.044	-0.0001, 0.3%	0.990
Stance time asy (s)	0.020 \pm 0.012	0.014 \pm 0.013	-0.006, 30.9%	0.035	0.022 \pm 0.009	0.023 \pm 0.045	0.001, 6.9%	0.846
Swing time asy (s)	0.010 \pm 0.010	0.013 \pm 0.015	0.003, 29.7%	0.387	0.018 \pm 0.016	0.019 \pm 0.024	0.001, 4.8%	0.848
Step length asy (m)	0.022 \pm 0.016	0.014 \pm 0.017	-0.008, 37.8%	0.049	0.024 \pm 0.017	0.014 \pm 0.015	-0.010, 4.6%	0.023

Mean difference: BWM – Instrumented walkway; Step vel.: Step velocity.

TABLE IV
RESULTS BETWEEN a_v FEATURES AND DIFFERENCES BETWEEN INSTRUMENTED WALKWAY AND BWM STEP VARIABILITY

Features	HC		PD	
	Mean \pm SD	r	Mean \pm SD	r
Mean a_v	-0.990 \pm 0.067	0.094	-1.001 \pm 0.037	< 0.001
SD a_v	0.127 \pm 0.050	0.353	0.166 \pm 0.058	< 0.001
RMS a_v	1.006 \pm 0.067	0.003	1.026 \pm 0.040	0.015
# of peaks	128 \pm 42	0.095	162 \pm 61	0.048
# of valleys	108 \pm 29	< 0.001	132 \pm 39	0.077
ZC	131 \pm 37	0.009	167 \pm 57	0.042
f95%	10.660 \pm 2.372	0.108	11.518 \pm 2.269	0.003

RMS: Root-mean-square values; SD: Standard deviations; #: number; ZC: Zero crossing; f95%: frequency below which is the 95% of the signal power spectrum.

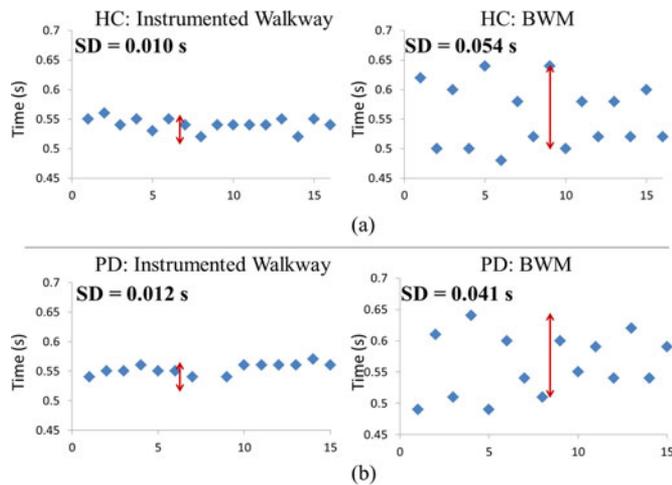


Fig. 5. Step time and step-time variability (SD) evaluated with the instrumented walkway and the BWM for HC and PD participant. The BWM show higher step-time variability for both (a) HC and (b) PD.

Fig. 6(b)]. This may explain the higher agreement for PD participants' asymmetry results compared to HC (step-time asymmetry, Tables II and III): people with PD often show a clear asymmetric gait pattern, while asymmetry is not pronounced as a feature in HC. This was confirmed in individual patient videos, which were used as a reference to identify subtle features of gait identified by expert physiotherapists and biomechanists.

IV. DISCUSSION

This study replicated 14 core characteristics of gait from a generic triaxial accelerometer-based movement monitor using a novel combination of gait algorithms (BWM) to segment the gait cycle into discrete events. It is the largest and most comprehensive evaluation to date, which incorporates the comparison of pathological and nonpathological cohorts.

We compared the BWM results to a known laboratory reference (instrumented walkway, GaitRite) and were able to explain the systematic differences between systems unresolved by previous research.

A. Mean Characteristics and Effect of Pathology

Excellent (ICCs > 0.900, LoA < 15.0%) agreement was found for mean step time, stance time, step length, and step velocity for HC (ICCs_{2,1} \geq 0.913) and for step time, stance time, and step velocity for PD (ICCs \geq 0.913), similar to other studies [12], [15]. Good agreement (ICCs 0.751–0.899, LoA > 15.0%) was found for swing time for HC (ICC_{2,1} = 0.766) and step length for PD (ICCs_{2,1} = 0.869) similar to previous findings [15]. In contrast, we only found moderate agreement (ICCs 0.500–0.750) for swing time for PD (ICCs = 0.511).

The poorer agreement for mean swing time could be related to the limitation of the FC/IC algorithm where swing time was

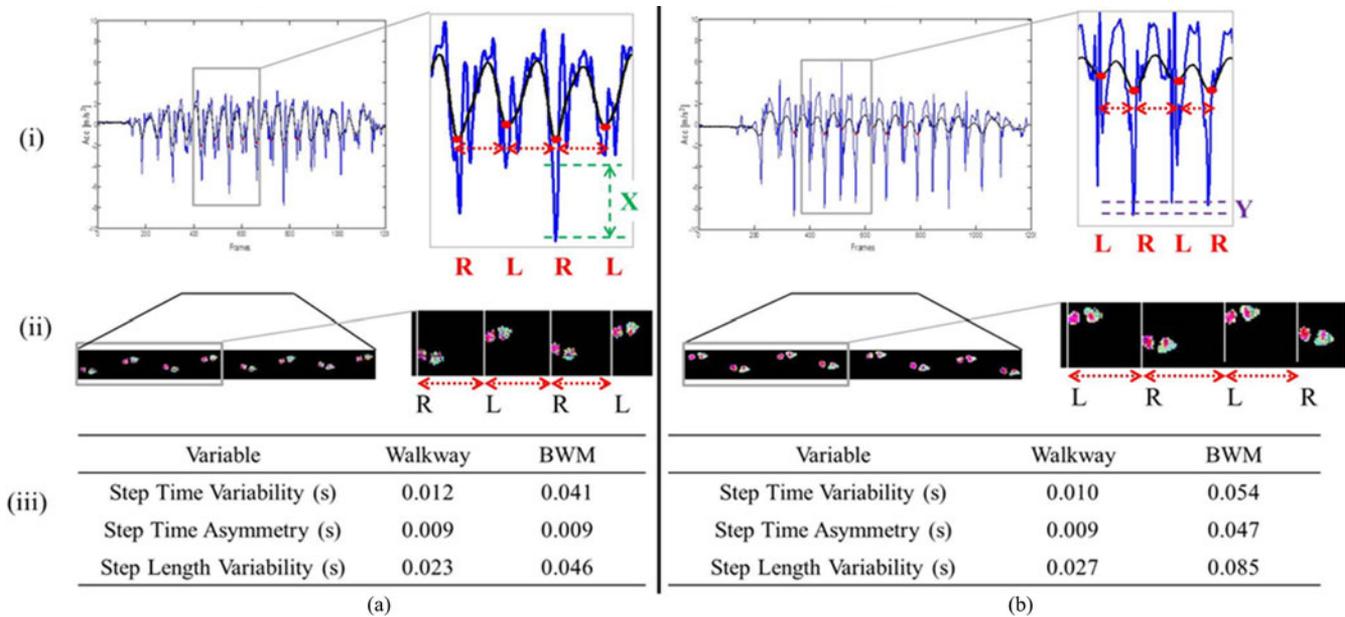


Fig. 6. (a) Example of clear asymmetric gait pattern of a PD participant (regular alternating of higher and lower absolute peak values of the acceleration signal, X) and (b) subtle asymmetric pattern of a HC (less regular alternating of higher and lower absolute peak values of the acceleration signal, Y). Each panel in (a) and (b) displays (i) accelerometer sensor waveform and a zoomed example of four consecutive steps (red dots/arrows), (ii) corresponding data from the instrumented walkway and a zoomed example of same four consecutive steps (red arrows), and (iii) mean results from the two systems for each example.

not accounted for in its design. Though the algorithm [12] evaluated IC and FC events, the authors presented step and stride time values, which is based on the IC estimation only. However, the detection of FCs allowed us to derive stance and swing time with contrasting results for both. Moreover, error is inherently assumed as swing time was computed in our study from the difference between stride and stance time, where small inaccuracies may also exist. Swing time estimation may be improved from direct IC and FC analysis rather than the method adopted here based on the relationship between stance, swing, and stride time within the gait cycle.

Good agreement was found for step length within the PD group, while the HC had excellent agreement ($ICC_{2,1} = 0.913$), similar to another study [15]. LoA for HC and PD were $< 16.0\%$ and mean percentage differences were 3.7% for HC and 6.7% for PD which equates to longer estimated distances of 0.026 and 0.043 m, respectively, which we consider acceptable [15]. Traditionally, high reproducibility has been problematic with step length due to adoption of the inverted pendulum model on which it is based [14], [40], [41]. The model assumes a compass gait cycle (circular trajectory) [14], which is not the case in an asymmetric disease (PD). Moreover, the model also assumes straight line walking at a constant pace, which makes it problematic when testing within pathology or during laboratory-based protocols where continuous walking for better gait variability estimation is the recommendation [42]. Thus, there is a need to better refine step length estimation where the calculation of vertical displacement (h), pendulum length (l), or the adoption of a generic correction factor are sources of error.

Algorithms independent of site specific variables (h , l) and correction factors will allow for more robust quantification of step length. To date individualized correction factors have been

recommended for improved step length estimation rather than generic or group specific values [18], [20]. However, these would be time consuming and difficult to implement in day-to-day clinical practice or in large-scale clinical/intervention-based studies where instrumentation of gait is often time constraint [43]. We were unable to calculate estimates for the remaining core gait characteristics, i.e., step width and step-width variability due to the limitations of the BWM and adoption of a single triaxial accelerometer. Moreover, step-width estimation is yet to be determined from a single accelerometer-based BWM due to the bipedal dynamics of human locomotion and relative mediolateral placement of feet.

B. Variability and Asymmetry Characteristics and Effect of Pathology

We found poor to moderate agreement between systems for all variability and asymmetry characteristics, similar to previous studies [23], [24], [38], [39], [44]. Therefore, we conducted an analysis to explore the lack of agreement to offer new insight into gait quantification with these systems. We hypothesized that the corrupt features of the filtered acceleration signal would impact the error between systems. However, there were no significant correlations in any of the extracted features, verifying that the standard filtering procedure (fourth-order Butterworth, cut off 20 Hz) and resulting signal were robust. Further exploration of all the filtered acceleration signals together with all participant videos highlighted subtle asymmetries in gait that were only evident in the BWM signal and not in instrumented walkway. A number of possible explanations account for these differences:

- 1) We found that height of the participants had an impact on the error of the estimation of stance time asymmetry

and swing time variability, and this can be related to the limitation of the FC/IC algorithm.

Asymmetry was more comparable between instruments for PD because it is a more prominent feature of pathological gait. Asymmetry in HC is subtle and more difficult to detect with an instrumented walkway due to slight variations in dynamics of the CoM rather than discrete footfalls. These results have impact on variability which were not comparable. Greater asymmetry increases the estimation of variability for accelerometry, given its sensitivity to detecting this feature of gait.

- 2) An instrumented walkway detects footfalls but an accelerometer-based BWM continuously tracks the position of the body resulting in a continuous signal (see Figs. 4 and 6). The resulting peak, therefore, represents the trajectory of the CoM rather than actually heel strike (IC) or toe-off (FC) events determined by an instrumented walkway.
- 3) Gait algorithms are dependent on the signal characteristics (e.g., peaks reliant on polynomial coefficients or local maxima to locate the maximum of a peak). Thus, delay in the location of the maximum/minimum due to peak detection methods or smoothness of peak as a result of filtering or processing can introduce timing differences between the BWM signal and instrumented walkway to a resolution required for variability/asymmetric outcomes (ms).

C. Instrumented Walkway: Functionality and Sources of Error

The instrumented walkway used in this study (GaitRite) has been previously shown to be a reliable method for measuring mean gait characteristics [45], but less so for asymmetry and variability [23], [24], [38], [39]. Another plausible explanation for these discrepancies is the operational functionality of the walkway itself. Specifically, the walkway is an array of pressure sensors that activate or trigger a footfall event when a load is applied. These events usually occur as a collective to define the entire surface area of the foot and subsequently IC and FC events. However, spurious contacts may result due to scuffing or a shuffling walk introducing false IC events. As a result, the technician/researcher can review the series of contacts (activated pressure sensors) for each footfall and subjectively include or exclude an individual sensor (within the array defining a foot) if they deem it suitable during a walk. With a spatial accuracy of 1.27 cm, this (subjective) inclusion/exclusion of sensors can be the difference of approximately 0.009 s based on an estimated stepping speed (step velocity 142 cm/s). With variability and asymmetry quantified at a similar resolution (see Table III), the inclusion/exclusion of a single pressure sensor in the walkway can be a further source of disagreement between systems.

D. Alternative Laboratory Reference

Previous work has used continuous tracking of the CoM with a 3-D motion analysis system [21], [46], [47]. Direct comparison of vertical acceleration, velocity, and position (displacement) traces together with spatial-temporal parameters showed

good agreement between the optical motion capture system and an inertial measurement unit (BWM) [21], [46]. Despite good agreement, the comparison of an accelerometer-based BWM to a 3-D system, though more similar in quantification of gait, measure different components: acceleration and displacement, respectively. Though acceleration and displacement can be related through single and double integration/derivation, that process introduces error through drift, where the error in the signal after each integration increases by $\varepsilon = t^{1.5}$, where t is the integration time and ε is the error [21], [48].

Therefore, systematic errors will always remain between systems (instrumented walkway versus accelerometer-based BWM on the lower back (L5) versus 3-D motion analysis system) even when measuring-related components explaining why in our study there is a lower agreement for the mean swing time, higher variability of step time (see Fig. 6), and estimation of (subtle) symmetry differences. This, however, does not infer that one system is less valid, rather that both systems are valid but differences can be explained by different methodological approaches used to estimate gait events.

BWM tend to have greater estimates for gait characteristics (a feature of the adopted algorithms), but was systematic in its nature and the values remained within expected ranges for both PD and HC. Importantly, pathology did not influence our findings, although this may change with increased disease severity and gait impairment.

E. Study Limitations and Future Work

This study achieved its aims of quantifying 14-core gait characteristics, while also deriving a new rationale to account for poor agreement between a BWM (worn at L5) and an instrumented walkway. However, some limitations do exist and, therefore, we make recommendations for future research. For instance, the methodology presented has been tested in a laboratory environment, considering walking at self-selected speed on a group of healthy participants and those with PD. Therefore, before being able to generalize our results in these groups, further analysis would be required to test the robustness of the combination of algorithms across different gait speeds.

Moreover, our PD group had mild motor symptoms and more severe motor symptoms may influence the gait pattern and algorithm performance. For instance, the lack of clearly identifiable signal characteristics (peaks/troughs) within the filtered signal may result in the miss or no detection of IC/FC events. While we included a range of PD participants (PIGD, ID, TD), there was no major (visually observant) limitation within their gait, such as shuffling.

The addition of a gyroscope sensor within the BWM would allow the complete quantification of the 16 gait characteristics identified as important [27], [28]. Additionally, the extra sensor would allow the correct identification and allocation of left/right steps. The improved step recognition methodology would allow the variance of left and right steps to be calculated separately and then be combined to find SD (see (8)). This method avoids confounding step-to-step variability with variation originating from asymmetry between left and right steps [42]. Moreover,

the correct identification of each left/right step could then be directly compared between systems

$$SD_{\text{left or right}} = \sqrt{\frac{\text{Variance}_{\text{left}} + \text{Variance}_{\text{right}}}{2}}. \quad (8)$$

V. CONCLUSION

A simple triaxial accelerometer device is able to replicate 14 clinically relevant core gait characteristics. Agreement with a laboratory reference system ranged from excellent (mean) to poor (variability and asymmetry), which we interpreted as primarily an intrinsic limitation of the comparison between two systems which measure different properties: continuous motion (BWM) versus single footfall events (instrumented walkway). Despite this, we feel confident from our results that a single triaxial accelerometer-based BWM is accurate for measuring gait variability and asymmetry.

Accelerometer-based BWM may offer advantages over standard laboratory systems for selected characteristics, potentially making them a more sensitive device to detect any subtle changes in gait pattern due to ageing and/or pathology. When compared to an instrumented walkway, systematically greater values of mean gait characteristics need to be taken into consideration. However, a system currently does not exist which captures a broad range of gait outcomes sensitive to early pathology, is low-cost (<£100), and capable of being deployed in multi-center large-scale studies for instrumented testing or within the community for real-world continuous data collection. This approach (use of a generic movement monitor and algorithms from the literature) may, therefore, offer a low-cost solution for quantitative gait evaluation in PD and HC during instrumented testing and in a wide variety of environments (including at home). Further work is going on to optimize gait quantification algorithms as well as to explore step-width estimation and the impact of algorithm sensitivity on disease progression and disease severity.

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Silvia Del Din (M'14) received the B.Eng. degree in information engineering in 2006, and the M.Eng. and Ph.D. degrees in bioengineering in 2008 and 2012, all from the University of Padova, Padova, Italy.

She was a Postdoctoral Researcher with the Department of Information Engineering, University of Padova, where her research involved fMRI-gait analysis assessment and Fugl-Meyer clinical scores estimation through wearable sensors.

Dr. Del Din is a Member of the Institute of Engineering and Technology. She received the BTS Bioengineering/SIMFER Award in 2010 and the Prof. Sergio Gambi Award, Second Edition in 2012.



Alan Godfrey (M'08) received the B.Eng. degree in electronic engineering and the Ph.D. degree in biomedical electronics from the University of Limerick, Limerick, Ireland in 2004 and 2008, respectively.

After research positions at the University of Limerick and University of Reading, Reading, U.K., he moved to the Institute of Neuroscience, Newcastle University, Newcastle upon Tyne, U.K., as a Research Associate. He is an Adjunct Lecturer of electronic engineering at the National University of Ireland, Galway, Ireland, and an Associate Fellow of the Faculty of Medical Science, Newcastle University. His current research interests include gait and ambulatory analysis using wearable devices with novel algorithm and signal processing techniques.

Dr. Godfrey is a Member of the IEEE Engineering in Medicine and Biology Society and a Member of the Institute of Engineering and Technology.



Lynn Rochester received the Graduation degree in physiotherapy specializing in neurorehabilitation and the Ph.D. degree in neuroscience from Northumbria University, Newcastle, UK, in 1983 and 1992, respectively.

She joined the Institute of Neuroscience, Newcastle University, Newcastle upon Tyne, U.K., in 2008 as a Professor of human movement science and set up a research program focused on age-related gait and mobility disorders and leads a multidisciplinary team of clinicians, clinical scientists, and clinical engineers.

She is with the Clinical Ageing Research Unit, a translational clinical research platform, where she is the Deputy Director. Her main research interests include neurodegenerative disease focused on the motor and nonmotor mechanisms of gait and falls, surrogate markers of disease and disease progression, development and evaluation of novel interventions, and technological applications in healthcare.

Prof. Rochester serves on various National and International committees and plays a key role in professional leadership within the university developing clinical academic careers for healthcare professionals. She also leads an academic physiotherapy team which is integrated into the regional movement disorders service.