

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

Aodhán Hickey¹, Silvia Del Din¹, Lynn Rochester¹, Alan Godfrey¹

¹Institute 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,

Word count: 3,537

Tables: 3

Figures: 4

1 **1. Introduction**

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

9 Early validation studies consisted of accelerometer-based wearables and focused on their ability to
10 detect steps and walking bouts. These typically consisted of protocols involving scripted activities [7,
11 8], comparison to pedometers on a treadmill [9, 10] or bout detection at low-resolutions of approx. 1min
12 [11, 12]. Many commercial wearable accelerometers utilise their own proprietary algorithms which can
13 be limited, the majority showing poor capacity to identify and quantify gait during non-scripted
14 activities, i.e. in free-living conditions [13, 14]. While manufacturers are moving towards the provision
15 of raw data for more bespoke analysis [8, 15], embedded ‘black box’ programming make it difficult to
16 understand why reliability and validity are poor, attributed to the closed system and exact algorithm
17 functionality [16]. This in turn limits their potential use as robust academic or clinical tools, particularly
18 for those unable to develop tailored algorithms from ad-hoc devices created in specialist facilities [17,
19 18].

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

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

29 [23, 24]. These constitute a clinically relevant conceptual model of gait inspired by the use of current
30 high resolution ($\geq 100\text{Hz}$) accelerometer-based wearables: examining micro as well as the broader signal
31 profiles representing walking activity (macro) within free-living environments [25]. This provides a
32 comprehensive, two-tiered approach to gait assessment and its potential use as a pragmatic and low-
33 cost diagnostic [26-28]. Utilising this approach one can gather habitual micro gait, while also examining
34 the broader trends in ambulatory behaviour within free-living, leading to novel insights on the
35 accumulation and distribution of macro gait [28-30]. Thus, a micro and macro approach offers a more
36 informative approach to gait analysis. However, macro outcomes measured by high resolution wearable
37 accelerometers rely on the correct identification and quantification of walking (gait) bouts from free-
38 living data in the first instance. Validation of free-living gait algorithms from high resolution devices
39 remains limited. Although some wearable accelerometers have demonstrated reliability in semi-
40 structured protocols [31-33], assessment in free-living uncontrolled environments has not been
41 completed. Additionally, validation studies usually compare algorithms to criterion pedometers [13],
42 fixed or observer video recording [33] which limits long-term feasibility. Wearable cameras have been
43 successfully used to validate gait detection of a single trunk-mounted wearable accelerometer [34] and
44 their concurrent use with devices in free-living conditions have help develop and analyse activity
45 taxonomies [35]. Therefore, wearable cameras can be viewed as the most appropriate comparative
46 measure currently available for validating devices that define free-living macro gait outcomes. This is
47 due to their ability to provide contextual information (e.g. type of terrain) as well as clarify exact
48 movement types (e.g. stair ascent/descent).

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

57 to accurately and robustly quantify gait during free-living. Here, we present a macro gait identification
58 and segmentation validation.

59

60 **2. Methods**

61 *2.1 Participants:*

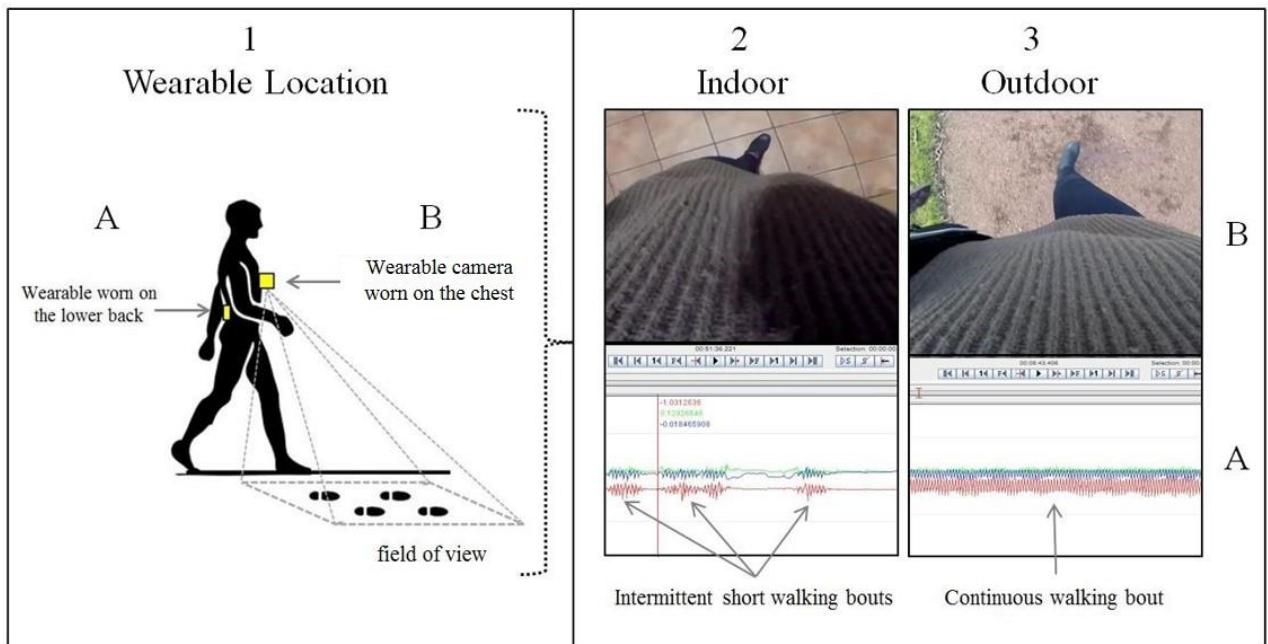
62 Ten healthy (free from physical and neurological conditions) participants ranging in age 20-33 years
63 (27.5 ± 4.7 yrs; 1.74 ± 0.07 m; 70.4 ± 8.8 kg) volunteered for this study. Ethical approval was granted by
64 the Newcastle University Research Ethics Committee, reference: 3759/2016. All participants provided
65 informed written consent prior to participating.

66

67 *2.2 Protocol:*

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

77



78 **Figure 1:** 1) Location of wearable accelerometer (A) and wearable camera (B). 2) Example of wearable (A) and
 79 wearable camera (B) data for multiple walking bouts in an indoor environment. 3) Example of wearable (A) and
 80 wearable camera (B) data for multiple walking bouts in an outdoor environment.
 81
 82
 83

84 **2.3 Equipment**

85 **2.3.1 Wearable**

86 Participants wore a low-cost (\approx £100) tri-axial accelerometer-based wearable (AX3; Axivity, York, UK;
 87 23.0mm \times 32.5mm \times 7.6mm, 9g) located on the fifth lumbar vertebra (L5). The wearable was attached
 88 using double sided tape and Hypafix (BSN Medical Limited, Hull, UK) and programmed to capture
 89 with a sampling frequency of 100Hz (16 bit resolution, range \pm 8g, battery life $>$ 7days). Recorded
 90 signals were stored locally on the sensor's internal memory (512MB) as a raw binary file and then
 91 downloaded to a computer via USB cable upon the completion of each testing session.
 92

93 **2.3.2 Wearable camera**

94 Participants also wore a single camera (GoPro HERO, GoPro Inc., CA, USA; 71.3mm \times 67.1mm \times
 95 39.0mm, 111g) attached to the chest (GoPro Chest Harness, GoPro Inc., CA, USA). The camera was
 96 programmed to capture with a sampling frequency of 50Hz, video resolution 720p, screen resolution
 97 1280 \times 720, and field of view 170°, and was directed at the participant's feet. Recorded video was
 98 stored locally on a micro-SDHC memory card (SanDisk UHS-1.32 GB, SanDisk Corporation, CA,

99 USA) before being downloaded upon completion of each testing session. This was the gold-standard
100 reference.

101

102 *2.4 Data processing*

103 *2.4.1 Algorithms*

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

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

112 Walking bout detection: The detection and segmentation algorithm (Figure 2) utilised for examining
113 walking bouts in free-living conditions relies on a logical heuristics paradigm as follows. A moving
114 window analysed the signal for bouts of ‘upright movement’ based on the combined standard deviation
115 (SD) of tri-axial accelerations and the corresponding mean of the vertical acceleration (a_v , -1g) every
116 0.1 seconds [41] with predefined thresholds ($g = 0.77$ and 0.05 , respectively). Due to device location
117 (L5) and orientation this identifies bouts that are ‘upright and moving’. Bouts $<0.5s$ were ignored and
118 treated as spurious movement, constituting an unrelated gait (step) time value [42]. Once the start/end
119 of these bouts are identified the segmented data are analysed with a secondary stage examining potential
120 gait events (step detection) within each identified bout (possible walking/gait).

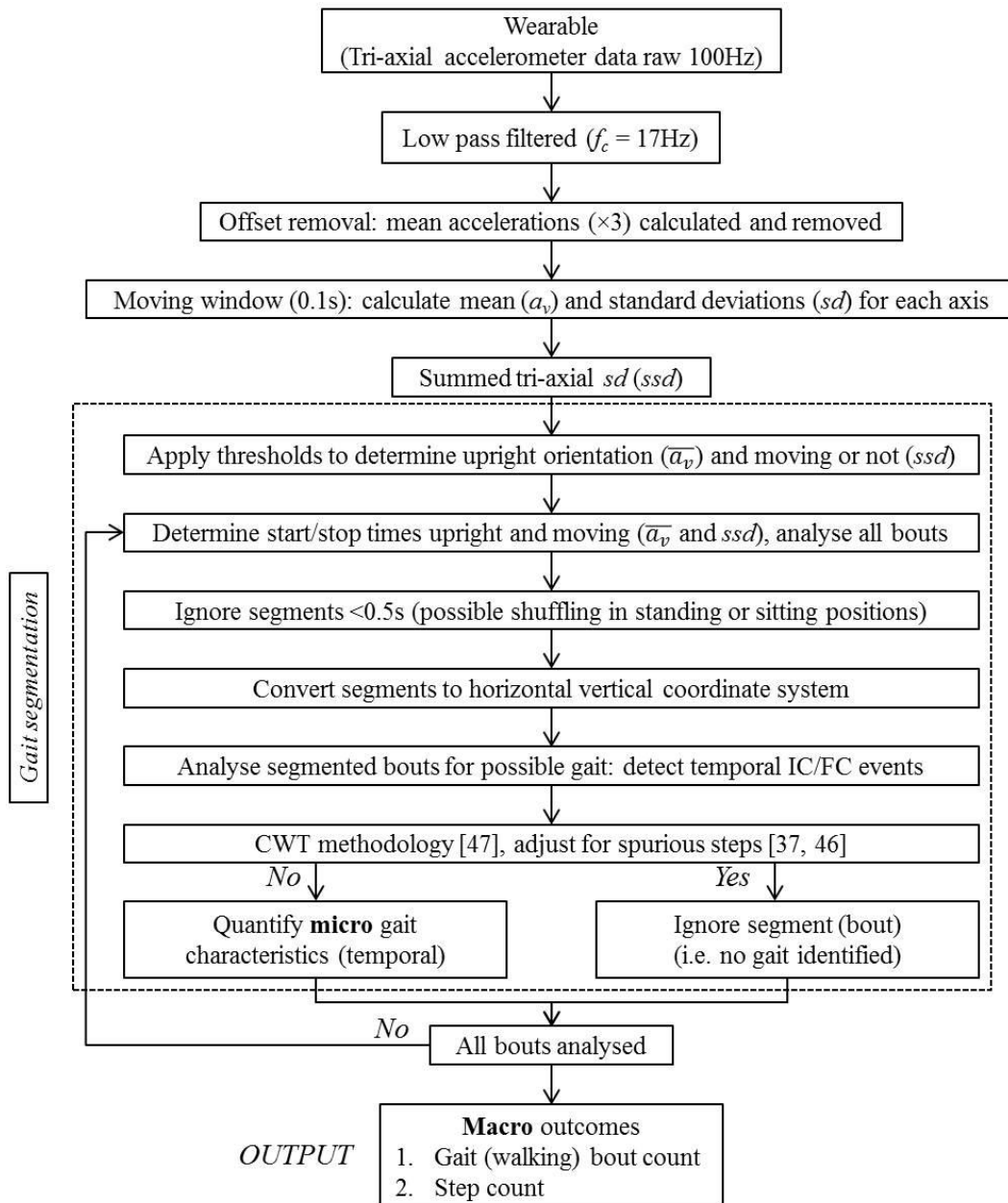
121 Step identification: Further correction of the acceleration data for misalignment, unaccounted for when
122 removing gravity (subtracting the mean acceleration) was performed by transforming data to a
123 horizontal-vertical coordinate system [43, 44], aligning with recommended gait data processing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

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

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

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

137



138
139 **Figure 2:** Processing flow of the gait detection and quantification algorithms performed by the MATLAB®
140 program.
141

142 2.4.2 Video data

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

- 147 • All events (walking, postural transitions, ADLs etc.) were recorded with their relative contextual
148 information (e.g. location, purpose, duration, etc.) from the video data. All periods of non-

149 walking ('non step-event') activity were removed and step events were collated into their
150 respective bouts with a minimum resting period of 2.5 seconds between bouts [48].

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

153 A single researcher with a background in applied movement science extracted all walking information
154 [33].

155

156 *2.5 Statistical analysis*

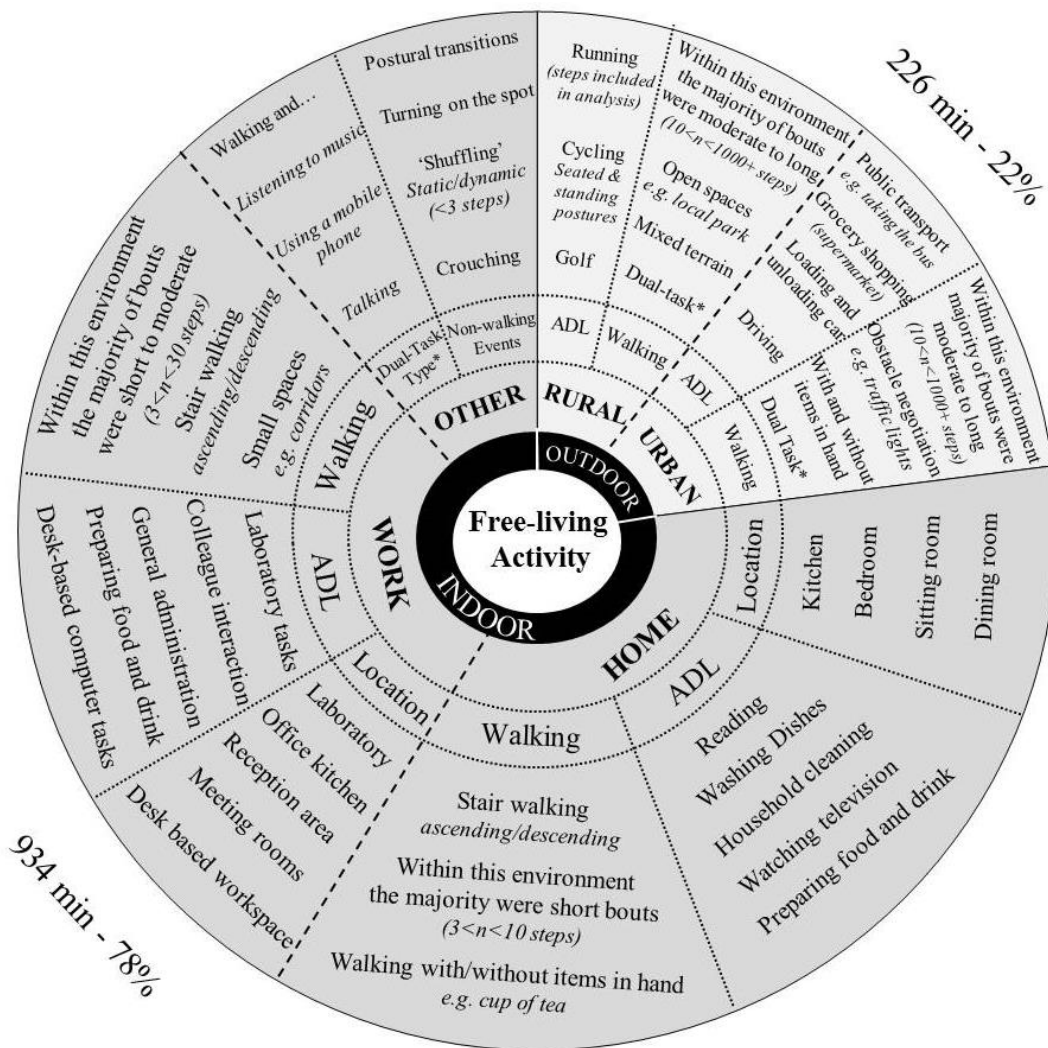
157 Validity of the algorithm (agreement to video) was assessed using SPSS v22 (IMB Inc., Armonk, NY,
158 USA). Shapiro-Wilks tests suggested the use of non-parametric measures for step and bout count
159 ($p < 0.04$). Spearman's correlations and intra-class correlations ($ICC_{(2,1)}$) were used to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

165

166 **3. Results**

167 *3.1 Environments and algorithm functionality*

168 A large range of activities were observed in the video data inclusive of both indoor (78%) and outdoor
169 (22%) environments. To provide context a pictorial representation of the different conditions and their
170 respective ADLs are provided, Figure 3. A summary of times spent during walking in different
171 environments is also presented, Table 1. Participants spent the majority of time walking sporadically
172 indoors (large number of bouts, few steps) or in long continuous bouts outdoors (small number of bouts,
173 many steps).



174 **Figure 3:** Pie chart containing contextual information for the walking and ADLs observed in the video data.
 175
 176

177 <Table 1, see end >
 178

179 A preliminary examination of the magnitude of error between the measurement systems (n=20
 180 sessions, 20 hrs) identified a single outlier, i.e. quantified step count differences between the algorithm
 181 and rater/video were excessively large in comparison to other data. Manual investigation of the data
 182 found that the difference related to two bouts and approximately 2262 steps. It was found that the
 183 participant had completed two bouts of high intensity cycling (windy conditions on a negative gradient)
 184 in both seated and standing postures (≈ 1942 revolutions) that had been incorrectly identified and
 185 segmented as gait by the algorithm. In order to compare the effect of including these two false-positive

186 events the results are presented with (all activities: n=20, ~20hrs) and without those bouts (removal of
187 cycling: n=20, ~19.68hrs), Table 2 and Table 3.

188 <Table 2, see end>

189 <Table 3, see end >

190

191 3.2 Algorithm analysis – all activities

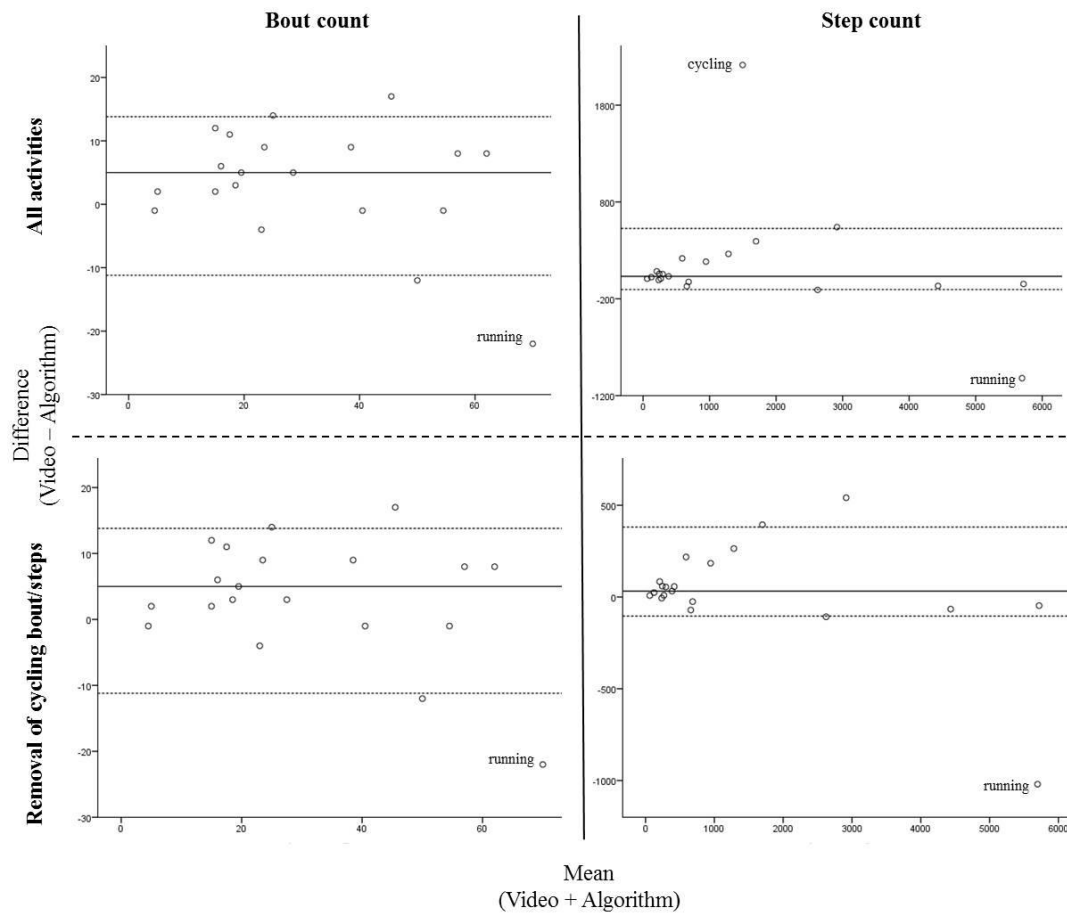
192 Spearman correlations demonstrated excellent relative agreement between the algorithm and video data
193 for step count ($\rho = 0.941, p \leq 0.0005$) and bout count ($\rho = 0.909, p \leq 0.0005$). Intra-class correlations
194 demonstrated excellent absolute agreement for step count ($ICC_{2,1} = 0.975, p \leq 0.0005$) and bout count
195 ($ICC_{2,1} = 0.941, p \leq 0.0005$). Wilcoxon matched pairs tests demonstrated no bias was observed for step
196 count ($Z = -1.456, p=0.154$) but significant bias between measures for bout count ($Z = -2.074, p =$
197 0.037).

198

199 3.3 Algorithm analysis – removal of cycling

200 Spearman correlations showed slight improvement in relative agreement between the algorithm and
201 video data for step count ($\rho = 0.985, p \leq 0.0005$) and bout count ($\rho = 0.909, p \leq 0.0005$) when the
202 false positive cycling activity was removed, Figure 4. Intra-class correlations also demonstrated similar
203 improvements for both step count ($ICC_{2,1} = 0.994, p \leq 0.0005$) and bout count ($ICC_{2,1} = 0.942, p \leq$
204 0.0005) and. Wilcoxon matched-pairs tests were consistent for step count ($Z = -1.307, p=0.202$) and
205 bout count ($Z = -2.036, p = 0.041$).

206



207
 208 **Figure 4:** Bland-Altman plots showing agreement between the algorithm and video for bout (left plots) and step
 209 (right plots) count values. Top plots show the cycling outlier incorrectly identified by the algorithm as stepping.
 210 Included in both stages are the values identified by the algorithm for running. Solid line in each plot represents
 211 the systematic bias; dashed lines represent 95% limits of agreement ($\pm SD \times 1.96$).
 212

213 4. Discussion

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

221

222 4.1 Algorithm Function

223 Step quantification in each walking bout demonstrated excellent relative ($\rho = 0.985, p < 0.0005$) and
224 absolute agreement ($ICC_{(2,1)} = .994, p < 0.0005$) and no presence of bias ($Z = -1.307, p = 0.202$). Any
225 marginal difference between the measurement systems may be attributed to the algorithm functionality
226 and classification of a step by the rater. The CWT methodology uses a timed IC/FC detection
227 methodology (micro outcomes) [37, 46] to prevent the presence of spurious events that may occur due
228 to scuffing ('dragging of the feet', [55]) a result of extraneous steps associated with functional tasks
229 during ADL, e.g. household cleaning, Figure 3. It is likely that the uncontrolled nature of the free-living
230 conditions facilitated the misidentification (algorithm or rater) of 'non-step' events leading to these
231 minor discrepancies between algorithm and video/rater. This remains a grey area within the field of
232 free-living gait algorithms: definition of a step and subsequent bout(s) of walking from acceleration
233 data. Presently no guidelines/classifications exist, leading to heterogeneity of step and bout definitions
234 [49, 56], making short bout (or single step) distinction, for algorithms or manual observation, less clear.

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

244 The algorithm quantified slightly larger values for both outcomes (Table 2, Figure 4), with bout
245 count showing a greater relative magnitude of error (median error between measurement systems/mean
246 observed value from video) ~13% in comparison to step count ~7%. In comparison previous validations
247 of single sensor gait algorithms have reported greater accuracy in both controlled [37] and semi-
248 controlled environments [13], however direct comparison is difficult due to the controlled protocols and
249 restrictive conditions employed in such studies. The logical heuristics approach showed excellent
250 relative ($\rho = .909, p < 0.0005$) and absolute agreement ($ICC_{(2,1)} = 0.942, p < 0.0005$) for walking bout

251 identification but had significant bias ($Z = -2.036, p=0.041$). Identification of prolonged walking bouts
252 (e.g. ≥ 10 -60s) were readily identifiable, periods that have been generally quantified and utilised within
253 free-living gait analysis [59, 60]. Generally these occur in outdoor environments or in work places with
254 long corridors, Figure 3 and Table 2. However, gait is largely accumulated in cluttered, indoor
255 environments where gait is limited to only a few strides, e.g. $\ll 10$ s in duration [52, 61]. Walking bouts
256 were predominantly short to moderate with few accumulating greater than 250 steps (approx. 2 mins of
257 continuous walking). Greater accuracy (reduced relative error) was observed in participants whose
258 walking was composed of these longer bouts (Figure 4), but in order to properly compare this to the
259 relative error of short bouts (a more prominent feature of free-living walking) more data is required.

260 It is also important to consider the detection of the false positive events, specifically the incorrect
261 recognition of ‘intense cycling’ as walking. The resultant effect of these non-walking bouts on results
262 was minimal (Table 2/3: all activities vs. all activities less cycling), and the validity observed did not
263 change when considering the data with and without this activity included. Appropriate methods for
264 eliminating the presence of extraneous activities that are incorrectly segmented and subsequently
265 quantified as gait events are still required. The emerging applications of machine learning techniques
266 for differentiating between gait and other ADL present a potential solution. The use of support vector
267 machine classifiers and artificial neural networking have already showed promise in gait identification
268 [62-64] and could be applied to the identification algorithm presented in this paper.

269

270 *4.2 Implications for Free-living Gait Outcomes*

271 These promising results have provided valuable insights into the validity of the algorithms embedded
272 in this single wearable accelerometer. This has implications for studies using more advanced macro
273 characteristics such as pattern and variability [26] which rely on the accurate identification of walking.
274 The success observed in both the identification and quantification of steps/bouts also has connotations
275 for the accuracy of subsequent micro spatio-temporal gait analysis stemming from the same CWT
276 methodology [26], whereby the accuracy in detecting a bout and its constituent steps will have a direct
277 influence on the accuracy of spatio-temporal characteristics derived from that bout. As such, these

278 results provide important information regarding the potential for accurately implementing gait
279 assessments and their outcomes in free-living community settings [52].

280

281 *4.3 Limitations*

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

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

294

295 *4.4 Future Research*

296 This study is the first attempt to validate a macro gait algorithm, defining step and bout detection for
297 free-living gait analysis and builds upon the micro laboratory based validations that already exist [26,
298 37, 38]. Further validations of the algorithm in older and pathological groups are required if this device
299 is to be used as a clinical research tool. Utilising machine learning paradigms to develop more accurate
300 activity profiling techniques, i.e. the development of more precise input thresholds for detection
301 algorithms, may eliminate the presence of false positive results and should be explored.

302

303 **5. Conclusion**

304 The algorithm successfully detected bouts of gait (walking/ambulation) and their respective step counts
305 in a range of free-living environments. Although the magnitude of error observed between the wearable

306 accelerometer and video reference analysis is small, appropriate methods for removing error in activity
307 recognition should be addressed for future examinations, especially in the assessment of young healthy
308 adults where the range of ADL could be more diverse. These results will inform the accuracy of future
309 studies utilising a single wearable accelerometer worn on the lower back for free-living gait analysis
310 seeking to adopt a two tiered approach, macro and micro.

311

312 **Acknowledgements**

313 The authors would also like to thank all participants. AH, LR and AG are supported by the Newcastle
314 Biomedical Research Centre/Unit (BRC/BRU) at Newcastle upon Tyne Hospitals NHS Foundation
315 Trust and Newcastle University. The work was also supported by the NIHR Newcastle Clinical
316 Research Faculty infrastructure funding. Opinions are those of the authors.

317

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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		
		<i>Mean</i>	<i>max</i>	<i>min</i>	<i>Mean</i>	<i>max</i>	<i>min</i>	<i>Median</i>	<i>IQR 25th</i>	<i>IQR 75th</i>
		All activities (20 hrs)	BC	30	81	4	33	66	4	5
	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				Bias	
			(<i>n</i>)	25 th	75 th	Relative		Absolute		<i>Z</i>	<i>p</i>
						<i>rho</i>	<i>p</i>	<i>ICC</i> _(2,1)	<i>p</i>		
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).