Accelerometer-based gait assessment: pragmatic deployment on an international scale

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Abstract

Gait is emerging as a powerful tool to detect early disease and monitor progression across a number of pathologies. Typically quantitative gait assessment has been limited to specialised laboratory facilities. However, measuring gait in home and community settings may provide a more accurate reflection of gait performance because: (1) it will not be confounded by attention which may be heightened during formal testing; and (2) it allows performance to be captured over time. This work addresses the feasibility and challenges of measuring gait characteristics with a single accelerometer based wearable device during free-living activity. Moreover, it describes the current methodological and statistical processes required to quantify those sensitive surrogate markers for ageing and pathology. A unified framework for large scale analysis is proposed. We present data and workflows from healthy older adults and those with Parkinson's disease (PD) while presenting current algorithms and scope within modern pervasive healthcare. Our findings suggested that free-living conditions heighten between group differences showing greater sensitivity to PD, and provided encouraging results to support the use of the suggested framework for large clinical application.

Keywords—Accelerometer, free-living gait, Parkinson's disease, wearable technology.

1. Introduction

Human gait (locomotion) is a surrogate biomarker of overall health [1], falls status [2] and longevity [3]. Therefore, accurate and reliable measurement of gait characteristics is becoming increasingly important as a robust method to determine many facets of health [4]. Typically, gait analysis is performed using expensive and large laboratory systems such as pressure-sensor walkways, force platforms, 2D photogrammetry, or 3D motion capture [5]. While such systems are essential for complex kinematics and kinetics analysis, their cost and size renders them unfeasible for quantifying gait outside laboratory settings [6]. This has driven the demand for inexpensive and portable, yet accurate, tools and methods that can be more readily deployed such as in large lifestyle based intervention studies [4] allowing cost effective and more pragmatic assessment of gait in a wide variety of environments [7]. As a result, the interest in wearable technologies (wearables) to accurately capture gait has steadily risen in recent years [8].

Wearable devices can provide continuous and objective data with numerous hardware configurations. They facilitate a range of possible deployment scenarios: short term monitoring utilising a wireless device with 9° of freedom (tri-axial accelerometers, gyroscopes and magnetometers with an integrated Bluetooth transmitter); or longitudinal 7 day monitoring (single tri-axial accelerometer with integrated memory). Currently, the latter configuration is of paramount interest within the field of gait research [9].

This study examines the use of a single tri-axial accelerometer within modern gait analysis and it's utility to shape pragmatic patient assessment in clinical free-living environments. We present our validated conceptual model of gait and apply it to a large cohort data to support its use in modern healthcare. We also define our planned framework for routine gait assessment.

2. Related work

Gait is characterised by a sequence of upright events conducted in a rhythmical fashion and more commonly represented by the gait cycle with some basic parameters, Fig. 1.

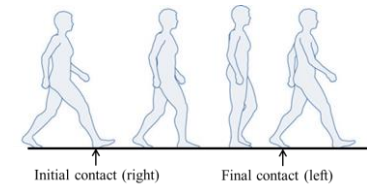


Fig 1: a snap shot of the gait cycle

Due to the complexity of gait there is the potential to derive a plethora of parameters from an accelerometer-based wearable device [6]. To date numerous gait outcomes have been proposed. However, clinically relevant spatio-temporal characteristics grounded within a theoretical framework are key to understanding gait for current treatment or rehabilitation strategies. Frequency-based [10] or other more novel outcomes [11] have utility in describing gait in ageing and pathological cohorts (e.g. Parkinson's disease, PD). Their true value however has yet to be realised or integrated into current clinical guidelines or pathways.

2.1. A conceptual model of gait

To aid the understanding of gait within modern healthcare a conceptual model of gait has been conceived, defining 16 (micro) gait characteristics within 5 domains (Fig. 2). These characteristics preferentially select for motor, cognitive, and behavioural attributes. The model is hypothesis-driven to explain underlying gait mechanisms, identify contributory features to gait disturbance, and examine the effect of intervention [1].

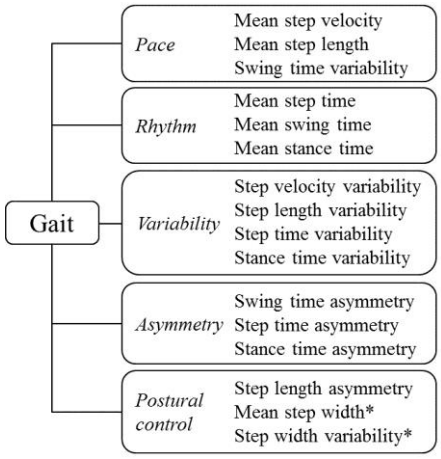


Fig 2: Conceptual gait model for domain and characteristic selection (*not quantifiable with an accelerometer on L5)

Capturing such micro gait characteristics with a single accelerometer is possible due to the peak to peak fluctuations within an acceleration signal [12]. Yet, the novelty of the referenced work expands the measurement of gait to the macro and the broad characteristics of the same acceleration signal, e.g. total time spent walking, number of occasions (bout) walked or the distribution of bouts. Thus, it is plausible to consider gait as a (higher-order) 2-dimensional component when quantifying with a single accelerometer, worn on the lower back which form the focus of this work. In addition, gait has been quantified with accelerometer and/or gyroscope devices (from various anatomical locations) [13]. However, fixation of a single accelerometer on the body is the most cost efficient and less complex configuration for a device. Moreover, attachment of the accelerometer at the lower back facilitates a holistic approach to patient assessment [14].

2.2. Micro and macro gait characteristics

Generic outcomes of macro gait characteristics (volume outcomes e.g. total walking time, number of bouts) have been used for many years yet more novel alternatives were recently presented. These include the (i) shape of the power-law distribution (alpha, α) based on a logarithmic scale from their density and length, or the distribution of bouts based on Lorenz and quantified by the outcomes (parameters) Gini (G), and (ii) the within bout variability (S_2) estimated using a maximum likelihood technique [15, 16]. These alternative outcomes have begun to be used with ageing and pathological studies, providing more statistically sensitive methods of analysis to examine differences between groups [17-20].

Micro gait characteristics derived from the within bout accelerations afford the added dimensionality of laboratory based outcomes from any environment. With a single accelerometer 14/16 characteristics (Fig. 2) have been validated within younger adults, older adults and those with PD [21, 22]. In brief, the accelerometer algorithms used for micro characteristics rely on the recognition of initial contact (IC) and final contact (FC) events within the gait cycle, Fig. 1. These are estimated from the filtered vertical accelerations by a Gaussian continuous wavelet transform (CWT) [23] which allow for temporal estimations, Fig 2. Spatial outcomes are estimated via IC/FC events along with an inverted pendulum model [24], (Fig. 3), and the change in centre of mass (CoM) height (h: double integration of a_v) and device height from ground (l), Eq. 1.

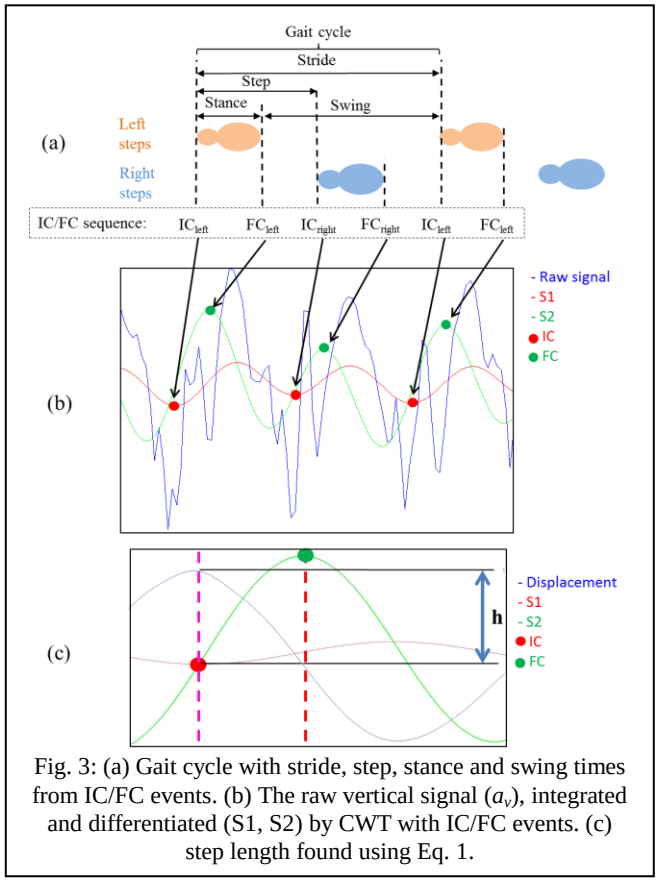


Fig. 3: (a) Gait cycle with stride, step, stance and swing times from IC/FC events. (b) The raw vertical signal (a_v), integrated and differentiated (S1, S2) by CWT with IC/FC events. (c) step length found using Eq. 1.

$$\text{Step Length} = 2\sqrt{2lh - h^2} \qquad (1)$$

Variations on characteristics such as deriving the variability and asymmetry facilitate a detailed investigation of the step to step fluctuations and limb co-ordination, respectively. This is useful for quantifying subtle differences in an asymmetrical disease, e.g. PD. Calculating variability may be estimated from the standard deviation between all steps or via the variance from left and right steps separately and then combined (Eq. 2). This method avoids confounding step-to-step variability with variation originating from asymmetry between left and right steps [25]. Asymmetry (Eq. 3) can be determined as the absolute difference between left and right steps (alternating if evaluated with an accelerometer or exactly with the addition of a gyroscope [23]).

$$\text{Variability}_{left\&right} = \sqrt{\frac{\text{variance}_{left} + \text{variance}_{right}}{2}} \qquad (2)$$

$$\text{Asymmetry}_{left\&right} = \left|\text{average}_{left} - \text{average}_{right}\right| \qquad (3)$$

3. Current Gait deployment

3.1. Accelerometer devices

There are a number of commercially available accelerometer devices for use on the lower back. However, most are reliant on proprietary software that may or may not quantify clinically relevant characteristics. Additionally, the amalgamation of

bespoke design and software could incur high cost. Alternatively, low cost accelerometer-based movement devices stemming from an open source model may provide transparent and affordable alternatives. One example of these devices is Axivity AX3 (Axivity, York, UK; dimensions: 23.0mm x 32.5mm x 7.6mm, 100Hz, ±8g, weight: 9grams). However, only raw data is provided leaving the aforementioned algorithms to be implemented. The device is attached the fifth lumbar vertebrae (L5) on the lower back, by means of a suitable double-sided adhesive and covered with an additional adhesive for added support/security.

3.2 Protocol - clinical

Gait testing protocols will be informed by the study specific research hypothesis. However, recommendations for supervised clinic-based assessments participants should perform a 2 minute continuous walk over a straight, or alternatively, looped path to record a sufficient number of gait cycles during steady state walking [25, 26]. If a testing environment does not permit a continuous walk, then repeated intermittent walks and pooling of all data may be a suitable alternative. However, current research aims to assess the patient in habitual environments thereby negating any observer (Hawthorne) effect and artificial improvement in performance due to clinical testing [27]. Moreover, longitudinal free-living monitoring facilitates micro/macro approach to gait assessment, yet currently involves a time consuming approach.

3.3 Protocol - free-living gait assessment (7 days)

Free-living recording requires participant instructions for device re-attachment (removed if not instructed to wear for 24/day due to showering, exercise and/or general hygiene to refresh adhesives). The device is returned to the research via pre-paid envelopes which can take days due to compliance and added dependency on a third party (postal service). Additionally, adopting the aforementioned signal processing algorithms requires a research analysis platform (typically MATLAB®) for analysing clinical and free-living data, where further delays in data uploading, segmenting (if needed) and analysis can also prove inefficient, especially with large files (e.g. 250MB raw binary data or 200MB MATLAB® format) analysed on a single computer. Extracting and analysing a single tri-axial accelerometer 7 day file for macro and micro outcomes can result in approximately 20min of computation time. One key component of that delay is the formal recognition of gait events within free-living which is heavily reliant on a standard deviation and mean moving windows [28] to identify the start/stop of a bout, Fig. 4.

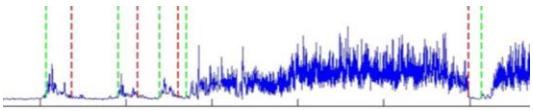


Fig 4: Example of standard deviation of the tri-axial accelerations with identified start (green) and stop (red) of bouts for gait analysis

Yet, current limitations of data collected in clinical (intermittent walking trials) vs. free-living settings are out weighted by preliminary data suggesting that free-living micro gait assessment may be more sensitive for patient discrimination, Fig. 5 (same characteristics as Fig. 2) [29]. Within clinical testing shows 2/14 compared to free-living 4/14 characteristics being more sensitive between those with PD (n=47) and healthy aged matched controls (n=50) (Fig. 5). For details on inclusion criteria, study protocol, demographics and statistical analysis please refer to [29].

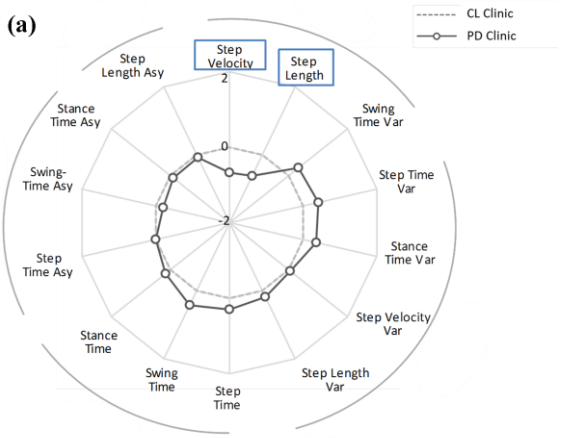
3. Future Gait deployment

Accelerometer-based gait assessment has been shown to be valid and reliable [14, 21, 22, 30]. Our preliminary results indicate that free-living assessment offers potential to better discriminate pathology compared to clinical testing.

3.2 Multi-centre clinical trials

The relative low cost of open source-based technology and the passive form-factor of miniaturised accelerometer devices has potential within modern multi-centre clinical trials. Devices can be acquired in large numbers and worn continuously on a range of different demographical cohorts (e.g. limited/reduced physical functioning, cognitive difficulties, age or those in remote geographical locations).

However, limitations alluded to in current gait deployment need to be overcome to enable its widespread use. Currently, multi-centre trials utilise a range of different web-based resources (within group or commercial, e.g. Dropbox) to transfer data post collection from the patient (postal or manual return during a clinical follow-up). This best facilitates data pooling and generally helps project workflow. Yet, data transfer remains inefficient: only raw data is transferred while algorithm processing remains limited to the end user, i.e. researcher on a standalone computer. There is a need to harmonise data transfer and end user algorithms for gait analysis, cloud based scientific data management.



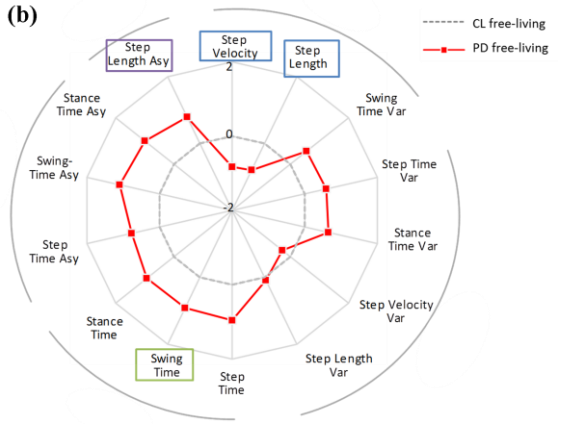


Fig. 5: Sensitivity between PD and Controls (CL) for (a) clinical characteristics (2/14) and (b) free-living characteristics (4/14), plots show ±z-scores from CL data (normal data at 0)

3.3 Cloud-based gait management

One approach for implementing such a framework is e-Science Central [31], a cloud based Science Platform that allows the storage, analysis and sharing of data in the cloud. Utilising this methodology, multi-centre studies could transfer and implement open source algorithms to process raw data to a central (or cloud) repository. The overall process relies on workflows based on html5 to arrange and link a number of programmable packages/applications. This approach has the advantage of widening the community access to such a platform (scalability), reducing the computational cost of the project workflow, multi user access, provenance, adherence to protocols [32].

However, implementing current algorithms on such a platform remains limited and complex. Algorithms are typically developed within MATLAB® due to the extensive toolbox options readily available. In contrast similar scripting languages like Octave and Python™ despite having the advantage of being open source software with obvious benefits in terms of low costs and widespread use, currently provide limited functionality due to their open source development. Thus, certain signal processing features utilised in MATLAB® for gait may not be readily available and directly translatable within Octave or Python™ (or another). Therefore variations in implementation methods in the code, language coding, architecture and cross platform licencing issues impedes current use but remains possible.

To demonstrate the current state of transferability between languages and feasibility of a cloud workflow we processed one participant data via validated manual MATLAB® methods, translated the same code to Octave and deployed an executable of the same MATLAB® scripts via the e-Science platform (e-MATLAB®) thereby generating a closed standalone analysis package, Table 1. Mean values between languages differ slightly (but not tested for statistical significance) due to the different functionalities of the MATLAB® CWT function (signal processing toolbox) and Octave (best replicated) equivalent within the '*ltfat*' library. Importantly, the e-MATLAB® was replicated exactly in this example, but remains a 'fixed' executable.

Table 1: MEAN MICRO GAIT CHARACTERISTICS ACROSS PLATFORMS

	MATLAB	Octave	e-MATLAB
Step time (s)	0.539	0.542	0.539
Stance time (s)	0.681	0.703	0.681
Swing time (s)	0.394	0.371	0.394
Step length (m)	0.570	0.570	0.570
Step velocity (m/s)	1.184	1.197	1.184
Step time var (s)	0.184	0.191	0.184
Stance time var (s)	0.198	0.232	0.198
Swing time var (s)	0.158	0.135	0.158
Step length var (m)	0.159	0.161	0.159
Step velocity var (m/s)	0.432	0.430	0.432
Step time asy (s)	0.099	0.107	0.099
Stance time asy (s)	0.094	0.100	0.094
Swing time asy (s)	0.099	0.077	0.099
Step length asy (m)	0.099	0.101	0.099

4. Discussion & Conclusion

Accelerometer-based gait assessment has utility as a low cost tool in the collection surrogate biomarkers in ageing, cognitive and health outcomes. The methodologies presented here demonstrate a conceptual model reliant on a macro/micro approach to gait to quantify behavioural and spatio-temporal performances, the latter suggesting greater sensitivity between patient groups during free-living monitoring. Rapid and integrated deployment of gait as a pragmatic tool in health or pathology studies is currently limited by a lack of integration between platforms and algorithm transferability due to lack of functionality between development software. Current work is aiming to overcome these limitations, cross-validating data, thereby upscaling and increasing gait data capture and transferability between platforms.

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