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# Measuring gait with an accelerometer-based wearable: influence of device location, testing protocol and age

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**Abstract**
Wearables such as accelerometers are emerging as powerful tools for quantifying gait in various environments. Flexibility in wearable location may improve ease of use and data acquisition during instrumented testing. However, change of location may impact algorithm functionality when evaluating associated gait characteristics. Furthermore, this may be exacerbated by testing protocol (different walking speed) and age. Therefore, the aim of this study was to examine the effect of an accelerometer-based wearable(s) (accW) location, walking speed, age and algorithms on gait characteristics. Forty younger (YA) and 40 older adults (OA) were recruited. Participants wore accW positioned at the chest, waist and lower back (L5, gold standard) and were asked to walk continuously for 2 min at preferred and fast speeds. Two algorithms, previously validated for accW located on L5, were used to quantify step time and step length. Mean, variability and asymmetry gait characteristics were estimated for each location with reference to L5. To examine impact of locations and speed on algorithm-dependant characteristic evaluation, adjustments were made to the temporal algorithm. Absolute, relative agreement and difference between measurements at different locations and L5 were assessed. Mean step time and length evaluated from the chest showed excellent agreement compared to L5 for both age groups and speeds. Agreement between waist

and L5 was excellent for mean step time for both speeds and age groups, good for mean step length at both speeds for YA and at preferred speed for OA. Step time and length asymmetry evaluated from the chest showed moderate agreement for YA only. Lastly, results showed that algorithm adjustment did not influence agreement between results obtained at different locations. Mean spatiotemporal characteristics can be robustly quantified from accW at the locations used in this study irrespective of speed and age; this is not true when estimating variability and asymmetry characteristics.

Keywords: accelerometer, algorithm, device location, gait, validation, wearables

S Online supplementary data available from stacks.iop.org/PM/37/1785/mmedia

(Some figures may appear in colour only in the online journal)

## Introduction

Wearables (wearable technology) is a term used to describe a large variety of devices (accelerometer and/or gyroscopes-based, etc) which present the advantage of being non-invasively worn on different body locations and are emerging as a powerful tool for continuous monitoring of a range of physical capabilities and body movements (Patel *et al* 2012,2015, Case *et al* 2015, Maetzler and Rochester 2015). Wearables have the potential to become increasingly useful in clinical-based settings as they are multifunctional and facilitate collection of robust, objective data which are potentially highly translatable between studies (Taraldsen *et al* 2012, Lara *et al* 2013, Rine *et al* 2013, Godfrey *et al* 2015b). The most commonly described types of wearable are accelerometer-based (Preece *et al* 2009). Due to the miniaturisation of integrated circuits and advances in computational processes, such devices are small enough to be worn directly on the skin and have the ability to gather highly accurate and continuous data (Culhane *et al* 2005).

Accelerometer-based wearables (accW) have the ability to capture most forms of human movement (Godfrey *et al* 2008), but a key area of deployment is in the estimation of gait characteristics to predict survival (Reuben *et al* 2013) or cognitive decline (Verghese *et al* 2007). Several accW algorithms have been used to quantify gait characteristics and have been validated for specific locations only. Two notable algorithms are those utilising the inverted pendulum model for step length (Zijlstra and Hof 2003) and the continuous wavelet transform (CWT) for the detection of initial (IC) and final contact (FC) events within the gait cycle (McCamley *et al* 2012).

A combination of both algorithms for use on the lower back (fifth lumbar vertebrae, L5) has been validated and can provide a useful means to quantify numerous gait characteristics (Godfrey *et al* 2014b, Del Din *et al* 2015) with potential wide application in large cohort or intervention-based studies (Lara *et al* 2013, Lord *et al* 2013, Godfrey *et al* 2015b). Device location however might influence participant compliance (Murphy 2009). Most algorithms are reliant on particular signal characteristics and may require adjustments, changing device location to overcome non-compliance can alter the features of the acceleration signal (Zijlstra and Hof 2003). Moreover different testing protocols (e.g. walking at preferred speed compared to fast) and age may further exacerbate this. It is still not clear whether this may compromise the validity of any results and therefore requires evaluation.

The aims of this study were therefore to (i) examine the impact on gait characteristics depending on variation of accW location (chest and waist compared to L5) during preferred and fast gait speeds, in a group of younger (20–40 years) and older (50–70 years) adults, (ii) investigate adjusted versions of accW algorithms to better inform their deployment due to change in device location. The ability to change accW location and ensure robust gait characteristics will increase participant compliance during instrumented testing and facilitate more complete data acquisition/collection within studies.

## Methods

### *Participant recruitment*

Forty younger adults aged 20–40 years (YA) and forty OA aged 50–70 years (OA) were recruited to ensure that at least 30 participants per group based on the statistical approaches adopted within the study, e.g. normality testing (Ghasemi and Zahediasl 2012), constituting one of the largest studies on this topic (Fortune *et al* 2014, Rispens *et al* 2014). Participants were recruited from staff and students at Newcastle University, and members of Newcastle University VOICENorth[3], an older adult volunteer group who participate in research. Participants were only included if they were healthy i.e. had no physical or neurological disabilities that might impede their movement or balance. All participants gave informed written consent and ethical approval for the project was granted by the National Research Ethics Service (County Durham and Tees Valley) and the Newcastle-upon-Tyne Hospitals NHS Foundation Trust (11/NE/0383).

### *Equipment*

Each participant wore three tri-axial accW (Axivity AX3, York, UK; dimensions: 23.0 × 32.5 × 7.6 mm; weight: 9 grams; accuracy: 20 parts per million, figure 1(a)). The accW were held in place by double sided tape and Hypafix (BSN Medical Limited, Hull, UK) with the height of each accW measured from the ground as the person remained in a comfortable stance. accW were located on the lower back (fifth lumbar vertebrae, L5), centrally on the sternum (chest) and laterally on the right hip (waist), figure 1(b). These locations were chosen as they typically reflect locations for device attachment on the trunk during gait assessment (Najafi *et al* 2003, Godfrey *et al* 2011, Kose *et al* 2012) while suiting algorithm functionality. They were programmed to capture data at a sampling frequency of 100 Hz (16-bit resolution) and at a range of ±8 g.

### *Experimental design*

All data were collected in a laboratory setting at the Clinical Ageing Research Unit, Newcastle University. During testing the participants wore their usual footwear and were asked to walk at preferred (self-selected) and fast speed over a 25 m route (figure 2) continuously for 2 min. Following each walk, participants were asked to remain still for 1 min before being told to commence their next walk. All walks were performed in the same order: preferred followed by fast. Continuous 2 min walks were adopted based upon previous findings that the use of a continuous walking protocol of no fewer than 30 steps (>50 steps optimal) is recommended when examining the reliability of gait (Galna *et al* 2013).

[3] www.ncl.ac.uk/changingage/engagement/VoiceNorth.

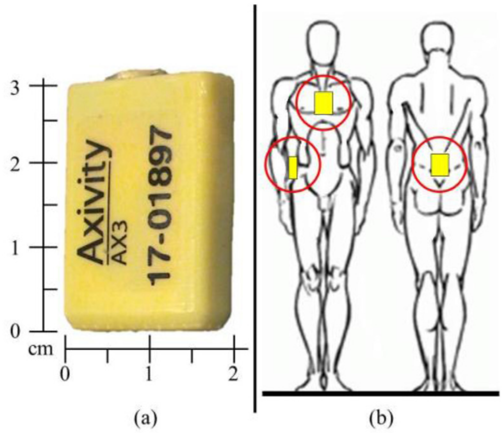


**Figure 1.** (a) The wearable used in this study: the Axivity AX3 accelerometry-based wearable with dimensions and (b) placement of the 3 accW.

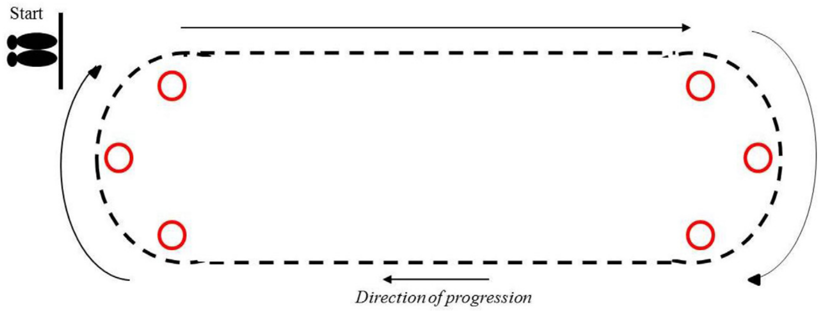


**Figure 2.** Schematic of the 25 m long route walked by the participants during the 2 min walking test.

*Accelerometer algorithms*

After testing was concluded, data from each accW were downloaded to a computer and analysed using a specially MATLAB® (R2012a[4]) program. Calculations of temporal (step time) and spatial (step length) gait characteristics were derived from the algorithms developed previously (Zijlstra and Hof 2003, McCamley *et al* 2012), both dependant based upon the location of initial contact (IC) events within the gait cycle. Gait data from L5 was chosen as the gold standard (reference) due to algorithm optimisation at that point. These algorithms have been used to quantify a wide range of gait characteristics (Del Din *et al* 2015, Godfrey *et al* 2015a). However, for the purposes of this study only the primary temporal (IC estimation) and spatial (change of wearable height in relation to leg length) components leading to step time and step length, respectively, are presented. Other gait characteristics (e.g. swing time, step velocity) are reliant on these primary components and deemed secondary to understanding impact of location and speed on algorithm functionality. Brief descriptions of both algorithms are provided here:

*Step time*: a CWT was used to estimate IC gait time events from the vertical acceleration ($a_v$). Firstly $a_v$ was integrated and then differentiated using a Gaussian CWT, resulting in signal 1 (S1). IC's were identified as the times of the minima. (The algorithm also provides

[4] MathWorks Inc., Natick, MA, USA.

a methodology for estimating FC events, but this was not used here). Initial inspection of the signal traces found that spurious IC (non-IC) events were detected (peaks that did not correspond to ICs). As a result the algorithm was updated to include a previous methodology for step detection (Najafi *et al* 2003), restricting IC peaks within a predetermined timed interval (Del Din *et al* 2015, Godfrey *et al* 2015a).

To further investigate the impact of algorithm performance on evaluation of gait characteristics for different device locations, we modified the IC detection (temporal) algorithm adopting three alternative scaling factors of the CWT (scale 7, scale 8, scale 9) in addition to the standard scale 10 (figure 3). This allowed the calculation of mean, variability and asymmetry gait characteristics for all locations for each scaling factor for both age groups. The rationale was to examine slight frequency adjustments to account for change of speed upon device location, i.e. movement intensities at different anatomical positions due to preferred and fast gait.

*Step length*: the IC events were also used to estimate step length using the inverted pendulum model applied to the centre of mass (CoM) movement in the vertical direction (Zijlstra and Hof 2003). Step length can be predicted from equation (1) where changes in height of the accW ($h$, vertical position) can be calculated using a double integration of the vertical acceleration ($a_v$) and $l$ represents the pendulum length, in this instance the manually measured height of the accW from the ground.

$$\text{step length} = 2\sqrt{2lh - h^2} \quad (1)$$

### *Data analysis*

In addition to mean values for step time and step length, variability and asymmetry values were calculated for each accW (L5, chest, waist). Variability was defined as the standard deviation (SD) from all steps (left and right combined) and asymmetry was determined as the absolute difference between left and right steps (alternating) as detailed elsewhere (Godfrey *et al* 2014b, Del Din *et al* 2015).

### *Statistical analysis*

Normality of the data was assessed using Shapiro–Wilks tests to examine the distributions of the paired residuals from the gold standard (wearable worn on L5 as wearable algorithms are optimised for this location using scale 10) and comparative measure. Statistical examinations thereafter were completed based on acceptance/rejection of normality. Effect of scale, device location and walking speed was examined for both age groups (YA and OA). Depending on normality results relative agreement was evaluated using Pearson's or Spearman's rank-order correlations, and absolute agreement was assessed using intraclass correlation coefficients ($ICC_{2,1}$). Bias between measures was examined using Paired-$t$ or Wilcoxon matched pair's tests. An alpha level for all statistical measures was set at $p < 0.05$.

## Results

Data from 37 YA and 36 OA were available for analysis. Within the YA group one chest and two waist accW data were excluded while three L5, waist and one chest were excluded in the OA group due to accW failing to record and participant satisfaction with attachment to their person at those locations. Table 1 shows the demographic characteristics of both age groups.

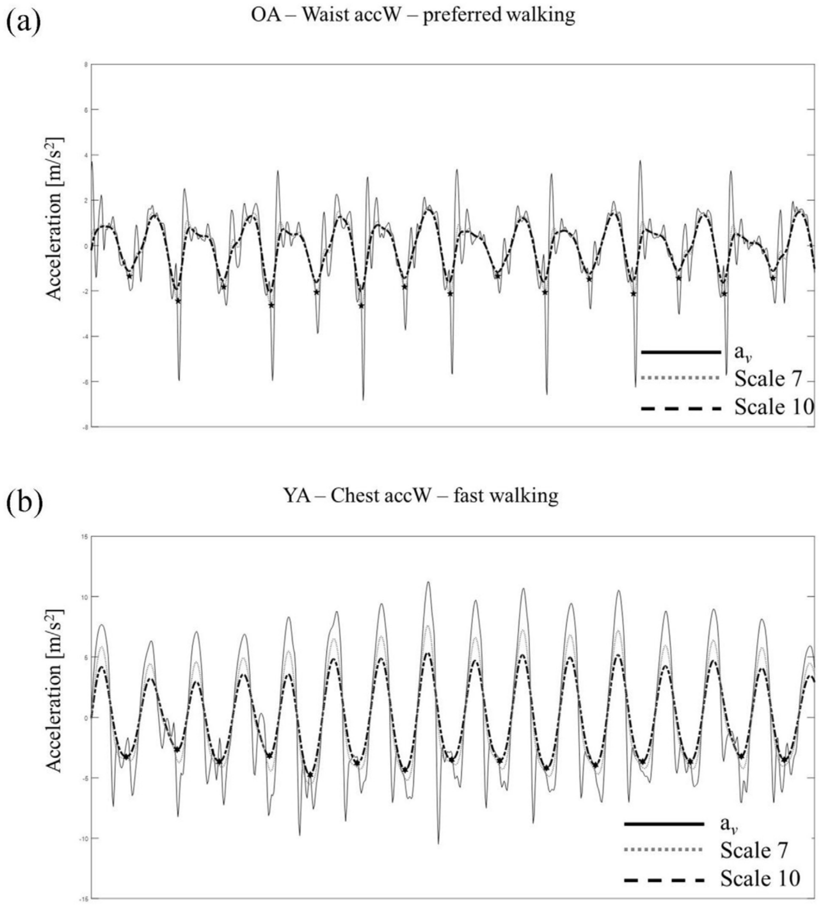


**Figure 3.** Example of use of different scaling factors with Gaussian CWT for IC detection. The black solid line represents the vertical acceleration ($a_v$), the grey dotted line represents the differentiated signal of $a_v$ with Gaussian CWT using scale 7, and the black dashed line the differentiated signal of $a_v$ with Gaussian CWT using scale 10. Asterisks represent detected ICs. (a) Results from accelerometer-based wearable (accW) worn on the waist for an older adult (OA) walking at preferred speed. (b) Results from accW worn on the chest for a younger adult (YA) walking at fast speed.

**Table 1.** Demographic details for both the YA and OA.

| | YA ($n$ = 37) | OA ($n$ = 36) |
|---|---|---|
| Age | 28.4 ± 5.1 | 64.0 ± 4.8 |
| Gender (M/F) | 18/19 | 14/22 |
| Height (m) | 1.7 ± 0.1 | 1.7 ± 0.1 |
| Weight (kg) | 73.3 ± 13.9 | 71.7 ± 15.4 |
| BMI (kg $m^{-2}$) | 24.7 ± 4.2 | 25.8 ± 4.8 |

*Impact of device location, protocol and age on gait characteristics*

*Mean.* Chest and waist mean step times during preferred and fast speeds for both age groups (YA and OA) were (not significantly) lower, while mean step length was significantly higher compared to L5 (table 2).

**Table 2.** Descriptive gait data for YA and OA derived from accelerometry-based wearable (accW) on L5. Differences between L5 and other accW locations (chest or waist) results evaluated using scale 10 depending on speed (preferred or fast) are reported as mean, standard deviation, minimum and maximum or median, range, 25th and 75th percentiles depending on normality of the data.

| | | | Mean | | | | | Variability | | | | | Asymmetry | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Gold standard | | | Mean | SD | Min | Max | | Mean | SD | Min | Max | | Mean | SD | Min | Max |
| L5 YA | Preferred | ST | 0.5365 | 0.0373 | 0.4578 | 0.6131 | ST | 0.0308 | 0.0182 | 0.0168 | 0.1077 | ST | 0.0235 | 0.0200 | 0.0027 | 0.0821 |
| | scale 10 | SL | 0.6184 | 0.0744 | 0.4680 | 0.7958 | SL | 0.0562 | 0.0159 | 0.0296 | 0.0950 | SL | 0.0240 | 0.0213 | 0.0008 | 0.0853 |
| | Fast scale 10 | ST | 0.4912 | 0.0402 | 0.4128 | 0.5723 | ST | 0.0327 | 0.0192 | 0.0162 | 0.1253 | ST | 0.0278 | 0.0247 | 0.0007 | 0.1339 |
| | | SL | 0.7068 | 0.0955 | 0.5411 | 0.8991 | SL | 0.0747 | 0.0213 | 0.0336 | 0.1333 | SL | 0.0248 | 0.0259 | 0.0001 | 0.1096 |
| L5 OA | Preferred | ST | 0.5256 | 0.0331 | 0.4520 | 0.5749 | ST | 0.0268 | 0.0127 | 0.0140 | 0.0781 | ST | 0.0274 | 0.0291 | 0.0011 | 0.1469 |
| | scale 10 | SL | 0.6233 | 0.0738 | 0.4701 | 0.7638 | SL | 0.0545 | 0.0176 | 0.0274 | 0.1025 | SL | 0.0277 | 0.0203 | 0.0002 | 0.0823 |
| | Fast scale 10 | ST | 0.4767 | 0.0399 | 0.3852 | 0.5839 | ST | 0.0243 | 0.0093 | 0.0131 | 0.0497 | ST | 0.0225 | 0.0188 | 0.0004 | 0.0818 |
| | | SL | 0.6832 | 0.0859 | 0.4834 | 0.8550 | SL | 0.0693 | 0.0237 | 0.0371 | 0.1366 | SL | 0.0243 | 0.0214 | 0.0001 | 0.0786 |
| | Parametric[a] | Mean | SD | Min | Max | P[a] | Mean | SD | Min | Max | P[a] | Mean | SD | Min | Max | |
| | Non-parametric[b] | Median | SD | 25th | 75th | NP[b] | Median | SD | 25th | 75th | NP[b] | Median | SD | 25th | 75th | |
| | | | | | | | | YA preferred | | | | | | | | |
| Chest | Scale 10 | ST[b] | 0.0000 | 0.0025 | −0.0006 | 0.0001 | ST[a] | 0.0016 | 0.0162 | −0.0296 | 0.0438 | ST[a] | 0.0016 | 0.0162 | −0.0296 | 0.0438 |
| | | SL[a] | −0.1909 | 0.0548 | −0.2989 | −0.0868 | SL[b] | −0.0125 | 0.0208 | −0.0197 | 0.0019 | SL[b] | −0.0125 | 0.0208 | −0.0197 | 0.0019 |
| Waist | Scale 10 | ST[b] | 0.0000 | 0.0030 | −0.0005 | 0.0001 | ST[b] | −0.0436 | 0.0426 | −0.0727 | −0.0023 | ST[b] | −0.0436 | 0.0426 | −0.0727 | −0.0023 |
| | | SL[b] | −0.0529 | 0.0376 | −0.0727 | −0.0241 | SL[b] | −0.0090 | 0.0306 | −0.0343 | 0.0033 | SL[b] | −0.0090 | 0.0306 | −0.0343 | 0.0033 |
| | | | | | | | | YA fast | | | | | | | | |
| Chest | Scale 10 | ST[b] | 0.0001 | 0.0047 | −0.0002 | 0.0002 | ST[b] | 0.0032 | 0.0196 | −0.0006 | 0.0095 | ST[a] | 0.0082 | 0.0187 | −0.0264 | 0.0625 |
| | | SL[a] | −0.1984 | 0.0570 | −0.3179 | −0.0948 | SL[a] | −0.0207 | 0.0272 | −0.1015 | 0.0278 | SL[b] | −0.0098 | 0.0234 | −0.0225 | 0.0008 |
| Waist | Scale 10 | ST[b] | 0.0001 | 0.0076 | −0.0002 | 0.0003 | ST[b] | −0.0161 | 0.0366 | −0.0233 | −0.0030 | ST[a] | −0.0372 | 0.0407 | −0.1091 | 0.0676 |
| | | SL[b] | −0.0289 | 0.0503 | −0.0613 | −0.0074 | SL[b] | 0.0119 | 0.0412 | −0.0017 | 0.0222 | SL[b] | −0.0109 | 0.0265 | −0.0278 | 0.0066 |
| | | | | | | | | OA preferred | | | | | | | | |
| Chest | Scale 10 | ST[b] | 0.0001 | 0.0019 | −0.0002 | 0.0002 | ST[b] | 0.0011 | 0.0238 | −0.0055 | 0.0064 | ST[a] | 0.0021 | 0.0251 | −0.0835 | 0.0543 |
| | | SL[a] | −0.1438 | 0.0459 | −0.2589 | −0.0544 | SL[b] | −0.0310 | 0.0337 | −0.0565 | −0.0076 | SL[b] | −0.0001 | 0.0250 | −0.0229 | 0.0116 |
| Waist | Scale 10 | ST[b] | 0.0001 | 0.0096 | −0.0004 | 0.0002 | ST[b] | −0.0157 | 0.0521 | −0.0439 | −0.0031 | ST[b] | −0.0218 | 0.0474 | −0.0559 | 0.0034 |
| | | SL[b] | −0.0600 | 0.1232 | −0.0769 | −0.0184 | SL[b] | −0.0244 | 0.0754 | −0.0689 | −0.0092 | SL[b] | −0.0211 | 0.0517 | −0.0513 | 0.0091 |
| | | | | | | | | OA fast | | | | | | | | |
| Chest | Scale 10 | ST[b] | 0.0001 | 0.0021 | −0.0001 | 0.0002 | ST[b] | −0.0012 | 0.0176 | −0.0042 | 0.0043 | ST[a] | 0.0016 | 0.0158 | −0.0429 | 0.0362 |
| | | SL[a] | −0.1517 | 0.0554 | −0.2685 | −0.0401 | SL[a] | −0.0250 | 0.0322 | −0.0861 | 0.0552 | SL[b] | −0.0039 | 0.0242 | −0.0146 | 0.0129 |
| Waist | Scale 10 | ST[b] | 0.0000 | 0.0050 | −0.0005 | 0.0002 | ST[b] | −0.0212 | 0.0332 | −0.0397 | −0.0043 | ST[a] | −0.0405 | 0.0461 | −0.1410 | 0.0284 |
| | | SL[b] | −0.0422 | 0.1299 | −0.0816 | −0.0076 | SL[b] | −0.0130 | 0.0673 | −0.0394 | 0.0017 | SL[b] | −0.0115 | 0.0434 | −0.0436 | 0.0086 |

[a] Normal.
[b] Non-normal.
ST: step time, SL: step length.

*Variability.* Chest and waist variability were all higher compared to L5 irrespectively of speed and age group (table 2). However, it was significantly so for chest step time in YA at fast speed and waist step time for both age groups and speeds. Chest step length was also significantly higher for both speeds and age groups; but not for waist step length at preferred speed in YA.

*Asymmetry.* Similarly, asymmetry characteristics were all higher irrespectively of speed and age group (table 2). Chest step time at fast speed and step length at both speeds resulted in significantly higher values in YA. Waist step time and length were significantly higher for both speeds and age groups.

### *Impact of device location, protocol and age on agreement*

*Mean.* Results obtained from the chest for all gait characteristics showed excellent agreement for both speeds and age groups ($ICC_{2,1} > 0.886$), table 3. Characteristics derived from the waist showed excellent agreement for mean step time and step length for YA at both speed ($ICC_{2,1} > 0.928$), excellent for OA step time at both speeds ($ICC_{2,1} > 0.981$), but moderate for OA step length at fast speed ($ICC_{2,1} = 0.589$).

*Variability.* Chest step time showed moderate agreement with L5 ($ICC_{2,1} = 0.513$) for OA at fast speed, while poor for YA at both speeds ($ICC_{2,1} < 0.394$). YA agreement was significantly poor for step length variability at fast speed ($ICC_{2,1} = 0.466$) and poor for OA at both speeds ($ICC_{2,1} < 0.250$). Waist results show poorer agreement for step time and length for both speeds and age groups ($ICC_{2,1} < 0.285$, table 3).

*Asymmetry.* Chest step time and length asymmetry showed moderate to good agreement ($ICC_{2,1} > 0.582$) for both speeds and age groups. Waist step length at fast speed in YA showed moderate agreement ($ICC_{2,1} = 0.603$), while moderate to poor agreement was found for step time for both speeds and age groups ($ICC_{2,1} < 0.529$, table 3).

### *Impact of algorithm adjustment—scaling factor*

For both age groups scaling factors (scale 7, 8 and 9) used for IC detection algorithms did not significantly improve or diminish agreement results depending on wearable location or walking speed (see the online supplementary material (stacks.iop.org/PM/37/1785/mmedia)).

## Discussion

To the authors knowledge this is the first study to determine the effect of device location, walking speed, age and algorithm scaling factor on the evaluation of temporal and spatial gait characteristics during continuous walking. We found that algorithm, device location, walking speed and age have a negative impact on variability and asymmetry gait characteristics but not on mean values.

### *Impact of device location, protocol and age*

Device location, speed and age had some impact on gait characteristics: findings showed that the chest accW showed better agreement for a larger number of gait characteristics (15/24 gait characteristics including mean, asymmetry and variability) with respect to the waist accW

**Table 3.** Absolute ($ICC_{2,1}$), relative agreement (R or Rho values) and bias (t or Z values) depending on normality of the data for different device locations (chest or waist) and speed (preferred or fast) for both OA and YA.

| | Mean | | | | | | Variability | | | | | | Asymmetry | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Step time | | | Step length | | | Step time | | | Step length | | | Step time | | | Step length | | |
| YA preferred | | | | | | | | | | | | | | | | | | |
| | Rel *r/RHO* | Abs ICC | Bias *t/Z* | Rel *r/RHO* | Abs ICC | Bias *t/Z* | Rel *r/RHO* | Abs *ICC* | Bias *t/Z* | Rel *r/RHO* | Abs *ICC* | Bias *t/Z* | Rel *r/RHO* | Abs *ICC* | Bias *t/Z* | Rel *r/RHO* | Abs *ICC* | Bias *t/Z* |
| Chest | 0.992[c] | 0.999[c] | −1.109 | 0.820[c] | 0.886[c] | −21.210[c] | 0.628[c] | 0.394 | −0.913 | 0.283 | 0.190 | −4.926[c] | 0.613[c] | 0.748[c] | 0.607 | 0.437[b] | 0.678[c] | −2.874[b] |
| Waist | 0.993[c] | 0.998[c] | −1.100 | 0.882[c] | 0.933[c] | −5.122[c] | 0.309 | 0.141 | −3.839[c] | 0.193 | −0.089 | −0.355 | 0.312 | 0.369 | −4.398[c] | 0.267 | 0.291 | −2.633[b] |
| YA fast | | | | | | | | | | | | | | | | | | |
| Chest | 0.997[c] | 0.996[c] | −0.641 | 0.871[c] | 0.922[c] | −21.187[c] | 0.324[a] | 0.167 | −2.995[b] | 0.420[a] | 0.466[b] | −4.629[c] | 0.651[c] | 0.743[c] | 2.648[a] | 0.537[b] | 0.635[b] | −3.176[b] |
| Waist | 0.994[c] | 0.991[c] | −1.124 | 0.872[c] | 0.928[c] | −4.156[c] | 0.115 | −0.237 | −3.221[b] | 0.401[a] | −0.237 | −2.693[b] | 0.203 | 0.313 | −5.562[c] | 0.356[a] | 0.603[b] | −2.255[a] |
| OA preferred | | | | | | | | | | | | | | | | | | |
| Chest | 0.995[c] | 0.999[c] | −0.801 | 0.829[c] | 0.904[c] | −18.806[c] | 0.420[a] | 0.403 | −0.204 | −0.006 | 0.033 | −4.493[c] | 0.572[c] | 0.721[c] | 0.507 | 0.233 | 0.612[b] | −0.896 |
| Waist | 0.959[c] | 0.981[c] | −0.503 | 0.461[b] | 0.417 | −4.053[c] | 0.516[b] | 0.245 | −4.619[c] | −0.099 | 0.058 | −4.556[c] | 0.183 | 0.509[a] | −3.378[c] | 0.090 | 0.274 | −3.126[a] |
| OA fast | | | | | | | | | | | | | | | | | | |
| Chest | 0.998[c] | 0.999[c] | −0.299 | 0.806[c] | 0.891[c] | −16.444[c] | 0.517[b] | 0.513[a] | −0.534 | 0.210 | 0.250 | −4.658[c] | 0.604[c] | 0.748[c] | 0.600 | 0.222 | 0.582[b] | −0.346 |
| Waist | 0.988[c] | 0.996[c] | −0.927 | 0.657[c] | 0.589[b] | −3.802[c] | 0.508[b] | 0.285 | −4.745[c] | 0.334[a] | 0.261 | −3.331[b] | 0.367[a] | 0.391 | −5.272[c] | 0.304 | 0.529[a] | −2.922[b] |

[a] $p$-value $< 0.05$.
[b] $p$-value $< 0.01$.
[c] $p$-value $< 0.001$.

**Table 4.** Simplified matrix summaries significant absolute and relative agreement results for step time and step length mean (in orange), variability (in blue) and asymmetry (in green) values depending on device location (chest or waist) and speed (preferred or fast) for both age groups (YA and OA).

| | | Preferred | | Fast | | Key |
|---|---|---|---|---|---|---|
| Group | Location | Step time | Step length | Step time | Step length | Data only accepted with both relative & absolute agreement compared to L5. |
| YA | Chest | ✓[a] ×[b] ✓[c] | ✓[a] ×[b] ✓[c] | ✓[a] ×[b] ✓[c] | ✓[a] ✓[b] ✓[c] | |
| | Waist | ✓[a] ×[b] ×[c] | ✓[a] ×[b] ×[c] | ✓[a] ×[b] ×[c] | ✓[a] ×[b] ✓[c] | Mean ✓[a] ×[a] |
| OA | Chest | ✓[a] ×[b] ×[c] | ✓[a] ×[b] ×[c] | ✓[a] ✓[b] ✓[c] | ✓[a] ×[b] ×[c] | Variability ✓[b] ×[b] |
| | Waist | ✓[a] ×[b] ×[c] | ×[a] ×[b] ×[c] | ✓[a] ×[b] ×[c] | ✓[a] ×[b] ×[c] | Asymmetry ✓[c] ×[c] |

[a] Orange.
[b] Blue.
[c] Green.
Combination of excellent significant (>0.850) absolute and relative agreement is reported as ✓, failure to compliance with these criteria is reported as ×.

(8/24). This is possibly due to the lateral placement of device on the waist where the algorithms are less sensitive due to reliance of CoM trajectory, directly influencing temporal and spatial sensitivity. Similarly better agreement was also found at fast speed (14/24 gait characteristics) than preferred (9/24) and for YA (14/24) with respect to OA (9/24, table 4).

While this study examined preferred and fast speeds, typical of current clinical gait assessment, self-selected reduced (slow) speed may negatively impact algorithm functionality and agreement due to change of location. This warrants investigation to determine the effect of device location in pathology (e.g. neurological) when reduced speed and clarity of movement is often evident. Additionally, the curvilinear trajectory within the walking protocol may contribute to variations within the acceleration traces where short and abrupt directional changes (observed in many participants) could result in temporal/spatial differences between device locations (Godfrey *et al* 2015a).

### *Mean, variability and asymmetry characteristics*

Step length evaluated with the accW on the waist in OA at preferred speed resulted in significantly higher values and moderate agreement. The significant bias found in step length for waist and chest accWs could be related to the use of the inverted pendulum model which may not be suitable for accW locations distant from the CoM and may require correction factors for a better step length estimation (Zijlstra and Zijlstra 2013). Use of a double inverted pendulum model could have been better suited for the chest wearable, nonetheless good to excellent agreement between chest and L5 mean step length results was found for both age groups and walking speeds.

Variability and asymmetry values were higher and bias was consistently poor, irrespective of device location, speed and age group. Previous studies reported that variability and asymmetry gait characteristics obtained from an accW worn on L5 were higher and showed poorer agreement when compared to gold standard (instrumented walking) (Godfrey *et al* 2014a, Del Din *et al* 2015); impact of variability and asymmetry characteristics should therefore be taken into account when using results from accW locations different from L5, i.e. optimal algorithm functionality location. Variability and asymmetry results may be improved with the use of a gyroscope embedded in the accW which would allow the correct identification and allocation of left/right steps (McCamley *et al* 2012, Godfrey *et al* 2014a) instead of considering right/left alternating steps. Despite overestimation of variability and asymmetry values, the chest accW provided better agreement for variability and asymmetry results than waist accW (table 3): this could be due to the lateral position (right hip) of the waist accW which could affect variability and asymmetry characteristics resulting in higher overestimation when comparing to results evaluated at a central/symmetric position (L5 or chest).

### *Impact of scaling factor*

To account for change of device location during different gait speeds variations of scaling factor were tested to determine any improvement for IC estimation and therefore any improvements in gait characteristics compared to L5. We decided to use various CWT scales, driven by the rationale that accW signals collected at alternate body positions (chest, waist) and speeds (preferred, fast) have different (higher or lower) amplitudes to signal collected at L5 (figure 3). Despite this, we did not observe improvement on agreement between chest or waist and L5 results, this corroborated the use of already validated standard algorithm for step time and step length evaluation (Godfrey *et al* 2015a). The use of scale 10 is therefore recommended for IC detection irrespectively of device location.

### *Clinical value*

To highlight the clinical importance of these findings a simplified matrix to guide pragmatic utility and general interpretation of results is presented in table 4: gait quantified from different accW locations (chest and wait) are the same as L5 (✓) or not (×). Algorithms are developed for accW use on L5, the gold standard location for optimal performance. Thus, shifting the accW to the chest and waist may produce spurious results. As can be seen from table 4, mean values are reproducible between locations, i.e. change of device location produces similar values (✓[a]) for step time and length during preferred and fast speeds compared to L5. However, at preferred speed variability values showed poor agreement (×[b]) in both age groups, while differences for asymmetry values were only slightly better for YA (greater number of ✓[c]), which could be attributed to natural ageing where algorithm dependant signal characteristics can differ to OA and therefore affect algorithm performance (Zijlstra and Hof 2003). Therefore with the algorithms deployed in this study; change of accW location is only recommended when quantifying mean characteristics or asymmetry in YA with an accW worn on the chest.

## Conclusion

Instrumented testing is becoming an important and routinely practiced methodology, where accurate and reliable quantification of gait is paramount in studying pathology or healthy ageing. The novel combination of two algorithms for the spatio-temporal reconstruction of gait from a single accW provides a simple and efficient means of gathering gait data in a wide range of settings which could be applied to different locations. The standard IC and step length algorithms utilised within this study have been shown to be transferrable methods to quantify mean step time and length from an accW placed at an alternate location (chest or waist) other than that which it was developed (L5). Device location, walking speed and age influenced the evaluation of gait characteristic: chest results showed better agreement than those evaluated from the waist; walking speed did not have impact on the evaluation of mean gait characteristics, while asymmetry and variability showed better agreement at fast speed. Age had an impact on mean, asymmetry and variability gait characteristics: better results were found for YA compared to OA. However change of algorithm scaling factor for improved step detection due to change of device location is not required. In conclusion while mean spatiotemporal gait characteristics were robustly quantified irrespectively of device location, walking speed and age group; this was not true for variability and asymmetry characteristics.

## Conflict of interest statement

There is no conflict of interest.

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