# Within trial validation and reliability of a single tri-axial accelerometer for gait assessment

Alan Godfrey-IEEE Member, Silvia Del Din-IEEE Member, Gillian Barry, John C. Mathers and Lynn Rochester

Abstract— Gait is a sensitive biomarker of decline in both cognitive and physical function. Therefore, the collection of gait data is an important feature of clinical assessments. Accelerometer-based body worn sensors are quickly becoming the preferred tool for assessing gait because they are small, useable in a wide variety of settings, offer more continuous spatio-temporal analysis and are inexpensive when compared with traditional gait assessment methodologies. The purpose of this study was to determine the validity and within test reliability of a low cost body worn movement sensor with associated algorithms to assess gait in a large group of older and younger healthy adults. We collected gait data over intermittent walks on an instrumented walkway for a within trial validation and also used the same accelerometer derived gait data for a within test reliability analysis. ICCs for validation and reliability were >0.756 and >0.965, respectively.

#### I. INTRODUCTION

The assessment of gait provides simple, low cost, quick and powerful clinical tool with a wide range of applications including investigations of ageing. For example, gait speed has been shown to predict longevity [1]. Gait is a multifaceted model comprising several different independent parameters [2]. Lord et al outlined the most important spatiotemporal parameters of gait including step time, stride time, step length, step velocity, stance time and swing time that relate to motor, cognitive and behavioural attributes [2]. Estimation of these gait parameters by objective means has begun to play a key part in investigation of numerous neurological-related pathologies and healthy ageing [3-5]. However, because the traditional, expensive and specialised equipment used to quantify gait is limited to locations such as academic research centres or specialised clinical units, gait remains an under-utilised outcome. The use of small body worn accelerometer-based sensors to characterise and quantify gait is seen as a potential solution to the problem of equipment restrictions [5]. Over the last 20 years, there have

Research supported by the LiveWell program (www.livewell.ac.uk) a project funded through the Lifelong Health and Wellbeing (LLHW) initiative, managed by the Medical Research Council (MRC) on behalf of the funders, grant number: G0900686. L. Rochester is supported by the National Institute for Health Research, Newcastle Biomedical Research Centre and Unit, 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, the NIHR or the Department of Health.

A. Godfrey, S. Del Din, G. Barry and L. Rochester are with the Clinical Ageing Research Unit and J.C. Mathers with the Human Nutrition Research Centre, Institute for Ageing and Health, Newcastle University, Newcastle upon Tyne, NE4 5PL, UK (S. Del Din phone: +441912081244; fax: +441912081251; e-mail: silvia.del-din@ncl.ac.uk).

been rapid developments in the use of accelerometry for assessment of human movement [6]. Within the domain of gait, there has been a steady rise in the number of algorithms developed for use in analysing data from accelerometerbased sensors located on the torso (chest, waist, lower back). Simple algorithms extracting basic gait parameters such as step detection and step count [7, 8] have been surpassed by those able to estimate specific spatio-temporal gait parameters including step time and step length [9, 10]. Through use of a combination of these algorithms it should be feasible to near replicate a full gait model as defined by [2].

Current approaches to assess gait in a clinical setting use mean values from repeated passes over a predefined distance [3, 4]. While it is vital that accelerometer-based sensors with associated algorithms undergo stringent testing to ensure they quantify gait data correctly, it is also necessary to test their reliability during continuous recording where averaged values are to be used. Therefore, the purpose of this study was to perform a within test reliability study for a low cost body worn sensor which employed a novel combination of two gait algorithms during prolonged walking at different walking speeds in healthy younger and older adults. The application of this system will show the potential of instrumenting gait assessment in any suitable environment.

## II. METHODS

## A. Participants

Twelve young healthy adults aged 20-40 years (YHP) and twelve older healthy adults (OHP) were recruited. Participants were recruited from staff and students at Newcastle University and members of Newcastle University VOICENorth, an older volunteer group who participate in research. Participants were recruited only if they had no physical or neurological disability that might impede their movement or balance. All participants gave informed written consent and ethical consent was granted by the National Research Ethics Service (County Durham and Tees Valley).

## B. Equipment

Each participant wore an Axivity AX3 sensor (Axivity, York, UK) located on the lumbar vertebrae (L5), Figure 1. The sensor was held in place by double sided tape and Hypafix (BSN Medical Limited, Hull, UK). The sensor was programmed to capture at 100-Hz (16-bit resolution) and at a range of  $\pm 8g$ . Recorded accelerations were stored locally on the sensor's internal memory as a raw binary file that was downloaded upon the completion of each walking trial.

To validate the accelerometer-based sensor and its algorithms, the GaitRite instrumented walkway was used as the gold standard reference. The GaitRite dimensions were 7.0m  $\times$  0.6m and had a spatial accuracy of 1.27cm and a temporal accuracy of 1 sample (240Hz, ~4.17ms). Previous studies have verified the GaitRite as a valid and reliable device for measuring mean gait characteristics in healthy younger and older adults [11]. In addition, video recording was used as the reference for total step count during each walking trial.



Figure 1. Attachment of the sensor on the lower back, L5

## C. Experimental protocol

Participants were instructed to perform 2 walking tasks at self-selected speeds under the normal (preferred) and fast conditions. Each walk was performed until 5 laps of a 25m route were completed as highlighted by Figure 2. Gait was repeatedly sampled as participants walked over the GaitRite mat which was placed in the circuit. This methodology was adopted based upon previous findings that the use of a continuous walk of no fewer than 30 steps is recommended when examining the reliability of gait [12]. Following each walk, participants were asked to remain still for 1 minute before being told to commence their next walk. All walks were performed in the same order: normal followed by fast. The first and last walks over the mat were ignored with the middle three walks used for analysis (labelled here as T1, T2 and T3) to compare as near as possible steady state walking speed.



Figure 2. Representation of the 25m track with highlighted section for direct comparison with the GaitRite instrumented walkway.

## D. Algorithms

After testing, data were downloaded to a computer and analysed using a specially written MATLAB program. Firstly

the times for initial and final contacts (IC and FC, respectively) were extracted from the accelerometer data resulting in the estimation of step time and stride time. Secondly, step length was estimated which then allowed for the final estimation of step velocity, based upon the relationship between step time and step length. These parameters were extracted using the following methods:

McCamley et al [9] estimated the IC and FC events from a continuous wavelet transform (CWT) of the vertical acceleration (*a<sub>v</sub>*) which was integrated and then differentiated using a Gaussian CWT with ICs being the local minima. A further differentiation resulted in the local maxima being defined as the FC events. During testing it was observed that the algorithm detected spurious (false) IC events, Figure 3. Thus the algorithm was updated based upon previous methodology to account for this error [8].



Figure 3. An example of the McCamley algorithm with supriously detected IC events (pink circles)

• Step length (1) was found from the method introduced by Zijlstra et al [10], which is derived from the inverted pendulum model. In this method, changes in the centre of height of the centre of mass (*h*, as derived from the accelerometer) as well as the know pendulum length (*l*, height of sensor from ground) provide an estimation for step length:

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

## E. Data segmentation

Data from the accelerometer were segmented for direct comparison with the steps on GaitRite. This was achieved from a combination of the video recording and the MATLAB program as follows: from initiation, the number of steps to GaitRite were counted as well as the number of steps on and back around to GaitRite for the 5 walks over GaitRite. The MATLAB program counted the number of steps (as estimated from the algorithms) and segmented the accelerometer data based upon the algorithm count and video count. For the purposes of this study the middle 3 trials (T1, T2 and T3) over the GaitRite were used for analysis. This was to assess walking at constant speeds and to avoid problems caused by higher and lower speeds during the first and fifth passes, respectively.

## F. Statistical analysis

Means and standard deviations were calculated for averaged data at each speed condition for both YHP and OHP. The normality of data distributions were tested with a Shapiro-Wilk test. A repeated measures general linear model (GLM) was used to test for within trial differences for the extracted gait parameters. Levels of agreement were expressed as intraclass correlation coefficients (ICCs) as type (2, k) for validation (GaitRite v. Axivity) and intrasession reliability (Axivity v. Axivity) analysis. Independent sample t-test compared group characteristics. The statistical significance was set at p < 0.05.

## III. RESULTS

Table I shows the group characteristics. Although this study was not designed to compare age groups it should be noted that there were no significant differences between YHP and OHP for height or weight.

TABLE I. PARTICIPANT CHARACTERISTICS

Characteristic	YHP (N=12)	OHP (N=12)
Gender (M/F)	7 / 5	5 / 7
Age (years)	$32.5\pm4.8$	$65.0\pm8.8$
Height (cm)	$171.3\pm9.2$	$169.2\pm8.7$
Weight (kg)	$67.9 \pm 14.7$	$70.1\pm14.4$

Tables II and III show the descriptive gait parameters during each trial for the YHP and OHP, respectively. There were no statistically significant differences between trials for most gait parameters in either age group except for step length (p = 0.001) and step velocity (p = 0.002) for the YHP. Trial 3 showed significantly lower step length in comparison with trial 1 (p = 0.003) and trial 2 (p = 0.017), respectively. As a result, there was a significantly lower value for step velocity in trial 3 compared to trial 1 (p = 0.005) and trial 2 (p = 0.035).

 
 TABLE II.
 Mean ± standard deviation of estimates of gait parameters obtained using Axivity for the YHP for 3 tests

Variable	T1	Τ2	Т3	
Preferred walking speed				
Step time (s)	$0.6 \pm 0.0$	$0.6 \pm 0.1$	$0.6 \pm 0.1$	
Stride time (s)	$1.1 \pm 0.1$	$1.10 \pm 0.1$	$1.1 \pm 0.1$	
Step length (cm)	$76.5\pm10.1$	$77.52 \pm 11.3$	$78.0\pm10.4$	
Step velocity (cm/s)	$140.9\pm22.8$	$142.95\pm23.8$	$143.8\pm23.4$	
Fast walking speed				
Step time (s)	$0.50\pm0.1$	$0.5\pm0.1$	$0.5\pm0.0$	
Stride time (s)	$1.0 \pm 0.1$	$1.0 \pm 0.1$	$1.1 \pm 0.1$	
Step length (cm)	$91.4\pm13.8$	$91.0\pm13.4$	$88.3\pm12.6^{\text{a}}$	
Step velocity (cm/s)	$184.3\pm30.1$	$182.8 \pm 31.4$	$176.0\pm26.4^{a}$	
p < 0.05				

 
 TABLE III.
 Mean ± standard deviation axivity values for the ohp for 3 tests with significant differences (if any)

Variable	T1	T2	Т3		
Preferred walking speed					
Step time	$0.5 \pm 0.0$	$0.5 \pm 0.0$	$0.5 \pm 0.0$		
Stride time	$1.1 \pm 0.1$	$1.1 \pm 0.1$	$1.1 \pm 0.1$		
Step length	$80.8\pm10.6$	81.2 ± 11.3	$79.9\pm10.8$		
Step velocity	$154.2 \pm 22.1$	$154.9\pm23.1$	$152.4\pm21.9$		
Fast walking speed					
Step time	$0.5 \pm 0.1$	$0.5 \pm 0.1$	$0.5 \pm 0.1$		
Stride time	$1.0 \pm 0.1$	$1.0 \pm 0.1$	$1.0 \pm 0.1$		
Step length	$89.0\pm10.8$	88.1 ± 10.2	87.0 ± 10.3		
Step velocity	$186.7 \pm 26.3$	$185.4\pm27.7$	$182.2\pm26.9$		

Tables IV and V show the ICCs for the validation (Gaitrite v. Axivity) and intrasession reliability (Axivity v. Axivity) analysis. There was excellent validation between all gait parameters for the YHP (ICCs, 0.865 - 0.999). Estimates of step time and stride time were excellent for the OHP (0.995 - 0.999) but validation values were slightly reduced for step length and step velocity during preferred and fast walking speeds (ICCs, 0.756 - 0.929).

TABLE IV. ICCs (2, k) FOR VALIDATION AND RELAIBILITY FOR EACH

Variable	Validation	Reliability	
	T1 / T2 / T3	T1-T2 / T1-T3 / T2-T3	
Preferred walking speed			
Step time	0.999 / 0.998 / 0.999	0.993 / 0.994 / 0.992	
Stride time	0.999 / 0.998 / 0.999	0.994 / 0.993 / 0.993	
Step length	0.929 / 0.926 / 0.929	0.983 / 0.974 / 0.984	
Step velocity	0.963 / 0.962 / 0.960	0.988 / 0.977 / 0.986	
Fast walking speed			
Step time	0.998 / 0.994 / 0.996	0.992 / 0.984 / 0.983	
Stride time	0.998 / 0.997 / 0.994	0.994 / 0.983 / 0.988	
Step length	0.910 / 0.906 / 0.865	0.988 / 0.979 / 0.980	
Step velocity	0.941 / 0.942 / 0.919	0.986 / 0.965 / 0.970	

TABLE V. ICCs (2, k) FOR VALIDATION AND RELIABILITY FOR EACH

Variable	Validation	Reliability
	T1 / T2 / T3	T1-T2 / T1-T3 / T2-T3
Preferred walking speed		
Step time	0.995 / 0.995 / 0.995	0.990 / 0.987 / 0.997
Stride time	0.997 / 0.995 / 0.998	0.994 / 0.992 / 0.998
Step length	0.929 / 0.832 / 0.787	0.990 / 0.983 / 0.973
Step velocity	0.853 / 0.855 / 0.810	0.990 / 0.979 / 0.973
Fast walking speed		
Step time	0.998 / 0.997 / 0.999	0.997 / 0.997 / 0.995
Stride time	0.997 / 0.998 / 0.999	0.998 / 0.997 / 0.997
Step length	0.782 / 0.756 / 0.788	0.977 / 0.969 / 0.986
Step velocity	0.853 / 0.862 / 0.859	0.982 / 0.973 / 0.985

The intrasession reliability of the Axivity and associated algorithms for the estimation of step time, stride time, step length and step velocity were excellent for both YHP and OHP during tests at both walking speeds (ICCs, 0.965 - 0.998).

## IV. DISCUSSION

The purpose of this study was to perform a within test validation and reliability study for a low cost body worn sensor which employed a novel combination of two gait algorithms during prolonged walking at 2 different speeds. This study shows that the instrumentation of gait can be easily achieved to capture the important spatio-temporal parameters in a cost effective and robust manner.

All gait parameters estimated by Axivity were validated within the YHP group for both walking speeds where ICCs were >0.865. For the OHP, there were similar levels of validity in step time and stride time but the estimates of step length (ICCs > 0.756) and subsequently step velocity (ICCs >0.853) were lower although still comparable to other similar studies [13] and within acceptable validation values [11]. The reduced agreement in older adult data can be attributed to natural ageing where algorithm dependant signal characteristics can differ to younger adults [10]. In addition, individualised correction factors for step length estimation should be considered during continuous walking in older adults where this has been previously recommended examined in a similar group and pathology [14, 15]. The intrasession reliability results also proved to be acceptable during steady state walking for 2 gait speeds. The intrasession results for the sensor and algorithms revealed excellent agreement for both groups (ICCs >0.965). This within test validation and reliability study was a necessary undertaking as many studies incorporate intermittent walks within their testing protocol and pool gait data from numerous passes [2]. We have shown that gait data acquired from the sensor and the algorithms used to quantify the gait parameters during steady state walking at 2 different gait speeds, can be pooled from intermittent passes as the data is highly valid and reliable.

Plausible explanations for the differences between the mat and sensor with algorithms have been reported previously [13]. In addition, manually observed steps on, and progression to the next pass on the mat were used to segment the accelerometer data via MATLAB. While the agreement between the two systems was excellent for step count estimation, the number of steps and subsequently the distinction between left and right for some passes over the mat were not identical for each pass leading to potential errors in the identification of left and right steps.

Future work will focus on a full replication of a gait model [2] in healthy older adults with a single body worn sensor, in large cohorts for intervention-based studies<sup>1</sup>.

#### V. CONCLUSION

This study has shown the within test validity and reliability of a low-cost accelerometer-based sensor with an algorithm combination for estimating the gait parameters of step time, stride time, step length and step velocity. The sensor arrangement and algorithm combination are valid and reliable tools for quantifying gait during continuous walking in both younger and older adults which will have practical applications in large clinical and intervention based studies<sup>1</sup> for measuring health and wellbeing in older adults [5].

## ACKNOWLEDGMENT

The authors thank those who participated in this study and VOICENorth for participant recruitment.

(www.ncl.ac.uk/changingage/engagement/VOICENorth).

#### REFERENCES

- S. Studenski, S. Perera, K. Patel, C. Rosano, K. Faulkner, M. Inzitari, et al., "Gait speed and survival in older adults," *JAMA*, vol. 305, pp. 50-8, Jan 5 2011.
- [2] S. Lord, B. Galna, J. Verghese, S. Coleman, D. Burn, and L. Rochester, "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*, vol. 68, pp. 820-7, Jul 2013.
- [3] J. Verghese, C. Wang, R. B. Lipton, R. Holtzer, and X. Xue, "Quantitative gait dysfunction and risk of cognitive decline and dementia," *J Neurol Neurosurg Psychiatry*, vol. 78, pp. 929-35, Sep 2007.
- [4] S. Lord, B. Galna, S. Coleman, D. Burn, and L. Rochester, "Mild depressive symptoms are associated with gait impairment in early Parkinson's disease," *Mov Disord*, vol. 28, pp. 634-9, May 2013.
- [5] J. Lara, A. Godfrey, E. Evans, B. Heaven, L. J. Brown, E. Barron, et al., "Towards measurement of the Healthy Ageing Phenotype in lifestyle-based intervention studies," *Maturitas*, vol. 76, pp. 189-99, Oct 2013.
- [6] A. Godfrey, R. Conway, D. Meagher, and O. L. G, "Direct measurement of human movement by accelerometry," *Med Eng Phys*, vol. 30, pp. 1364-86, Dec 2008.
- [7] A. Godfrey, A. K. Bourke, G. M. Olaighin, P. van de Ven, and J. Nelson, "Activity classification using a single chest mounted tri-axial accelerometer," *Med Eng Phys*, vol. 33, pp. 1127-35, Nov 2011.
- [8] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. J. Bula, and P. Robert, "Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly," *IEEE Trans Biomed Eng*, vol. 50, pp. 711-23, Jun 2003.
- [9] J. McCamley, M. Donati, E. Grimpampi, and C. Mazza, "An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data," *Gait Posture*, vol. 36, pp. 316-8, Jun 2012.
- [10] W. Zijlstra and A. L. Hof, "Assessment of spatio-temporal gait parameters from trunk accelerations during human walking," *Gait Posture*, vol. 18, pp. 1-10, Oct 2003.
- [11] H. B. Menz, M. D. Latt, A. Tiedemann, M. Mun San Kwan, and S. R. Lord, "Reliability of the GAITRite walkway system for the quantification of temporo-spatial parameters of gait in young and older people," *Gait Posture*, vol. 20, pp. 20-5, Aug 2004.
- [12] B. Galna, S. Lord, and L. Rochester, "Is gait variability reliable in older adults and Parkinson's disease? Towards an optimal testing protocol," *Gait Posture*, vol. 37, pp. 580-5, Apr 2013.
- [13] A. Hartmann, K. Murer, R. A. de Bie, and E. D. de Bruin, "Reproducibility of spatio-temporal gait parameters under different conditions in older adults using a trunk tri-axial accelerometer system," *Gait Posture*, vol. 30, pp. 351-5, Oct 2009.
- [14] P. Esser, H. Dawes, J. Collett, M. G. Feltham, and K. Howells, "Assessment of spatio-temporal gait parameters using inertial measurement units in neurological populations," *Gait Posture*, vol. 34, pp. 558-60, Oct 2011.
- [15] A. Zijlstra and W. Zijlstra, "Trunk-acceleration based assessment of gait parameters in older persons: a comparison of reliability and validity of four inverted pendulum based estimations," *Gait Posture*, vol. 38, pp. 940-4, Sep 2013.

<sup>&</sup>lt;sup>1</sup> LiveWell: developing and piloting lifestyle-based interventions to promote health and wellbeing in later life. <u>www.livewell.ac.uk</u>