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Detecting free-living steps and walking bouts: validating an algorithm for macro gait analysis

Aodhán Hickey[1], Silvia Del Din[1], Lynn Rochester[1], Alan Godfrey[1]

[1]Institute of Neuroscience, Newcastle University Institute for Ageing, Newcastle University, UK

Corresponding author:

Dr Alan Godfrey,
Clinical Ageing Research Unit,
Campus for Ageing and Vitality,
Newcastle University,
NE4 5PL
Fax: +44 (0) 191 208 1251
Email: alan.godfrey@ncl.ac.uk

Abstract (258/300 words)

Research suggests wearables and not instrumented walkways are better suited to quantify gait outcomes in clinic and free-living environments, providing a more comprehensive overview of walking due to continuous monitoring. Numerous validation studies in controlled settings exist, but few have examined the validity of wearables and associated algorithms for identifying and quantifying step counts and walking bouts in uncontrolled (free-living) environments. Studies which have examined free-living step and bout count validity found limited agreement due to variations in walking speed, changing terrain or task. Here we present a gait segmentation algorithm to define free-living step count and walking bouts from an open-source, high-resolution, accelerometer-based wearable (AX3, Axivity). Ten healthy participants (20-33years) wore two portable gait measurement systems; a wearable accelerometer on the lower-back and a wearable body-mounted camera (GoPro HERO) on the chest, for one hour on two separate occasions (24hrs apart) during free-living activities. Step count and walking bouts were derived for both measurement systems and compared. For all participants during a total of almost 20 hours of uncontrolled and unscripted free-living activity data, excellent relative (*rho* $\geq$ 0.941) and absolute ($ICC_{(2,1)} \geq 0.975$) agreement with no presence of bias were identified for step count compared to the camera (gold standard reference). Walking bout identification showed excellent relative (*rho* $\geq$0.909) and absolute agreement ($ICC_{(2,1)} \geq 0.941$) but demonstrated significant bias. The algorithm employed for identifying and quantifying steps and bouts from a single wearable accelerometer worn on the lower-back has been demonstrated to be valid and could be used for pragmatic gait analysis in prolonged uncontrolled free-living environments.

Keywords:

free-living, gait, GoPro, walking bouts, wearable, step count,

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Tables: 3
Figures: 4

1. Introduction

Typically gait analysis is performed using complex systems like pressure sensor walkways and force platforms [1]. However, such techniques are expensive, require expert personnel for operation and are limited to specialist facilities [2]. Wearable technology (wearables) in combination with published algorithms and open-source platforms provide a more pragmatic approach to gait analysis and facilitate cost effective assessment in a range of environments [3-5]. Accelerometer-based wearables can provide comprehensive, continuous and objective measures of gait [6] with greater flexibility than their laboratory-restricted counterparts.

Early validation studies consisted of accelerometer-based wearables and focused on their ability to detect steps and walking bouts. These typically consisted of protocols involving scripted activities [7, 8], comparison to pedometers on a treadmill [9, 10] or bout detection at low-resolutions of approx. 1min [11, 12]. Many commercial wearable accelerometers utilise their own proprietary algorithms which can be limited, the majority showing poor capacity to identify and quantify gait during non-scripted activities, i.e. in free-living conditions [13, 14]. While manufacturers are moving towards the provision of raw data for more bespoke analysis [8, 15], embedded 'black box' programming make it difficult to understand why reliability and validity are poor, attributed to the closed system and exact algorithm functionality [16]. This in turn limits their potential use as robust academic or clinical tools, particularly for those unable to develop tailored algorithms from ad-hoc devices created in specialist facilities [17, 18].

The use of bespoke wearable accelerometers, designed by individual research groups has grown due to the necessity for access to the raw acceleration data, benefiting algorithm development. Utilising novel algorithm techniques on accelerometer data has resulted in an increase in the number of more (clinically) useful outcomes. Specifically, these relate to spatio-temporal gait characteristics [19-21] which require a more stringent approach to validation procedures. Algorithm methodologies for this purpose must be systematically assessed prior to application [22], transparency ensuring appropriate methods are implemented for new systems or conditions.

Spatio-temporal gait characteristics have been collectively termed 'micro', the step to step timings/lengths and fluctuations that have been shown to be sensitive in ageing and pathological studies

[23, 24]. These constitute a clinically relevant conceptual model of gait inspired by the use of current high resolution (≥100Hz) accelerometer-based wearables: examining micro as well as the broader signal profiles representing walking activity (macro) within free-living environments [25]. This provides a comprehensive, two-tiered approach to gait assessment and its potential use as a pragmatic and low-cost diagnostic [26-28]. Utilising this approach one can gather habitual micro gait, while also examining the broader trends in ambulatory behaviour within free-living, leading to novel insights on the accumulation and distribution of macro gait [28-30]. Thus, a micro and macro approach offers a more informative approach to gait analysis. However, macro outcomes measured by high resolution wearable accelerometers rely on the correct identification and quantification of walking (gait) bouts from free-living data in the first instance. Validation of free-living gait algorithms from high resolution devices remains limited. Although some wearable accelerometers have demonstrated reliability in semi-structured protocols [31-33], assessment in free-living uncontrolled environments has not been completed. Additionally, validation studies usually compare algorithms to criterion pedometers [13], fixed or observer video recording [33] which limits long-term feasibility. Wearable cameras have been successfully used to validate gait detection of a single trunk-mounted wearable accelerometer [34] and their concurrent use with devices in free-living conditions have help develop and analyse activity taxonomies [35]. Therefore, wearable cameras can be viewed as the most appropriate comparative measure currently available for validating devices that define free-living macro gait outcomes. This is due to their ability to provide contextual information (e.g. type of terrain) as well as clarify exact movement types (e.g. stair ascent/descent).

Current research has identified the need for robust validation of free-living gait algorithms and the need to harmonise analytical methods, for a unified approach to gait assessment [25, 36]. The aim of this study was to examine the validity of an algorithm for macro gait detection (step count and walking bout) using a single accelerometer-based wearable worn on the lower-back in uncontrolled free-living conditions. We adopt the novel use of a body worn camera as a gold standard, eliminating any potential for observer bias and allowing a more habitual collection of data. The novelty of the algorithm presented here is the utility of a methodology to quantify micro and macro gait characteristics, the former previously validated within controlled laboratory settings [26, 37, 38]. This constitutes ongoing work to accurately and robustly quantify gait during free-living. Here, we present a macro gait identification and segmentation validation.

2. **Methods**

2.1 Participants:

Ten healthy (free from physical and neurological conditions) participants ranging in age 20-33 years (27.5 ± 4.7yrs; 1.74 ± 0.07m; 70.4 ± 8.8kg) volunteered for this study. Ethical approval was granted by the Newcastle University Research Ethics Committee, reference: 3759/2016. All participants provided informed written consent prior to participating.

2.2 Protocol:

Participants simultaneously wore two synchronised body worn devices (Figure 1, section 2.3) for one hour on two separate occasions (approx. 24 hours apart) while performing their normal activities of daily living (ADL). Participants were aware of the study aim but free to perform their normal activities (inc. running, cycling) to ensure a comprehensive stress test of the algorithm. Collected data were unscripted and took place in a variety of different environments, e.g. home, leisure (descriptions provided in the results). Systems were synchronised by gesture recognition (tapping the wearable accelerometer 3 times) in field view of the camera before attachment to the lower-back. This was repeated upon removal of the wearable accelerometer. Start and stop times were determined from the manual recognition of the peaks in acceleration (3 taps) when overlaid to video (section 2.4.2).

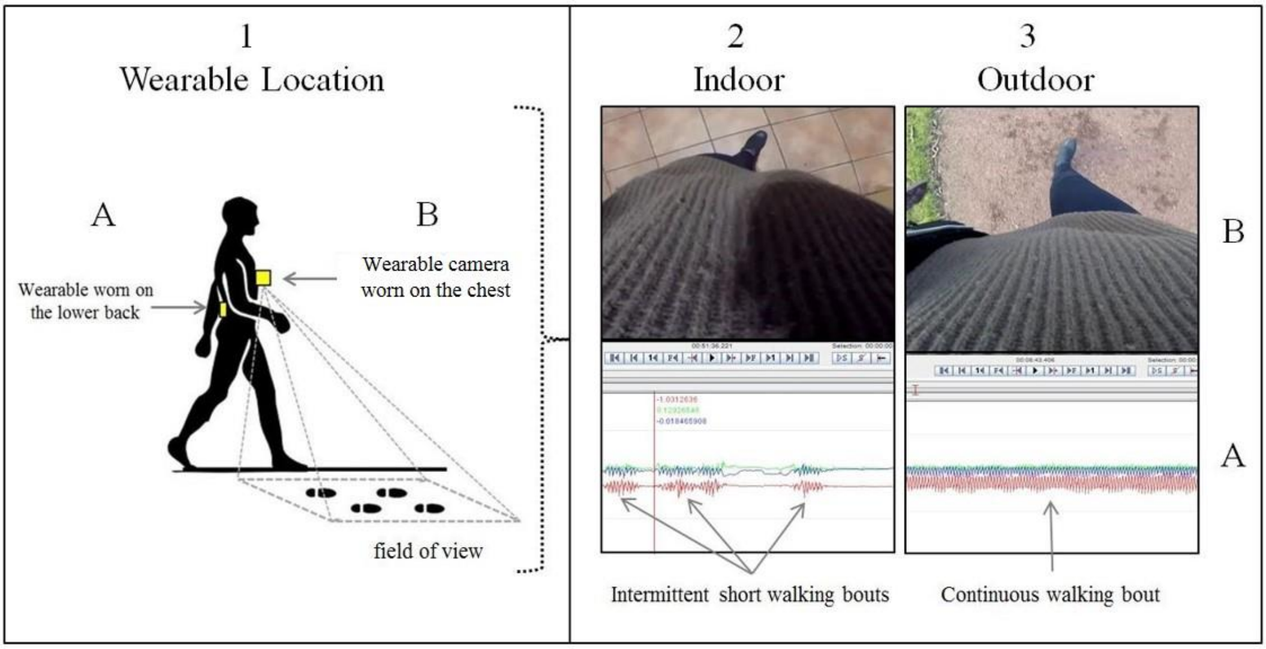

Figure 1: 1) Location of wearable accelerometer (A) and wearable camera (B). 2) Example of wearable (A) and wearable camera (B) data for multiple walking bouts in an indoor environment. 3) Example of wearable (A) and wearable camera (B) data for multiple walking bouts in an outdoor environment.

2.3 Equipment

2.3.1 Wearable

Participants wore a low-cost (≈£100) tri-axial accelerometer-based wearable (AX3; Axivity, York, UK; 23.0mm ×32.5mm ×7.6mm, 9g) located on the fifth lumbar vertebra (L5). The wearable was attached using double sided tape and Hypafix (BSN Medical Limited, Hull, UK) and programmed to capture with a sampling frequency of 100Hz (16 bit resolution, range ±8g, battery life >7days). Recorded signals were stored locally on the sensor's internal memory (512MB) as a raw binary file and then downloaded to a computer via USB cable upon the completion of each testing session.

2.3.2 Wearable camera

Participants also wore a single camera (GoPro HERO, GoPro Inc., CA, USA; 71.3mm × 67.1mm × 39.0mm, 111g) attached to the chest (GoPro Chest Harness, GoPro Inc., CA, USA). The camera was programmed to capture with a sampling frequency of 50Hz, video resolution 720p, screen resolution 1280 × 720, and field of view 170°, and was directed at the participant's feet. Recorded video was stored locally on a micro-SDHC memory card (SanDisk UHS-1.32 GB, SanDisk Corporation, CA, USA) before being downloaded upon completion of each testing session. This was the gold-standard reference.

2.4 Data processing

2.4.1 Algorithms

The purpose of this study is to validate the algorithm (used on the wearable accelerometer data) to detect gait in free-living environments for step and bout count. The algorithm was written using a bespoke MATLAB® (version 2015a) program utilising previously validated methods [26, 37] and employing a two stage approach to processing and gait detection, similar to previous methodologies [17, 39]. An overview is provided here:

Data preparation: Mean accelerations were computed and subtracted from each axes to account for offset (i.e. gravity and misalignment due to placement). Data were filtered using a low-pass, second-order low-pass Butterworth two-pass digital filter, with a cut-off frequency of 17-Hz [40].

Walking bout detection: The detection and segmentation algorithm (Figure 2) utilised for examining walking bouts in free-living conditions relies on a logical heuristics paradigm as follows. A moving window analysed the signal for bouts of 'upright movement' based on the combined standard deviation (SD) of tri-axial accelerations and the corresponding mean of the vertical acceleration (a_v, -1g) every 0.1 seconds [41] with predefined thresholds (g = 0.77 and 0.05, respectively). Due to device location (L5) and orientation this identifies bouts that are 'upright and moving'. Bouts <0.5s were ignored and treated as spurious movement, constituting an unrelated gait (step) time value [42]. Once the start/end of these bouts are identified the segmented data are analysed with a secondary stage examining potential gait events (step detection) within each identified bout (possible walking/gait).

Step identification: Further correction of the acceleration data for misalignment, unaccounted for when removing gravity (subtracting the mean acceleration) was performed by transforming data to a horizontal-vertical coordinate system [43, 44], aligning with recommended gait data processing guidelines [45]. Once corrected, data for each bout is subjected to a continuous wavelet transform ('CWT'; a convolution of the acceleration data and analysing function) technique to identify initial contact (IC), within a predefined timed period from a previous step (0.25-2.25s [46]), and final contact

(FC) events within the gait cycle [47]. These temporal IC/FC micro [26, 37] events are used to verify the presence of micro gait and subsequently used to calculate the step count within each, i.e. macro values. The functionality of the CWT for IC/FC detection consists of the following:

- Integration and differentiation of a_v using a Gaussian CWT, where IC's were identified as the times of the minima.
- The differentiated signal undergoes a further CWT differentiation from which FC's were identified as the times of the maxima.
- Use of a timing classification for absolute step detection [26]: restricting IC peaks within the predetermined timed interval (above).

A complete representation of the algorithm is presented in Figure 2.

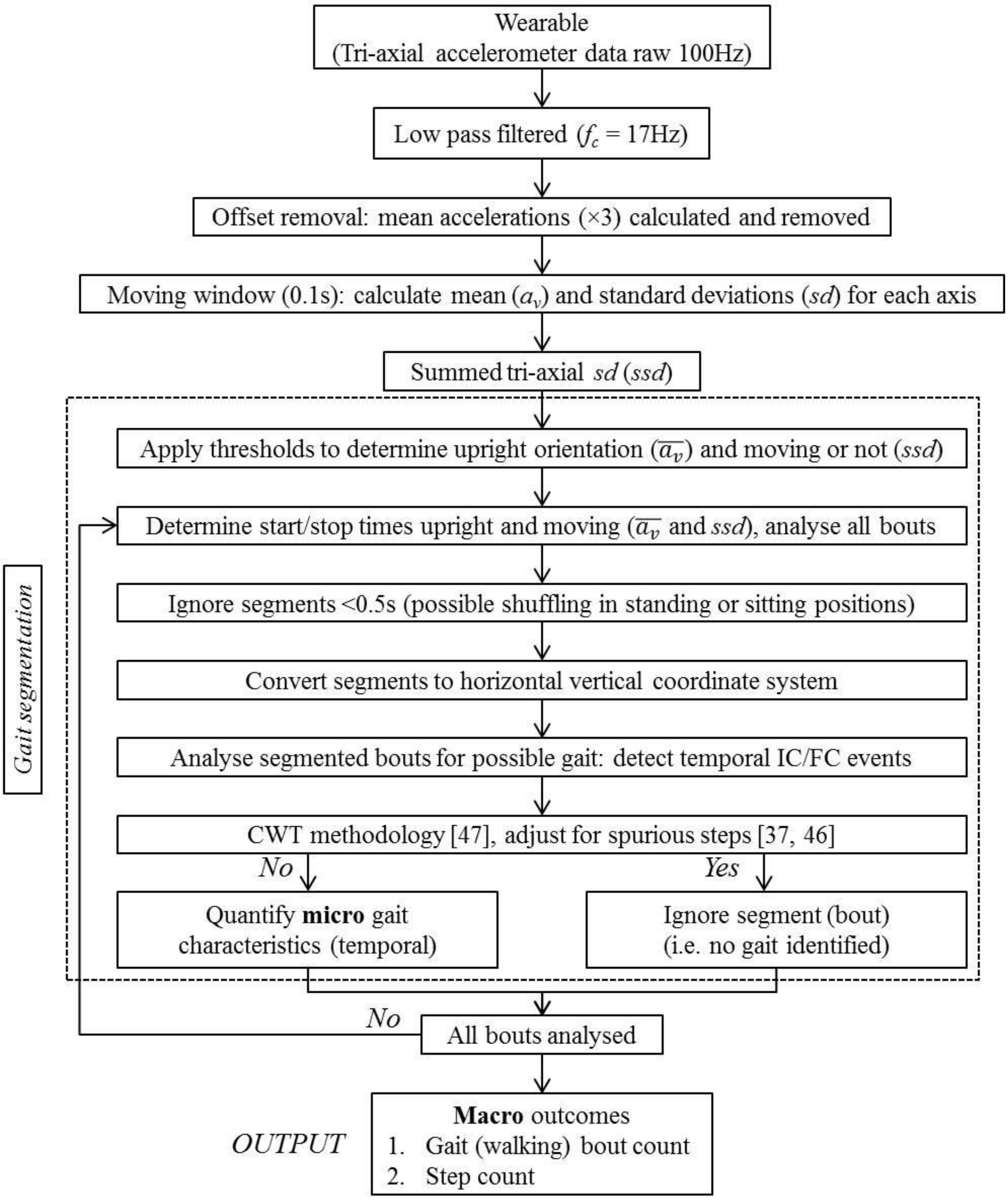

Figure 2: Processing flow of the gait detection and quantification algorithms performed by the MATLAB® program.

2.4.2 *Video data*

Video data extracted from the wearable camera were analysed for macro gait (step and bout count) using ELAN Linguistic Annotator (Version 4.9.2, The Language Archive, Nijmegen, Netherlands) and annotated alongside the wearable acceleration signals. Video data were further processed (see points below) in order to be consistent with current research directives for the wearable:

- All events (walking, postural transitions, ADLs etc.) were recorded with their relative contextual information (e.g. location, purpose, duration, etc.) from the video data. All periods of non-walking ('non step-event') activity were removed and step events were collated into their respective bouts with a minimum resting period of 2.5 seconds between bouts [48].

- Furthermore, all bouts less than three steps were removed as this sequence previously defined walking bout detection [46, 49].

A single researcher with a background in applied movement science extracted all walking information [33].

2.5 Statistical analysis

Validity of the algorithm (agreement to video) was assessed using SPSS v22 (IMB Inc., Armonk, NY, USA). Shapiro-Wilks tests suggested the use of non-parametric measures for step and bout count (p<0.04). Spearman's correlations and intra-class correlations ($ICC_{(2,1)}$) were used to examine the relative and absolute agreement between the video and algorithm, respectively [17, 39]. Predefined acceptance ratings for $ICC_{(2,1)}$ were: excellent (>0.900), good (0.750–0.899), moderate (0.500–0.749) and poor (<0.500) [50, 51]. Bias (difference of video – algorithm) of the two measurement systems were assessed using Wilcoxon matched-pairs tests. Bland-Altman plots were examined for wearable systems to check for nonlinear or heteroscedastic distributions of error.

3. Results

3.1 Environments and algorithm functionality

A large range of activities were observed in the video data inclusive of both indoor (78%) and outdoor (22%) environments. To provide context a pictorial representation of the different conditions and their respective ADLs are provided, Figure 3. A summary of times spent during walking in different environments is also presented, Table 1. Participants spent the majority of time walking sporadically indoors (large number of bouts, few steps) or in long continuous bouts outdoors (small number of bouts, many steps).

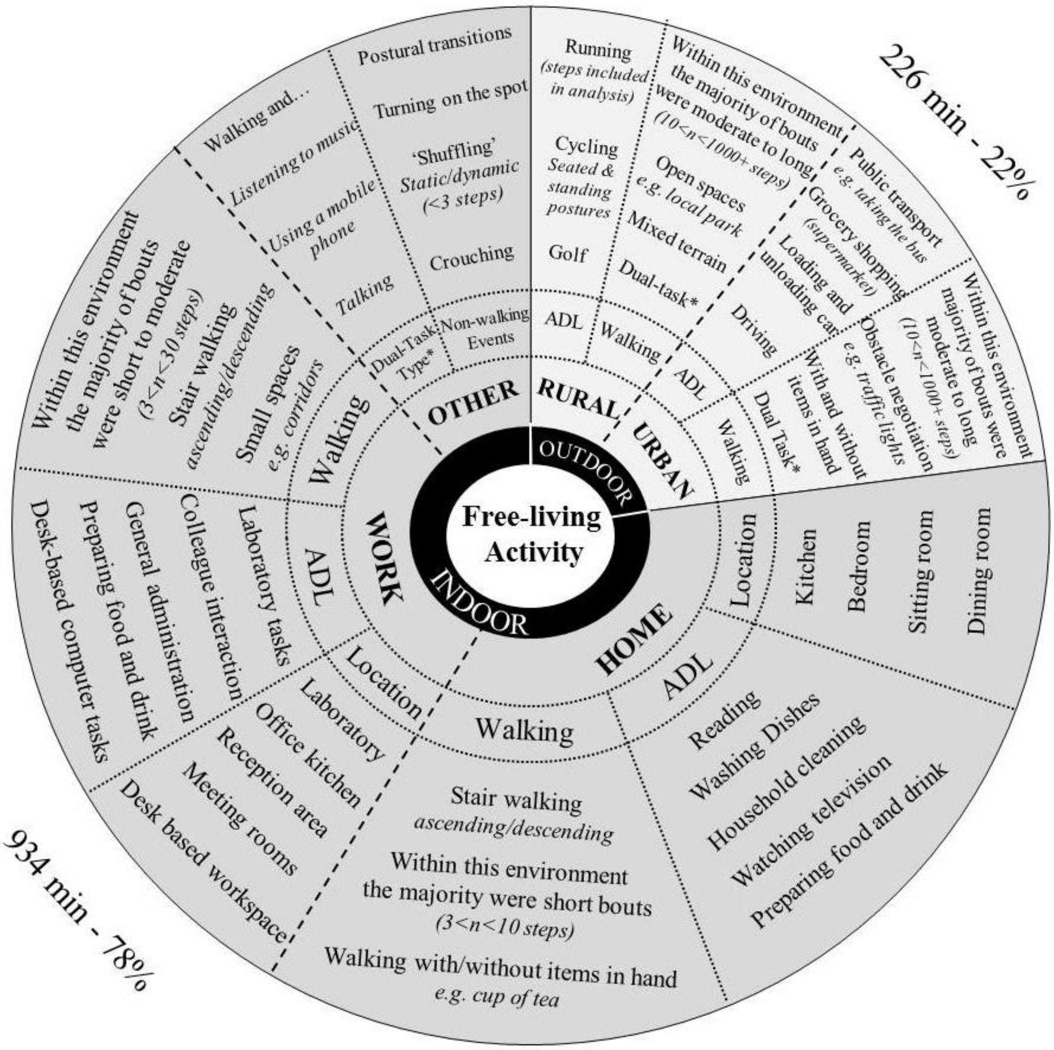

Figure 3: Pie chart containing contextual information for the walking and ADLs observed in the video data.

<Table 1, see end >

A preliminary examination of the magnitude of error between the measurement systems (n=20 sessions, 20 hrs) identified a single outlier, i.e. quantified step count differences between the algorithm and rater/video were excessively large in comparison to other data. Manual investigation of the data found that the difference related to two bouts and approximately 2262 steps. It was found that the participant had completed two bouts of high intensity cycling (windy conditions on a negative gradient) in both seated and standing postures (≈1942 revolutions) that had been incorrectly identified and segmented as gait by the algorithm. In order to compare the effect of including these two false-positive events the results are presented with (all activities: n=20, ~20*hrs*) and without those bouts (removal of cycling: n=20, ~19.68*hrs*), Table 2 and Table 3.

<Table 2, see end>

<Table 3, see end >

3.2 Algorithm analysis – all activities

Spearman correlations demonstrated excellent relative agreement between the algorithm and video data for step count ($rho = 0.941$, $p \leq 0.0005$) and bout count ($rho = 0.909$, $p \leq 0.0005$). Intra-class correlations demonstrated excellent absolute agreement for step count ($ICC_{2,1} = 0.975$, $p \leq 0.0005$) and bout count ($ICC_{2,1} = 0.941$, $p \leq 0.0005$). Wilcoxon matched pairs tests demonstrated no bias was observed for step count ($Z = -1.456$, $p=0.154$) but significant bias between measures for bout count ($Z = -2.074$, $p = 0.037$).

3.3 Algorithm analysis – removal of cycling

Spearman correlations showed slight improvement in relative agreement between the algorithm and video data for step count ($rho = 0.985$, $p \leq 0.0005$) and bout count ($rho = 0.909$, $p \leq 0.0005$) when the false positive cycling activity was removed, Figure 4. Intra-class correlations also demonstrated similar improvements for both step count ($ICC_{2,1} = 0.994$, $p \leq 0.0005$) and bout count ($ICC_{2,1} = 0.942$, $p \leq 0.0005$) and. Wilcoxon matched-pairs tests were consistent for step count ($Z = -1.307$, $p=0.202$) and bout count ($Z = -2.036$, $p = 0.041$).

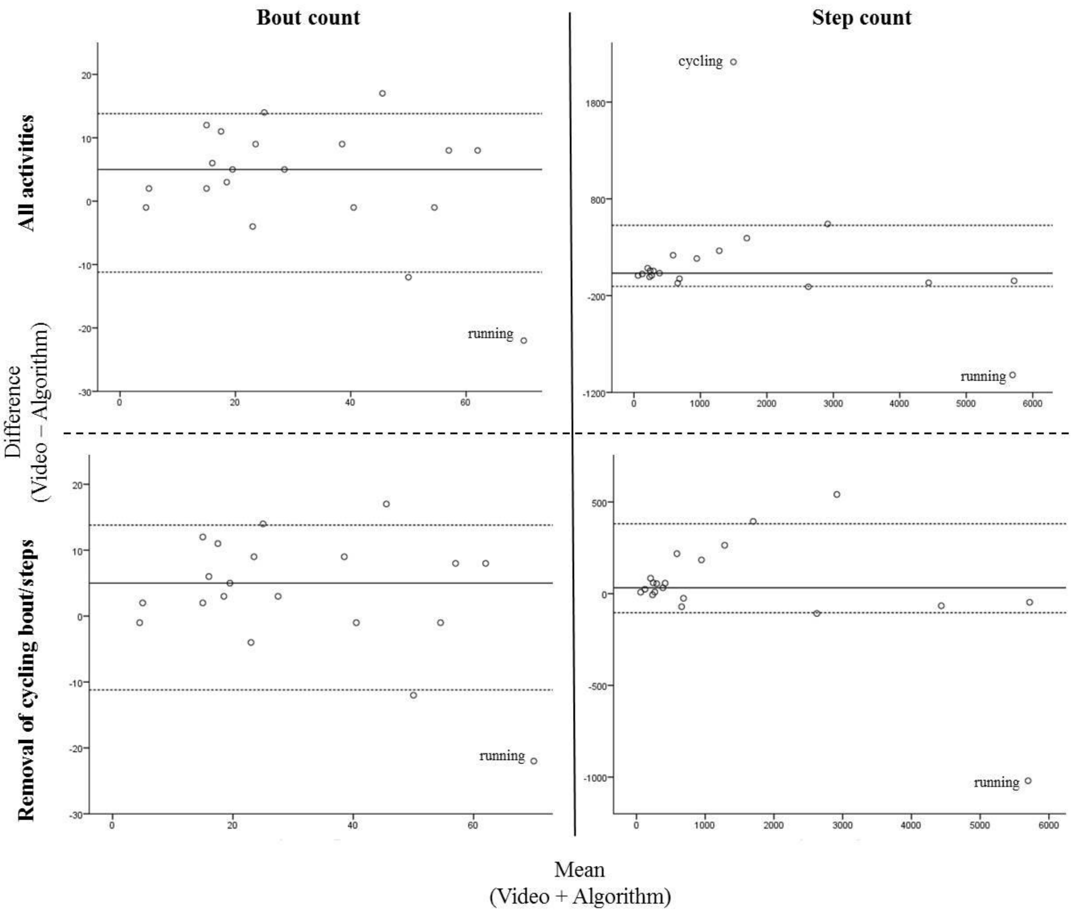

Figure 4: Bland-Altman plots showing agreement between the algorithm and video for bout (left plots) and step (right plots) count values. Top plots show the cycling outlier incorrectly identified by the algorithm as stepping. Included in both stages are the values identified by the algorithm for running. Solid line in each plot represents the systematic bias; dashed lines represent 95% limits of agreement (±SD×1.96).

4. Discussion

Current research uses free-living macro gait outcomes (steps, bouts) derived from wearable accelerometers to examine the behaviour of older adults and people with neurodegenerative diseases during free-living [26, 52-54]. However, many commercial devices with proprietary (non-descript, 'black box') algorithms have been shown to be inaccurate when quantifying free-living macro gait [13]. This study validated a gait identification and segmentation algorithm for step and bout count (macro) in uncontrolled free-living conditions with the aid of temporal events (micro). The approach used here can facilitate a combined micro and macro approach to free-living gait analysis [25].

4.1 Algorithm Function

Step quantification in each walking bout demonstrated excellent relative (*rho* = 0.985, $p<0.0005$) and absolute agreement ($ICC_{(2,1)}$=.994, $p<0.0005$) and no presence of bias (Z = -1.307, p=0.202). Any marginal difference between the measurement systems may be attributed to the algorithm functionality and classification of a step by the rater. The CWT methodology uses a timed IC/FC detection methodology (micro outcomes) [37, 46] to prevent the presence of spurious events that may occur due to scuffing ('dragging of the feet', [55]) a result of extraneous steps associated with functional tasks during ADL, e.g. household cleaning, Figure 3. It is likely that the uncontrolled nature of the free-living conditions facilitated the misidentification (algorithm or rater) of 'non-step' events leading to these minor discrepancies between algorithm and video/rater. This remains a grey area within the field of free-living gait algorithms: definition of a step and subsequent bout(s) of walking from acceleration data. Presently no guidelines/classifications exist, leading to heterogeneity of step and bout definitions [49, 56], making short bout (or single step) distinction, for algorithms or manual observation, less clear.

To date, algorithm studies have defined steps, solely for the purposes of their work: change of acceleration profiles with zero-crossing [56], detected peaks [57] and subsequently bouts as a consecutive number of steps e.g. 2 or 3 [33, 46]. Inevitably, these events are reliant on heel strikes (IC) that may not always be defined/identified by clear and distinctive peaks in the accelerometer signal due to reduced/varied gait speed [15], often evident during habitual activities. Yet, defining steps/bouts from free-living data is complex due to the abundance of gait variations and tasks that may be undertaken, Figure 3. Overcoming these limitations may be realised with more stringent algorithms, such as those utilising regions of interest within an acceleration period and learned template gait features [15, 58], and the clear ratification of how these outcomes are to be physiologically defined in all populations.

The algorithm quantified slightly larger values for both outcomes (Table 2, Figure 4), with bout count showing a greater relative magnitude of error (median error between measurement systems/mean observed value from video) ~13% in comparison to step count ~7%. In comparison previous validations of single sensor gait algorithms have reported greater accuracy in both controlled [37] and semi-controlled environments [13], however direct comparison is difficult due to the controlled protocols and restrictive conditions employed in such studies. The logical heuristics approach showed excellent relative (*rho*=.909, $p<0.0005$) and absolute agreement ($ICC_{(2,1)}$ = 0.942, $p<0.0005$) for walking bout identification but had significant bias (Z = -2.036, p=0.041). Identification of prolonged walking bouts (e.g. ≥10-60s) were readily identifiable, periods that have been generally quantified and utilised within free-living gait analysis [59, 60]. Generally these occur in outdoor environments or in work places with long corridors, Figure 3 and Table 2. However, gait is largely accumulated in cluttered, indoor environments where gait is limited to only a few strides, e.g. <<10s in duration [52, 61]. Walking bouts were predominantly short to moderate with few accumulating greater than 250 steps (approx. 2 mins of continuous walking). Greater accuracy (reduced relative error) was observed in participants whose walking was composed of these longer bouts (Figure 4), but in order to properly compare this to the relative error of short bouts (a more prominent feature of free-living walking) more data is required.

It is also important to consider the detection of the false positive events, specifically the incorrect recognition of 'intense cycling' as walking. The resultant effect of these non-walking bouts on results was minimal (Table 2/3: all activities vs. all activities less cycling), and the validity observed did not change when considering the data with and without this activity included. Appropriate methods for eliminating the presence of extraneous activities that are incorrectly segmented and subsequently quantified as gait events are still required. The emerging applications of machine learning techniques for differentiating between gait and other ADL present a potential solution. The use of support vector machine classifiers and artificial neural networking have already showed promise in gait identification [62-64] and could be applied to the identification algorithm presented in this paper.

4.2 Implications for Free-living Gait Outcomes

These promising results have provided valuable insights into the validity of the algorithms embedded in this single wearable accelerometer. This has implications for studies using more advanced macro characteristics such as pattern and variability [26] which rely on the accurate identification of walking. The success observed in both the identification and quantification of steps/bouts also has connotations for the accuracy of subsequent micro spatio-temporal gait analysis stemming from the same CWT methodology [26], whereby the accuracy in detecting a bout and its constituent steps will have a direct influence on the accuracy of spatio-temporal characteristics derived from that bout. As such, these results provide important information regarding the potential for accurately implementing gait assessments and their outcomes in free-living community settings [52].

4.3 Limitations

Although a small sample size (n=10) was examined, it was inclusive of 20 hours of data which could be considered as sufficient for the purpose of this investigation. The fundamental differences in the capture methods (differences in sampling frequencies between systems) is viewed as necessary due to the lack of validated gold-standard activity tracking technology.

The gait algorithms generated false positive events, in particular, mistaking intense cycling for walking. This occurred due to cycling generating similar acceleration profiles for the centre of mass making it a suitable input for the algorithm. In consideration of the range of uncontrolled environmental conditions that were observed in one hour of free-living gait, encompassing a range of indoor and outdoor activities, it is unlikely that these 'false' events would have statistical effect on bout count and step count outcomes when examining up to 7 days (~112 waking hours) of data, as the additional gait events would be absorbed by measures of central tendency. Moreover, this would likely see a reduction in relative magnitude of bout count error due to a greater number of bout events [52].

4.4 Future Research

This study is the first attempt to validate a macro gait algorithm, defining step and bout detection for free-living gait analysis and builds upon the micro laboratory based validations that already exist [26, 37, 38]. Further validations of the algorithm in older and pathological groups are required if this device is to be used as a clinical research tool. Utilising machine learning paradigms to develop more accurate activity profiling techniques, i.e. the development of more precise input thresholds for detection algorithms, may eliminate the presence of false positive results and should be explored.

5. Conclusion

The algorithm successfully detected bouts of gait (walking/ambulation) and their respective step counts in a range of free-living environments. Although the magnitude of error observed between the wearable accelerometer and video reference analysis is small, appropriate methods for removing error in activity recognition should be addressed for future examinations, especially in the assessment of young healthy adults where the range of ADL could be more diverse. These results will inform the accuracy of future studies utilising a single wearable accelerometer worn on the lower back for free-living gait analysis seeking to adopt a two tiered approach, macro and micro.

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References

1. Muro-de-la-Herran, A., B. Garcia-Zapirain, and A. Mendez-Zorrilla, *Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications.* Sensors (Basel, Switzerland), 2014. **14**(2): p. 3362-3394.
2. Taborri, J., et al., *Gait Partitioning Methods: A Systematic Review.* Sensors, 2016. **16**(1): p. 66.
3. Del Din, S., et al. *Accelerometer-based gait assessment: pragmatic deployment on an international scale*. in *IEEE Workshop on Statistical Signal Processing*. 2016. IEEE.
4. Ladha, C., et al. *Toward a low-cost gait analysis system for clinical and free-living assessment*. in *Engineering in Medicine and Biology Society (EMBC), 2016 38th Annual International Conference of the IEEE*. 2016. IEEE.
5. Godfrey, A., et al., *iCap: Instrumented assessment of physical capability.* Maturitas, 2015.
6. Lara, J., et al., *Towards measurement of the Healthy Ageing Phenotype in lifestyle-based intervention studies.* Maturitas, 2013. **76**(2): p. 189-199.
7. Grant, P.M., et al., *The validation of a novel activity monitor in the measurement of posture and motion during everyday activities.* Br J Sports Med, 2006. **40**(12): p. 992-7.
8. Dijkstra, B., et al., *Detection of walking periods and number of steps in older adults and patients with Parkinson's disease: accuracy of a pedometer and an accelerometry-based method.* Age Ageing, 2008. **37**(4): p. 436-41.
9. Ryan, C.G., et al., *The validity and reliability of a novel activity monitor as a measure of walking.* British Journal of Sports Medicine, 2006. **40**(9): p. 779-784.
10. Foster, R.C., et al., *Precision and accuracy of an ankle-worn accelerometer-based pedometer in step counting and energy expenditure.* Prev Med, 2005. **41**(3-4): p. 778-83.
11. Godfrey, A., K.M. Culhane, and G.M. Lyons, *Comparison of the performance of the activPAL Professional physical activity logger to a discrete accelerometer-based activity monitor.* Med Eng Phys, 2007. **29**(8): p. 930-4.
12. Coleman, K.L., et al., *Step activity monitor: long-term, continuous recording of ambulatory function.* J Rehabil Res Dev, 1999. **36**(1): p. 8-18.
13. Storm, F.A., B.W. Heller, and C. Mazzà, *Step detection and activity recognition accuracy of seven physical activity monitors.* PloS one, 2015. **10**(3): p. e0118723.

14. Evenson, K.R., M.M. Goto, and R.D. Furberg, *Systematic review of the validity and reliability of consumer-wearable activity trackers.* Int J Behav Nutr Phys Act, 2015. **12**: p. 159.
15. Soaz, C. and K. Diepold, *Step Detection and Parameterization for Gait Assessment Using a Single Waist-Worn Accelerometer.* IEEE Transactions on Biomedical Engineering, 2016. **63**(5): p. 933-942.
16. Barry, G., et al., *Defining ambulatory bouts in free-living activity: Impact of brief stationary periods on bout metrics.* Gait & Posture, 2015. **42**(4): p. 594-597.
17. Fortune, E., et al., *Validity of using tri-axial accelerometers to measure human movement - Part II: Step counts at a wide range of gait velocities.* Med Eng Phys, 2014. **36**(6): p. 659-69.
18. Fortune, E., et al., *Step detection using multi- versus single tri-axial accelerometer-based systems.* Physiol Meas, 2015. **36**(12): p. 2519-35.
19. Donath, L., et al., *Validity and reliability of a portable gait analysis system for measuring spatiotemporal gait characteristics: comparison to an instrumented treadmill.* Journal of NeuroEngineering and Rehabilitation, 2016. **13**(1): p. 1.
20. Trojaniello, D., et al., *Comparative assessment of different methods for the estimation of gait temporal parameters using a single inertial sensor: application to elderly, post-stroke, Parkinson's disease and Huntington's disease subjects.* Gait & Posture, 2015. **42**(3): p. 310-316.
21. López-Nava, I.H., et al., *Comparison of a Vision-Based System and a Wearable Inertial-Based System for a Quantitative Analysis and Calculation of Spatio-Temporal Parameters*, in *Ambient Intelligence for Health*. 2015, Springer. p. 116-122.
22. Tao, W., et al., *Gait analysis using wearable sensors.* Sensors, 2012. **12**(2): p. 2255-2283.
23. Lord, S., et al., *Independent domains of gait in older adults and associated motor and nonmotor attributes: validation of a factor analysis approach.* J Gerontol A Biol Sci Med Sci, 2013. **68**(7): p. 820-7.
24. Verghese, J., et al., *Quantitative gait dysfunction and risk of cognitive decline and dementia.* J Neurol Neurosurg Psychiatry, 2007. **78**(9): p. 929-35.
25. Lord, S., B. Galna, and L. Rochester, *Moving forward on gait measurement: toward a more refined approach.* Mov Disord, 2013. **28**(11): p. 1534-43.
26. Del Din, S., A. Godfrey, and L. Rochester, *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.* IEEE J Biomed Health Inform, 2015.
27. Lord, S., et al., *Ambulatory activity in incident Parkinson's: More than meets the eye?* Journal of Neurology, 2013. **260**(12): p. 2964-2972.
28. Godfrey, A., et al., *The association between retirement and age on physical activity in older adults.* Age Ageing, 2014. **43**(3): p. 386-93.
29. Chastin, S.F.M. and M.H. Granat, *Methods for objective measure, quantification and analysis of sedentary behaviour and inactivity.* Gait & Posture, 2010. **31**(1): p. 82-86.
30. Rochester, L., et al., *Understanding the impact of deep brain stimulation on ambulatory activity in advanced Parkinson's disease.* Journal of Neurology, 2012. **259**(6): p. 1081-1086.
31. Salarian, A., et al., *Ambulatory Monitoring of Physical Activities in Patients With Parkinson's Disease.* Biomedical Engineering, IEEE Transactions on, 2007. **54**(12): p. 2296-2299.
32. Larkin, L., et al., *THU0630-HPR Validation of the Activpal™ Activity Monitor for Sedentary and Physical Activity Patterns in People with Rheumatoid Arthritis.* Annals of the Rheumatic Diseases, 2015. **74**(Suppl 2): p. 1319-1319.
33. Dijkstra, B., Y.P. Kamsma, and W. Zijlstra, *Detection of gait and postures using a miniaturized triaxial accelerometer-based system: accuracy in patients with mild to moderate Parkinson's disease.* Arch Phys Med Rehabil, 2010. **91**(8): p. 1272-7.
34. Full, K., et al. *Comparative study on classifying gait with a single trunk-mounted inertial-magnetic measurement unit*. in *Wearable and Implantable Body Sensor Networks (BSN), 2015 IEEE 12th International Conference on*. 2015.
35. Buso, V., et al. *Recognition of Activities of Daily Living in natural "at home" scenario for assessment of Alzheimer's disease patients*. in *Multimedia & Expo Workshops (ICMEW), 2015 IEEE International Conference on*. 2015.

36. Del Din, S., et al. *Free-living monitoring of Parkinson's disease: lessons from the field*. Movement Disorders, 2016. **In Press**.
37. Godfrey, A., et al., *Instrumenting gait with an accelerometer: a system and algorithm examination.* Med Eng Phys, 2015. **37**(4): p. 400-7.
38. Godfrey, A., et al., *Within trial validation and reliability of a single tri-axial accelerometer for gait assessment.* Conf Proc IEEE Eng Med Biol Soc, 2014. **2014**: p. 5892-5.
39. Lugade, V., et al., *Validity of using tri-axial accelerometers to measure human movement - Part I: Posture and movement detection.* Med Eng Phys, 2014. **36**(2): p. 169-76.
40. Godfrey, A., et al., *Activity classification using a single chest mounted tri-axial accelerometer.* Med Eng Phys, 2011. **33**(9): p. 1127-35.
41. Lyons, G.M., et al., *A description of an accelerometer-based mobility monitoring technique.* Med Eng Phys, 2005. **27**(6): p. 497-504.
42. Hollman, J.H., E.M. McDade, and R.C. Petersen, *Normative spatiotemporal gait parameters in older adults.* Gait Posture, 2011. **34**(1): p. 111-8.
43. Moe-Nilssen, R., *A new method for evaluating motor control in gait under real-life environmental conditions. Part 1: The instrument.* Clin Biomech (Bristol, Avon), 1998. **13**(4-5): p. 320-327.
44. Moe-Nilssen, R., *A new method for evaluating motor control in gait under real-life environmental conditions. Part 2: Gait analysis.* Clin Biomech (Bristol, Avon), 1998. **13**(4-5): p. 328-335.
45. Millecamps, A., et al., *Understanding the effects of pre-processing on extracted signal features from gait accelerometry signals.* Comput Biol Med, 2015. **62**: p. 164-74.
46. Najafi, B., et al., *Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly.* IEEE Trans Biomed Eng, 2003. **50**(6): p. 711-23.
47. McCamley, J., et al., *An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data.* Gait Posture, 2012. **36**(2): p. 316-8.
48. Aminian, K., et al., *Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes.* Journal of biomechanics, 2002. **35**(5): p. 689-699.
49. Brodie, M.A., et al., *Wearable pendant device monitoring using new wavelet-based methods shows daily life and laboratory gaits are different.* Med Biol Eng Comput, 2016. **54**(4): p. 663-74.
50. Hartmann, A., et al., *Concurrent validity of a trunk tri-axial accelerometer system for gait analysis in older adults.* Gait Posture, 2009. **29**(3): p. 444-8.
51. Portney, L.G. and M.P. Watkins, *Foundations of Clinical Research: Applications to Practice*. 2009: Pearson/Prentice Hall.
52. Del Din, S., et al., *Free-living gait characteristics in ageing and Parkinson's disease: impact of environment and ambulatory bout length.* Journal of NeuroEngineering and Rehabilitation, 2016. **13**(1): p. 1.
53. van Schooten, K.S., et al., *Ambulatory fall-risk assessment: amount and quality of daily-life gait predict falls in older adults.* The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 2015. **70**(5): p. 608-615.
54. Weiss, A., et al., *Does the evaluation of gait quality during daily life provide insight into fall risk? A novel approach using 3-day accelerometer recordings.* Neurorehabilitation and neural repair, 2013. **27**(8): p. 742-752.
55. Snijders, A.H., et al., *Neurological gait disorders in elderly people: clinical approach and classification.* The Lancet Neurology, 2007. **6**(1): p. 63-74.
56. Zijlstra, W. and A.L. Hof, *Assessment of spatio-temporal gait parameters from trunk accelerations during human walking.* Gait Posture, 2003. **18**(2): p. 1-10.
57. Menz, H.B., S.R. Lord, and R.C. Fitzpatrick, *Acceleration patterns of the head and pelvis when walking on level and irregular surfaces.* Gait Posture, 2003. **18**(1): p. 35-46.
58. Kose, A., A. Cereatti, and U. Della Croce, *Bilateral step length estimation using a single inertial measurement unit attached to the pelvis.* J Neuroeng Rehabil, 2012. **9**: p. 9.
59. van Schooten, K.S., et al., *Assessing physical activity in older adults: required days of trunk accelerometer measurements for reliable estimation.* J Aging Phys Act, 2015. **23**(1): p. 9-17.

60. Weiss, A., et al., *Objective assessment of fall risk in Parkinson's disease using a body-fixed sensor worn for 3 days.* PLoS One, 2014. **9**(5): p. e96675.
61. Orendurff, M.S., et al., *How humans walk: bout duration, steps per bout, and rest duration.* J Rehabil Res Dev, 2008. **45**(7): p. 1077-89.
62. Mannini, A., et al., *A Machine Learning Framework for Gait Classification Using Inertial Sensors: Application to Elderly, Post-Stroke and Huntington's Disease Patients.* Sensors, 2016. **16**(1): p. 134.
63. Safi, K., et al. *Physical activity recognition using inertial wearable sensors—A review of supervised classification algorithms*. in *Advances in Biomedical Engineering (ICABME), 2015 International Conference on*. 2015. IEEE.
64. Joyseeree, R., R.A. Sabha, and H. Mueller, *Applying Machine Learning to Gait Analysis Data for Disease Identification.* Studies in health technology and informatics, 2014. **210**: p. 850-854.

TABLES

FREE-LIVING ACTIVITY	Work		Home		Rural		Urban		Other	
	Location	**mins**	**Location**	**mins**	**Location**	**mins**	**Location**	**mins**	**Activity**	**mins**
	Total	77.1	Total	14.8	Total	71.9	Total	100.6	Total	88.2
	Desk-based workspace (cluttered office environment)	51.8	Sitting-room	4.9			Supermarket	2.0	Golf	48.4
	Office-Kitchen	10.6	Kitchen	3.7					Running	21.6
	Laboratory	6.8	Bedroom	2.7					Cycling	18.2
	Stair-walking	4.1	Dining-room	1.7						
	Other	3.2	Stair-walking	0.7						
	Reception	0.6	Other	1.1						

Table 1: Ranked time spent by all participants (all test sessions/occasions) walking in the broad range of environments.

	(n=20)	Video Observed Values			Algorithm Observed Values			Difference Magnitude of error		
		Mean	*max*	*min*	*Mean*	*max*	*min*	Median	*IQR 25th*	*IQR 75th*
All activities (*20 hrs*)	BC	30	81	4	33	66	4	5	-1	9
	SC	1459	6207	57	1596	5696	65	28	-31	193
Removal of cycling (*19.68hrs*)	BC	30	81	4	33	66	4	4	-1	9
	SC	1459	6207	57	1489	5696	65	28	-30	109

Table 2: Descriptive data demonstrating the range of outcomes observed from the video and algorithm, and the difference between each. All activities contain all walking data detected by the algorithms. Removal of cycling presents the findings from all activities but without the false positive cycling events included. (BC = bout count and SC = step count).

	(n=20)		Median	Percentiles		Agreement Relative		Agreement Absolute		Bias	
			(n)	*25th*	*75th*	*rho*	*p*	*ICC(2,1)*	*p*	*Z*	*p*
All activities (*20 hrs*)	BC	Video	22	13	50	0.909	<0.0005	0.941	<0.0005	-2.074	0.037
		Algorithm	30	20	52						
	SC	Video	587	244	2359	0.941	<0.0005	0.975	<0.0005	-1.456	0.154
		Algorithm	685	272	2596						
Removal of cycling (*19.68 hrs*)	BC	Video	22	13	50	0.909	<0.0005	0.942	<0.0005	-2.036	0.041
		Algorithm	29	20	52						
	SC	Video	587	244	2359	0.985	<0.0005	0.994	<0.0005	-1.307	0.202
		Algorithm	647	272	2401						

Table 3: Relative and absolute agreement, and bias between the video and algorithm. All activities contain all walking data detected by the algorithms. Removal of cycling presents the findings from all activities but without the false positive cycling events included. (BC = bout count and SC = step count).