
Godfrey A, Lara J, Munro A, Wiuff C, Chowdhury S, Del-Din S, Hickey A, Mathers J, Rochester L. [Instrumented assessment of test battery for physical capability using an accelerometer: a feasibility study](#). *Physiological Measurement* 2015, 36(5), N71-N83.

Copyright:

© 2015 Institute of Physics and Engineering in Medicine. Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

DOI link to article:

<http://dx.doi.org/10.1088/0967-3334/36/5/N71>

Date deposited:

23/04/2015



This work is licensed under a [Creative Commons Attribution 3.0 Unported License](#)

Instrumented assessment of test battery for physical capability using an accelerometer: a feasibility study

This content has been downloaded from IOPscience. Please scroll down to see the full text.

2015 Physiol. Meas. 36 N71

(<http://iopscience.iop.org/0967-3334/36/5/N71>)

View [the table of contents for this issue](#), or go to the [journal homepage](#) for more

Download details:

IP Address: 128.240.229.72

This content was downloaded on 23/04/2015 at 13:34

Please note that [terms and conditions apply](#).

Note

Instrumented assessment of test battery for physical capability using an accelerometer: a feasibility study

A Godfrey^{1,2}, J Lara^{3,4}, C A Munro^{3,4}, C Wiuff^{3,4},
S A Chowdhury^{3,4}, S Del Din^{1,2}, A Hickey^{1,2}, J C Mathers^{3,4}
and L Rochester^{1,2}

¹ Institute of Neuroscience, Newcastle University, Campus for Ageing and Vitality, Newcastle upon Tyne, UK

² Clinical Ageing Research Unit, Newcastle University, Campus for Ageing and Vitality, Newcastle upon Tyne, UK

³ Institute of Cellular Medicine, Newcastle University, Campus for Ageing and Vitality, Newcastle upon Tyne, UK

⁴ Human Nutrition Research Centre, Newcastle University, Campus for Ageing and Vitality, Newcastle upon Tyne, UK

E-mail: lynn.rochester@ncl.ac.uk

Received 10 November 2014, revised 7 January 2015

Accepted for publication 3 February 2015

Published 22 April 2015



CrossMark

Abstract

Recent work has identified subdomains (tests) of physical capability that are recommended for assessment of the healthy ageing phenotype (HAP). These include: postural control, locomotion, endurance, repeated sit-to-stand-to-sit and TUG. Current assessment methods lack sensitivity and are error prone due to their lack of consistency and heterogeneity of reported outcomes; instrumentation with body worn monitors provides a method to address these potential weaknesses. This work proposes the use of a single tri-axial accelerometer-based device with appropriate algorithms (referred to here as a body worn monitor, BWM) for the purposes of instrumented testing during physicality capability assessment. In this pilot study we present 14 BWM-based outcomes across the subdomains which include magnitude, frequency and spatio-temporal characteristics. Where possible, we compared BWM outcomes with manually recorded values and found no significant differences between locomotion and TUG tasks ($p \geq 0.319$). Significant differences were found for the total distance walked during endurance ($p = 0.037$) and times for repeated sit-to-stand-to-sit transitions ($p < 0.000$). We identified reasons for



Content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](https://creativecommons.org/licenses/by/3.0/). Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

differences and make recommendations for future testing. We were also able to quantify additional characteristics of postural control and gait which could be sensitive outcomes for future HAP assessment. Our findings demonstrate the feasibility of this method to enhance measurement of physical capacity. The methodology can also be applied to a wide variety of accelerometer-based monitors and is applicable to a range of intervention-based studies or pathological assessment.

Keywords: accelerometer, instrumented, healthy ageing phenotype, algorithm

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

1. Introduction

The gain in human life longevity observed over recent decades has been accompanied by additional years of poor health (Vaupel 2010, Lara *et al* 2013). The ability to retain good health is the foundation to ageing well since poor health disrupts daily life and reduces the ability to manage the activities of daily living (Black 2009, Parsons *et al* 2014). Those elements of daily life which have strong associations with functional capacity can be quantified as an individual's physical capability (Cooper *et al* 2010, 2011). Earlier attempts to quantify physical capability used questionnaire based assessments (Townsend 1979, Ware *et al* 1993). More recently measures of physical capability include timed tests quantified with a stopwatch such as; chair rise times, walking speed, timed up and go (TUG) and standing balance that have been shown to predict health in later life (Cooper *et al* 2010, Cooper *et al* 2011). However, quantification of tasks in this manner requires accurate identification of the beginning/end of a test to be carried out in a reliable and consistent manner across raters which can lead to large heterogeneity of reported outcomes (Studenski *et al* 2011). Finally, measurement protocols and reported outcomes lack consistency making it impossible to pool results (Cooper *et al* 2011).

As a result the use of electronic devices able to accurately quantify and consistently record human movement for instrumented testing has steadily risen in recent years (Godfrey *et al* 2008, Narayanan *et al* 2010, Weiss *et al* 2011, Mancini *et al* 2012, Mellone *et al* 2012, Godfrey *et al* 2014). Instrumented testing is not limited to any patient group, is not biased by age or gender differences and can provide highly accurate and objective data (Godfrey *et al* 2008, Murphy 2009). In addition the U.S. national institute of health (NIH) proposed a set of tests (NIH Toolbox⁵) for the assessment of motor functioning across the life course (Gershon *et al* 2013). Those tests aimed to define a standard set of measures to be used as 'common currency' across diverse studies making it easier to compare results (Lara *et al* 2013).

Recently, we have proposed a minimum set of (bio) markers for the assessment of the healthy ageing phenotype (HAP) (Lara *et al* 2013). Physical capability is one of 5 domains characterising the HAP, and here we have adopted the testing recommendations of the NIH Toolbox. Specifically the instrumentation of those tests (and others) is a key area of ongoing work within the LiveWell Programme⁶, which aims to assess the effect of intervention through instrumented testing of physical capabilities. The aim of this feasibility study was to test a methodology to instrument the physical capability assessments for use with a group of healthy

⁵ www.nihtoolbox.org.

⁶ LiveWell is a research programme intended to develop interventions to enhance health and well-being in later life: www.livewell.ac.uk.

older adults. We adopted a low-cost single tri-axial accelerometer with algorithms (referred to here as a body worn monitor, BWM) worn on the lower back to quantify the characteristics of physical capability. We compared results from the BWM with those obtained using conventional (traditional) subjective techniques to provide a comparison with current methods. We also quantified a range of postural control and gait characteristics which have shown utility as measures of healthy ageing and pathology. It is proposed that the new method will provide an objective and translatable approach to physical capability assessment to compare results of physical capability outcomes across similar/diverse studies.

2. Materials and methods

2.1. Participant recruitment

Older healthy participants (OHP, 50–70 years) were recruited in the North East of England as part of a pilot intervention study⁷ within LiveWell which evaluated internet-based lifestyle interventions in people in the retirement transition (approximately 2 years before/after retirement). Ethical consent for the project was granted by the Newcastle University Faculty of Medical Sciences ethics committee (00745/2014) and all participants gave informed written consent. Participant recruitment was arranged at baseline through large employers on Teesside and on Tyneside. Testing took place at Newcastle University facilities or at a leisure centre in Redcar.

2.2. Equipment

Each participant wore a low cost (<£100) tri-axial accelerometer-based device⁸ (figure 1, dimensions: 2.3 × 3.3 × 0.8 cm, weight 9 g) on the fifth lumbar vertebrae (L5). This location was chosen to minimise device attachment during instrumented testing while also optimising algorithm usage, i.e. numerous algorithms developed for use on L5. The device was held in place by double sided tape and Hypafix⁹. The device recorded at a sampling frequency of 100 Hz (16 bit resolution) and at a range of ±8 g. A trained researcher used a stop watch and measurement tape (as appropriate) to record outcomes for each physical capability task.

2.3. Experimental protocol

The HAP assessment consisted of the following:

- (a) Postural control, standing balance: five tests were performed each lasting 50 s without shoes, arms folded across their chest while focusing on a wall-mounted fixed point (target) at a horizontal distance of 1 m. Variations included: (i) flat surface, feet together, eyes open (FLFTEO), (ii) flat surface, feet together, eyes closed (FLFTEC), (iii) foam surface¹⁰ (50.0 × 41.0 × 6.0 cm), feet together, eyes open (FOFTEO), (iv) foam surface, feet together, eyes closed (FOFTEC) and (v) flat surface, tandem stance, eyes open (FLTMEO). Due to the nature of the task and derived outcomes (section 2.5) this was quantified by the BWM only.
- (b) Locomotion, 4 m walk gait speed (×2): after a practice walk, participants walked at their usual speed between two markers. Manual and BWM timing began upon the first footfall,

⁷ Protocol registered at ClinicalTrials.gov (NCT02136381).

⁸ Axivity AX3, York, UK.

⁹ BSN Medical Limited, Hull, UK.

¹⁰ Balance-pad Elite, AIREX, Switzerland.

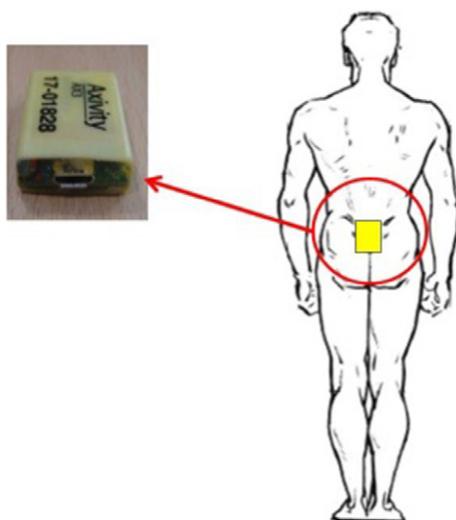


Figure 1. Attachment of the BWM to the lower back (L5).

i.e. participant's first step over the starting point. Recording ended after the participant completed the walk (manual) or last 'purposeful' footfall (BWM), i.e. vertical acceleration (a_v) exceeded a predetermined threshold. The threshold excluded any non-purposeful steps after the 4 m marker where the participant had slowed. Time to complete the 4 m walk was converted into a meters-per-second metric.

- (c) Endurance, 2 min walk: participants walked continuously and as fast as they could without running. The route consisted of walking back and forth around cones placed 25 feet (7.62 m) apart. Once completed, the total distance walked was calculated manually.
- (d) Lower limb strength, repeated sit-to-stand-to-sit ($\times 2$): after a practice, participants performed five sit-to-stand-to-sit posture transitions (PT), with arms folded across their chest, as quickly as possible. Participants were instructed to stand fully and not to touch the back of the chair during each repetition.
- (e) Lower limb strength and locomotion, TUG ($\times 3$): after a practice, participants stood up from a chair (height: 40–50 cm), walked 2 m at a normal pace, around a cone, back to the chair, turned and sat down. The TUG time was recorded manually as the time from initiation of chair rise to the time when the participant's back touched the backrest of the chair at the end of the manoeuvre.

2.4. BWM algorithms

The following is a brief overview of the algorithms used to instrument each of the tasks outlined in section 2.3:

- (a) Algorithm #1 (postural control): jerk (rate of change of a_M , equation(1)), root mean square (RMS, a_M magnitude equation (2)) and frequency components (95% percentile (F95%), ellipsis) were implemented (Moe-Nilssen and Helbostad 2002, Mancini *et al* 2012). Figure 2(a) shows an example of the data with the segmentation markers to extract

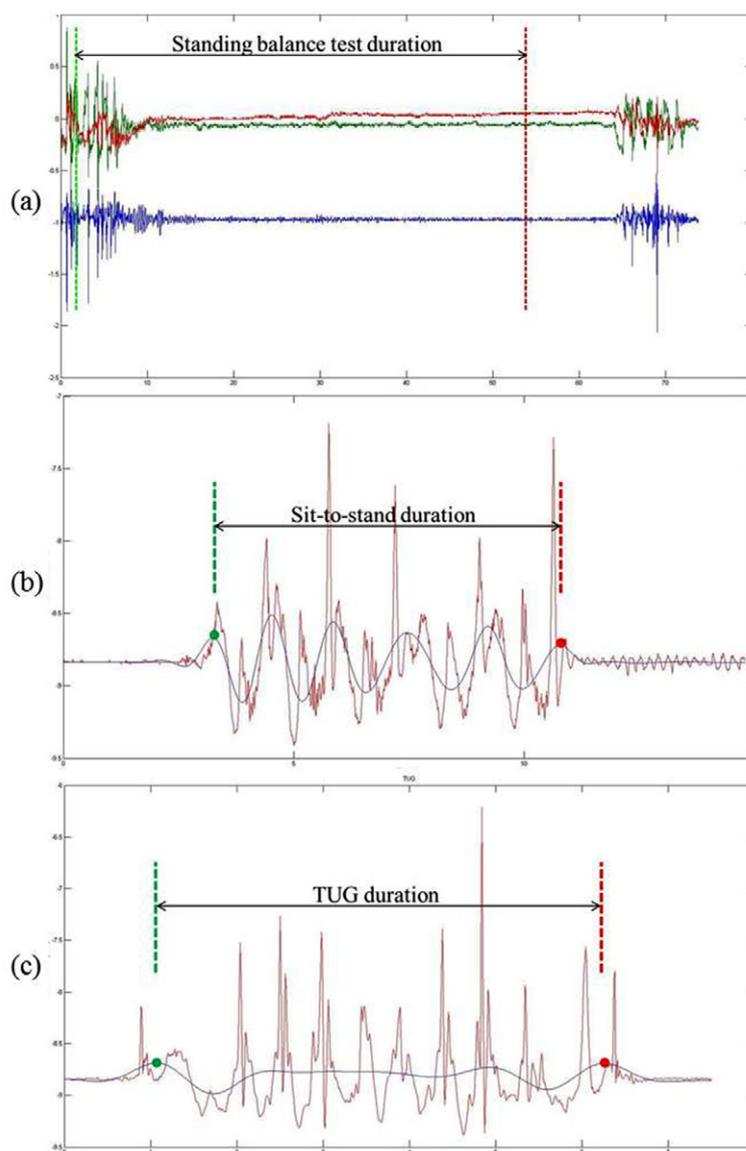


Figure 2. (a) An example of the tri-accelerometer output during the standing balance test under the condition of FOFTEO. The red and green vertical dashed lines signify the start and end times of the tests obtained from observer reported times and which were used by MATLAB to crop the data. (b) An example of the SVM (red) and continuous peaks (blue) from the DWT detected during a repeated sit-to-stand transition. The wavelet algorithm identified the transition type and the time between the first (green dot, sit-to-stand) and last (red dot, stand-to-sit) peak to determine the total time to complete the task. (c) An example of the SVM (red) and continuous peaks (blue) from the DWT detected during a TUG test. The wavelet algorithm identified the transition type and the time between the first (green dot, sit-to-stand) and last (red dot, stand-to-sit) peak to determine the total time to complete the task. The DWT successfully suppressed the period of walking between transitions.

the exact period of standing data. Due to its sensitivity, we present acceleration data within the mediolateral (a_M) direction only (Moe-Nilssen and Helbostad 2002).

$$\text{Jerk} = \frac{1}{2} \int_0^t \left(\frac{da_M}{dt} \right)^2 \quad (1)$$

$$\text{RMS} = \sqrt{\frac{1}{n}(a_{M1}^2 + \dots + a_{Mn}^2)} \quad (2)$$

- (b) Algorithm #2 (locomotion, endurance): we utilised a Gaussian continuous wavelet transform to estimate the initial contact (IC) and final contact (FC) gait time events from a_V (McCamley *et al* 2012). From the calculation of IC/FC times, we recorded total time to complete the 4 m (time between the first IC and last FC). In addition, during the endurance task, we calculated numerous temporal gait characteristics based on the estimated IC/FC events and their sequence within the gait cycle, i.e. step, stride, stance and swing times.
- (c) Algorithm #3 (locomotion, endurance): we applied the inverted pendulum model to estimate step length (Zijlstra and Hof 2003) and, from this, calculated the total distance walked during the endurance task (summation of step lengths). The model is based on the vertical movement of the centre of mass (h) due to the double integration of a_V and length of the pendulum (l , height of sensor from ground), equation (3).

$$\text{step length} = 2\sqrt{2lh - h^2} \quad (3)$$

Algorithm #2 + #3 (locomotion, endurance): the estimates of step time and step length were combined to generate values for mean step velocity, equation (4).

$$\text{step velocity} = \frac{\text{step length}}{\text{step time}} \quad (4)$$

- (d) Algorithm #4 (lower extremity strength, TUG): timed PT were estimated from a discrete wavelet transform (DWT, using a fifth-order approximation and Meyer wavelet) of the signal vector magnitude (SVM) from all three axes of the accelerometer (Bidargaddi *et al* 2007). The total time for five PT repetitions was derived from the initial trough (sit-to-stand) to the final peak (stand-to-sit), figure 2(b).

This method also estimated total time to complete the TUG. Similar to the lower strength task the peak and trough of the transitions were used to calculate the time from start to finish, figure 2(c).

2.5. Statistical analysis

Paired sample t -tests were used to test for differences between manual and BWM quantified tasks. A repeated measures analysis of variance (ANOVA) with a Greenhouse–Geisser correction was used to examine differences in balance tests. For all analysis, statistical significance was set at $p < 0.05$.

Table 1. Demographic characteristics of the participants.

Characteristic	Mean \pm SD
Gender (M/F)	7/13
Age	61.4 \pm 3.3
Height (m)	1.65 \pm 0.09
Weight (kg)	74.36 \pm 14.57

Table 2. Parameter estimates from the standing balance test as quantified by the BWM (body worn monitor).

Task—test	Trial	Characteristics			
		Jerk ML (m ² s ⁻⁵)	RMS ML (mm s ⁻²)	Ellipsis (mm ²)	F95% ML (Hz)
Postural control (standing balance)	(1) FLFTEO	0.07 \pm 0.16	0.01 \pm 0.01	0.20 \pm 0.39	1.96 \pm 0.64
	(2) FLFTEC	0.05 \pm 0.06	0.01 \pm 0.00	0.16 \pm 0.16	1.91 \pm 0.57
	(3) FOFTEO	0.33 \pm 1.16	0.01 \pm 0.01	0.65 \pm 1.63	1.78 \pm 0.69
	(4) FOFTEC	0.54 \pm 0.62	0.03 \pm 0.01	1.43 \pm 1.72	1.91 \pm 0.53
	(5) FLTMEO	0.16 \pm 0.24	0.01 \pm 0.01	0.28 \pm 0.31	2.25 \pm 0.62

Task 4 was significantly different from the rest. FLFTEO = flat surface feet together eyes open; FLFTEC = flat surface, feet together, eyes closed; FOFTEO = foam surface, feet together, eyes open, FOFTEC = foam surface, feet together eyes closed; FLTMEO = flat surface, tandem stance, eyes open.

3. Results

Twenty participants were recruited and their demographics are presented in table 1.

3.1. Postural control

Table 2 shows values for a_M for each task. The varying complexity of task from flat to foam surface is highlighted by the significantly increased RMS ($p < 0.000$) and Elliptical ($p = 0.006$) values. Jerk marginally increased between tests ($p = 0.072$) where greatest differences are observed between eye closed on flat surface compared to foam. There was no significant difference between tests for F95% ($p = 0.122$).

3.2. Locomotion

In trial 1, the BWM had a longer duration (greater) time compared with manual recording (-0.04 s) but this was not significant ($p = 0.682$). Mean difference (0.00 s) improved for trial 2 with no significant differences between times ($p = 0.981$).

3.3. Endurance

The BWM significantly overestimated ($p = 0.037$) the total distance walked (approx. 11 m or 6.6%) compared with manually recording (table 3). It was also possible to determine additional gait characteristics from the BWM (table 4).

Table 3. Mean \pm SD values for the manual and BWM (body worn monitor) quantified tasks. Shown are the parametric, non-parametric and ICC tests. (* $p < 0.05$, ** $p < 0.001$.) TUG = Timed up and go.

Task—test	Trial #	Manual	BWM	<i>p</i>
		Mean \pm SD	Mean \pm SD	
Locomotion—gait speed (m s^{-1})	1	1.38 \pm 0.14	1.43 \pm 0.43	0.682
	2	1.42 \pm 0.19	1.42 \pm 0.41	0.981
Endurance—2 min walk (m)	1	171.19 \pm 18.05	182.54 \pm 28.52	0.037
Lower extremity strength—repeated sit-to-stand-to-sit (s)	1	8.06 \pm 1.73	6.91 \pm 1.50	0.000
	2	7.79 \pm 1.73	6.77 \pm 1.68	0.000
Lower extremity strength and locomotion—TUG (s)	1	4.93 \pm 0.71	5.18 \pm 2.47	0.629
	2	4.87 \pm 0.73	4.47 \pm 1.71	0.319
	3	4.81 \pm 0.69	4.75 \pm 2.29	0.905

Table 4. Estimates of spatio-temporal gait characteristics obtained from the 2 min endurance walking test by the BWM (body worn monitor).

Task	Gait characteristic	Result		
		Mean	Variability	Asymmetry
Endurance	Step time (s)	0.47 \pm 0.03	0.08 \pm 0.04	0.01 \pm 0.01
	Stride time (s)	0.94 \pm 0.06	0.12 \pm 0.06	0.00 \pm 0.00
	Stance time (s)	0.60 \pm 0.04	0.08 \pm 0.04	0.01 \pm 0.01
	Swing time (s)	0.34 \pm 0.02	0.08 \pm 0.04	0.01 \pm 0.01
	Step length (m)	0.70 \pm 0.08	0.11 \pm 0.04	0.01 \pm 0.01
	Step velocity (m s^{-1})	1.53 \pm 0.21	0.25 \pm 0.08	0.03 \pm 0.04

3.4. Lower limb strength

The BWM had significantly shorter duration (faster) time estimates for repeated PT (by approx. 1 s for both trials) compared with manual recordings ($p < 0.000$).

3.5. Lower limb strength and locomotion

There were no significant differences between the BWM and manual recording for the total time to complete the TUG ($p \geq 0.319$).

4. Discussion

This feasibility study reports further developments of our work on the measurement of the HAP (Lara *et al* 2013). We present a methodology to objectively quantify physical capability using a low cost accelerometer-based BWM with a novel combination of algorithms as an instrumented form of assessment. We were able to demonstrate that there were no significant differences between the BWM and manual recordings for most tasks suggesting it is a feasible alternative to quantify physical capability. Moreover, the adoption of the standardised instrumented protocol offers the ability to objectively quantify physical capability and use the

outcomes in a pooled comparison of results across similar/diverse studies while also yielding additional sensitive outcomes.

4.1. Postural control

Quantifying balance with a BWM on the lower back has previously been shown to be reliable and suitable for vestibular impairment screening (Rine *et al* 2013). Moreover, similar work has shown accelerometry related outcomes (similar to those derived here) to be better or consistent with centre of pressure outcomes quantified using traditional methods, e.g. force plates (Whitney *et al* 2011). Exact comparison to other accelerometer-based postural control data from the literature is difficult due to the novelty of the work (use of a BWM) and variation in protocols. The outcomes quantified in this study were similar to other work (Mancini *et al* 2012) and also showed sensitivity to the difficulty of the protocol as seen previously (Rine *et al* 2013). We observed that F95% (ML direction) was the least discriminatory between trials. Therefore its use in HAP testing warrants further investigation.

4.2. Locomotion

This is the first study to utilise the timing sequence of IC/FC within the gait cycle to estimate total time to complete the 4 m walk and hence determine speed. Compared with manual recordings, the BWM had shorter durations (faster). Slight differences in trial 1 may be due to the subjective nature of manual recording, i.e. researcher error in timing the beginning/end of the walk. Conversely, the dependence of the BWM algorithm on identifying the final (purposeful) FC to mark the end of the trial may also impact upon timing error. However, in trial 2, mean difference between methods improved suggesting a learning effect for the observer and, perhaps, better participant compliance (complete stop after 4 m). One possible method for improving the FC event estimations is the alternative use of wavelet where it has been suggested that a bi-orthogonal spine wavelet is superior to that used here, i.e. Gaussian (Shao and Ma 2003). This will be evaluated in future studies.

4.3. Endurance

The pendulum technique overestimated step length and subsequently total distance walked due to the spatial parameter being sensitive to linear deviations of gait (rounding/turning the cones) (Zijlstra and Hof 2003). Estimated distance by the BWM may be improved by introducing a more linear walking route, i.e. limit abrupt turning. We quantified numerous spatio-temporal gait characteristics to highlight the added benefit of a BWM. While this task has been recommended by the NIH Toolbox for assessing overall cardiovascular endurance, the inclusion of a BWM allows researchers to assess the gait characteristics (over a suitable period) (Galna *et al* 2013, Lord *et al* 2013a) which have been shown to be sensitive to age (Lord *et al* 2013b) and pathology (Rochester *et al* 2012) and could prove useful for future testing. Moreover, the quantified gait characteristics presented here are similar to other studies that used an instrumented walkway (Senden *et al* 2009, Hollman *et al* 2011, Lord *et al* 2013b, Kobsar *et al* 2014b). However, notable differences are observed for the variability of all gait characteristics which is similar to other work (Kobsar *et al* 2014a). This can be attributed to the functional differences between systems (pressure sensor versus continuous tracking of a body and its acceleration through space) and drift due to integration (Hartmann *et al* 2009). However, this approach offers another important dimension to the endurance task which will be investigated in future HAP work within LiveWell.

4.4. Lower limb strength

This is the first study to use the wavelet algorithm to quantify repeated PT as it has been specifically designed for individual sit-to-stand and stand-to-sit transitions only. The mean times had a significantly shorter duration (faster) for the BWM compared to manual recordings ($p < 0.000$). This could be due to observer variability in recording the start and finish times of the transitions which can be difficult to achieve due to participant performance. Other factors that may impact on calculations include BWM time to complete repeated PT, taken as the time between first and last peaks, figure 2(b). Methodologically the correct timing sequence for a single transition is the time between successive peak/trough or trough/peak $\times 2$ (Bidargaddi *et al* 2007). Multiplication by the correction factor of 2 was excluded here due to the nature of the task, i.e. a continuous sequence of sit-to-stand-to-sit. The adaptation of the algorithm to include a correction < 2 may help refine the slight timing anomaly, which appears systematic in nature, figure 3(a). To test this hypothesis, we calculated a new correction factor for future use with this algorithm during repeated PT. Based on the percentage difference between both methods we computed and subsequently recommend a value of 1.16. When applied to BWM values and compared to those from manual recordings, no significant differences were found ($p \geq 0.603$), figure 3(b).

Furthermore, the shorter duration PT estimates by the BWM compared to manually recorded times can be attributed to algorithm functionality due to BWM location and definition of PT (Godfrey *et al* 2014). This is because the algorithm is best suited to estimation of the dominant vertical rise (DVR) transition whereas momentum transfer is quantified by the visual observation of the researcher and that which is normally adopted by OHP (Scarborough *et al* 2007). However, due to its mechanics the DVR may be a good proxy for assessing lower extremity strength within this task but remains untested (Godfrey *et al* 2014). Change of sensor location (chest) to suit the momentum transfer strategy is likely to improve agreement but impact negatively on the ability to holistically and accurately quantify the subdomain of physical capability outlined in this study (Godfrey *et al* 2014).

4.5. Lower limb strength and locomotion

There were no significant differences between times quantified by the BWM and observer although the BWM had (generally) shorter durations in comparison to manual recordings. This could be explained by the algorithm adopted to quantify PT (exclusion of the correction factor) and the PT strategy adopted (see discussion above, section 4.4). However, this is the first time that the wavelet algorithm has been used to quantify the TUG test and it performed well in recognising the PT at the beginning/end of the task as well as suppressing the walk and turning components of a_v , figure 2(c). Slight differences by the BWM can be attributed to the nature of the composite task (sit-to-stand, walk, turn, walk, turn and stand-to-sit), which may negatively impact on the peak detection accuracy and hence timing. Segmenting the task into its various components with the summation of their individually timed sections may improve results, though this is only attainable with the use of a gyroscope (Salarian *et al* 2010).

5. Conclusion

This study explores the feasibility of a methodological approach to objectively quantify physical capability within the HAP by using a single low-cost BWM. Comparative analysis with manual observation demonstrated that a BWM is a suitable and objective measure to quantify

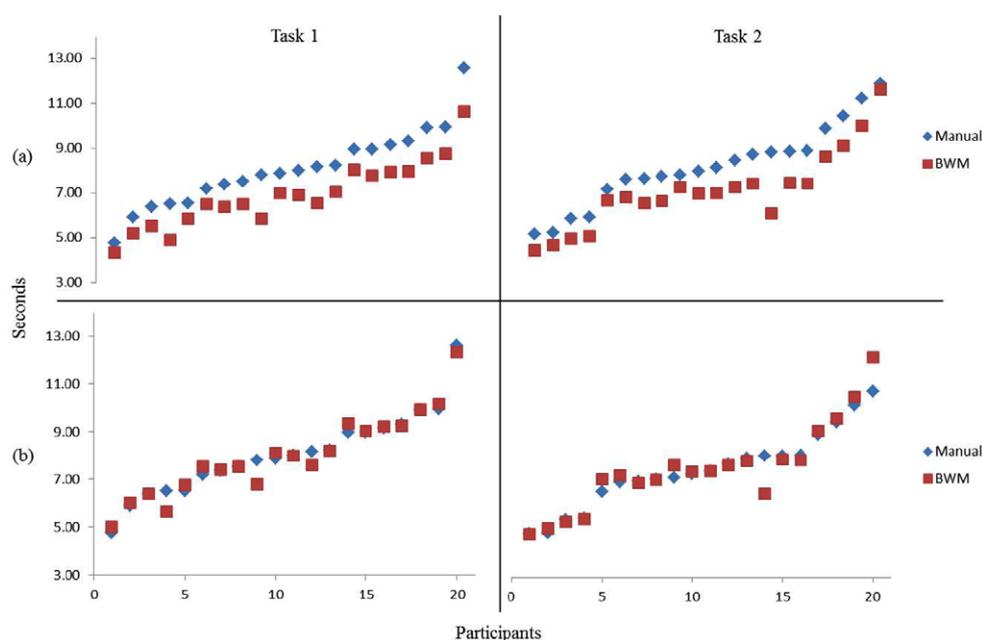


Figure 3. (a) Scatter plot of repeated sit-to-stand-to-sit PT showing the systematic shorter duration (faster) nature of times as quantified by the BWM. (b) After a correction factor of 1.16 was applied there was no significant difference between BWM and manual recording. (Participant times arranged from lowest to highest for clarity.)

postural control, locomotion, lower limb strength (with new correction factor of 1.16) and lower limb strength and locomotion. Though the BWM overestimated total distance, gait characteristics derived during this test may prove more useful in future tests. As a result, the method presented here should be a focus of constant re-evaluation to ensure ‘fit-for-purpose’ equipment and techniques. Our findings suggest that the use of a BWM can provide the basis for a more objective and transferrable depiction of capability which has practical implications for instrumented testing in large scale interventions and could also be extended to studies involving pathology. It also serves to limit the potential for ‘human-error’ through adoption of algorithmic analysis, and provides the added dimension of novel postural control outcomes and gait characteristics during the endurance task. Future work will involve refinement of the methodology for large scale deployment within the LiveWell to assess the effect of intervention through instrumented testing.

Conflict of interest

There is no conflict of interest.

Funding

Authors acknowledge support from the LiveWell program a research project funded through a collaborative grant from the lifelong health and wellbeing (LLHW) initiative, managed by the medical research council (MRC) on behalf of the funders: Biotechnology and Biological

Sciences Research Council, Engineering and Physical Sciences Research Council, Economic and Social Research Council, Medical Research Council, Chief Scientist Office of the Scottish Government Health Directorates, National Institute for Health Research (NIHR)/The Department of Health, The Health and Social Care Research and Development of the Public Health Agency (Northern Ireland), and Wales Office of Research and Development for Health and Social Care and the Welsh Assembly Government (grant number: G0900686). LR and AG are supported by the national institute for health research (NIHR) Newcastle Biomedical Research Centre and Unit based at Newcastle upon Tyne Hospitals NHS Foundation Trust and Newcastle University. The views expressed are those of the authors and not necessarily those of the NHS or NIHR or the Department of Health. SDD is supported by the V-Time project, which is a European Union 7th Framework Programme (FP7) under the Health theme (FP7: 278169).

Acknowledgments

The authors thank those who participated in the study.

References

- Bidargaddi N, Klingbeil L, Sarela A, Boyle J, Cheung V, Yelland C, Karunanithi M and Gray L 2007 Wavelet based approach for posture transition estimation using a waist worn accelerometer *Proc. Ann. Int. IEEE Conf. of the Engineering in Medicine and Biology Society (Lyon, France)* pp 1884–7
- Black H K 2009 Pictures of suffering in elders' narratives *J. Aging Stud.* **23** 82–9
- Cooper R, Kuh D, Cooper C, Gale C R, Lawlor D A, Matthews F, Hardy R, Falcon and Teams H A S 2011 Objective measures of physical capability and subsequent health: a systematic review *Age Ageing* **40** 14–23
- Cooper R, Kuh D, Hardy R, Mortality Review G, Falcon and Teams H A S 2010 Objectively measured physical capability levels and mortality: systematic review and meta-analysis *Bmj* **341** c4467
- Galna B, Lord S and Rochester L 2013 Is gait variability reliable in older adults and Parkinson's disease? towards an optimal testing protocol *Gait Posture* **37** 580–5
- Gershon R C, Wagster M V, Hendrie H C, Fox N A, Cook K F and Nowinski C J 2013 NIH toolbox for assessment of neurological and behavioral function *Neurology* **80** S2–6
- Godfrey A, Barry G, Mathers J C and Rochester L 2014 A comparison of methods to detect postural transitions using a single tri-axial accelerometer *Proc. of the 36th Ann. Int. IEEE Conf. of the Engineering in Medicine and Biology Society (Chicago, IL)* pp 3574–7
- Godfrey A, Conway R, Meagher D and O'laighin G 2008 Direct measurement of human movement by accelerometry *Med. Eng. Phys.* **30** 1364–86
- Hartmann A, Luzi S, Murer K, de Bie R A and de Bruin E D 2009 Concurrent validity of a trunk tri-axial accelerometer system for gait analysis in older adults *Gait Posture* **29** 444–8
- Hollman J H, McDade E M and Petersen R C 2011 Normative spatiotemporal gait parameters in older adults *Gait Posture* **34** 111–8
- Kobsar D, Olson C, Paranjape R and Barden J M 2014a The validity of gait variability and fractal dynamics obtained from a single, body-fixed triaxial accelerometer *J. Appl. Biomech.* **30** 343–7
- Kobsar D, Olson C, Paranjape R, Hadjistavropoulos T and Barden J M 2014b Evaluation of age-related differences in the stride-to-stride fluctuations, regularity and symmetry of gait using a waist-mounted tri-axial accelerometer *Gait Posture* **39** 553–7
- Lara J, Godfrey A, Evans E, Heaven B, Brown L J, Barron E, Rochester L, Meyer T D and Mathers J C 2013 Towards measurement of the healthy ageing phenotype in lifestyle-based intervention studies *Maturitas* **76** 189–99
- Lord S, Galna B and Rochester L 2013a Moving forward on gait measurement: toward a more refined approach *Mov. Disord.* **28** 1534–43

- Lord S, Galna B, Verghese J, Coleman S, Burn D and Rochester L 2013b 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.* **68** 820–7
- Mancini M, Salarian A, Carlson-Kuhta P, Zampieri C, King L, Chiari L and Horak F B 2012 ISway: a sensitive, valid and reliable measure of postural control *J. Neuroeng. Rehabil.* **9** 59
- McCamley J, Donati M, Grimpampi E and Mazza C 2012 An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data *Gait Posture* **36** 316–8
- Mellone S, Tacconi C and Chiari L 2012 Validity of a smartphone-based instrumented timed up and go *Gait Posture* **36** 163–5
- Moe-Nilssen R and Helbostad J L 2002 Trunk accelerometry as a measure of balance control during quiet standing *Gait Posture* **16** 60–8
- Murphy S L 2009 Review of physical activity measurement using accelerometers in older adults: considerations for research design and conduct *Prev. Med.* **48** 108–14
- Narayanan M R, Redmond S J, Scalzi M E, Lord S R, Celler B G and Lovell Ast N H 2010 Longitudinal falls-risk estimation using triaxial accelerometry *IEEE Trans. Bio-med. Eng.* **57** 534–41
- Parsons S, Gale C R, Kuh D and Elliott J 2014 Physical capability and the advantages and disadvantages of ageing: perceptions of older age by men and women in two British cohorts *Ageing Soc.* **34** 452–71
- Rine R M *et al* 2013 Vestibular function assessment using the NIH Toolbox *Neurology* **80** S25–31
- Rochester L, Yarnall A J, Baker M R, David R V, Lord S, Galna B and Burn D J 2012 Cholinergic dysfunction contributes to gait disturbance in early Parkinson's disease *Brain: J. Neurol.* **135** 2779–88
- Salarian A, Horak F B, Zampieri C, Carlson-Kuhta P, Nutt J G and Aminian K 2010 iTUG, a sensitive and reliable measure of mobility *IEEE Trans. Neural Syst. Rehabil. Eng.* **18** 303–10
- Scarborough D M, McGibbon C A and Krebs D E 2007 Chair rise strategies in older adults with functional limitations *J. Rehabil. Res. Dev.* **44** 33–42
- Senden R, Grimm B, Heyligers I C, Savelberg H H and Meijer K 2009 Acceleration-based gait test for healthy subjects: reliability and reference data *Gait Posture* **30** 192–6
- Shao X and Ma C 2003 A general approach to derivative calculation using wavelet transform *Chemometr. Intell. Lab. Syst.* **69** 157–65
- Studenski S *et al* 2011 Gait speed and survival in older adults *JAMA: J. Am. Med. Assoc.* **305** 50–8
- Townsend P 1979 *Poverty in the United Kingdom* (Harmondsworth, UK: Pelican)
- Vaupel J W 2010 Biodemography of human ageing *Nature* **464** 536–42
- Ware J E, Snow K K, Kosinski M and Gandek B 1993 *SF-36 Health Survey: Manual And Interpretation Guide* (Boston: The Health Institute, New England Medical Center)
- Weiss A, Herman T, Plotnik M, Brozgol M, Giladi N and Hausdorff J M 2011 An instrumented timed up and go: the added value of an accelerometer for identifying fall risk in idiopathic fallers *Physiol. Meas.* **32** 2003–18
- Whitney S L, Roche J L, Marchetti G F, Lin C C, Steed D P, Furman G R, Musolino M C and Redfern M S 2011 A comparison of accelerometry and center of pressure measures during computerized dynamic posturography: a measure of balance *Gait Posture* **33** 594–9
- Zijlstra W and Hof A L 2003 Assessment of spatio-temporal gait parameters from trunk accelerations during human walking *Gait Posture* **18** 1–10