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A wireless accelerometer node for reliable and valid measurement of lumbar accelerations during treadmill running

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Abstract
This study investigated the reliability of a wireless accelerometer and its agreement with optical motion capture for the measurement of root mean square (RMS) acceleration during running. RMS acceleration provides a whole-body metric of movement mechanics and economy. Fifteen healthy college-age participants performed treadmill running for two 60-s trials at 2.22, 2.78, and 3.33 m/s and one trial of 150 s (five 30-s epochs) at 2.78 m/s. We assessed between-trial and within-trial reliability, and agreement in each axis between a trunk-mounted wireless accelerometer and a reflective marker on the accelerometer measured by optical motion capture. Intraclass correlations assessing between-trial repeatability were 0.89–0.97, depending on the axis, and intraclass correlations assessing within-trial repeatability were 0.99–1.00. Bland–Altman analyses assessing agreement indicated mean difference values between −0.03 and 0.03 g, depending on the axis. Anterio-posterior acceleration had the greatest limits of agreement (LOA) (±0.12 g) and vertical acceleration had the smallest LOA (±0.03 g). For measuring RMS acceleration of the trunk, this wireless accelerometer node provides repeatable and valid measurement compared with the standard laboratory method of optical motion capture.

Keywords: *Optical motion capture, root mean square, agreement*

Introduction

In recent years, there has been increasing interest in the use of accelerometers to quantify human movement. When accelerometers are used as activity monitors, the raw data are summarised over time to estimate energy expenditure and classify levels of physical activity (Bassett, Mahar, Rowe, & Morrow, 2008; Butte, Ekelund, & Westerterp, 2012). Accelerometers can also provide information regarding movement dynamics from continuous data captured at high frequencies (Halsey et al., 2008; McGregor, Busa, Yaggie, &

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Bollt, 2009). In particular, accelerometers can be used to describe walking gait characteristics (Moe-Nilssen & Helbostad, 2004), identify differences in energy expenditure and movement patterns between trained and untrained runners (McGregor, Busa, Yaggie, et al., 2009), and identify constraints of walking and running via a non-linear dynamic systems approach (McGregor, Busa, Parshad, Yaggie, & Bollt, 2011; McGregor, Busa, Skufca, Yaggie, & Bollt, 2009; Parshad, Skufca, Bollt, McGregor, & Busa, 2012). In this paper, we consider the implications of whole-body dynamics using RMS as a single linear measure to quantify the net magnitude of a continuous acceleration signal captured at high sample frequency. Such measures may provide athletes, coaches, and clinicians critical information regarding economy, technique, and running mechanics that may influence performance (McGregor, Busa, Yaggie, et al., 2009).

Despite widespread use, accelerometers have typically been validated against measures of energy expenditure using indirect calorimetry, room calorimetry, or doubly labelled water techniques (Bassett, Rowlands, & Trost, 2012; Chen & Bassett, 2005). These approaches to determine the reliability and validity of low-resolution accelerometers are likely sufficient if the goal is to monitor general physical activity, but high-resolution applications may require a different approach. The reliability and validity of accelerometers for RMS measurement has been established against optical motion capture for walking (Henriksen, Lund, Moe-Nilssen, Bliddal, & Danneskiod-Samsøe, 2004; Moe-Nilssen, 1998b, 1998c), yet there are differences in walking and running movement patterns that warrant a specific focus on running. One difference is a higher magnitude of the raw signal and a plateau in vertical accelerations at higher running speeds (McGregor, Busa, Yaggie, et al., 2009). Additionally, the surface mounting of accelerometers may make them more susceptible to soft tissue vibration during running compared to walking. Thus, if accelerometers are to be used to determine differences in overall movement magnitude between groups during running, it is necessary to assess their reliability and validity.

Three-dimensional optical motion capture is a standard laboratory method to quantify the kinematic characteristics of running gait and other exercise movements (Holden, Selbie, & Stanhope, 2003). Optical motion capture uses the global (horizontal–vertical) axis system rather than the body (cranial–caudal) axis system, which is subject to variable tilt due to the lumbar curve and forward lean of the trunk (Moe-Nilssen, 1998a). Correction of this tilt is possible, but it is only an estimate (Moe-Nilssen, 1998a). Optical motion capture, not being subject to these issues, may therefore be used as a criterion standard for the validation of other devices (Wundersitz, Gastin, Richter, Robertson, & Netto, 2015). Several studies focusing on running kinematics have been performed utilising a wireless accelerometer (Chapman et al., 2012; McGregor et al., 2011; McGregor, Busa, Skufca, et al., 2009; McGregor, Busa, Yaggie, et al., 2009; Parshad et al., 2012), but there are no data in the literature to establish the agreement between this device and optical motion capture for RMS acceleration measurement of running gait. Therefore, the purpose of this study was to first establish the between-trial and within-trial reliability of this accelerometer and then to determine the validity of this accelerometer using optical motion capture as the criterion standard. We hypothesised that accelerometer measurement would be highly reliable and agree with optical motion capture to a suitable precision necessary to identify important differences in acceleration found in common research comparisons. These results would provide an external reference for data collected in previous studies, as well as a justification for the further use of the device in future field-based research.

Methods

Participants

Fifteen healthy, active, college-age individuals (11 males, 4 females) volunteered to participate in this study. Participants had $M \pm SD$ age 23.7 ± 4.7 years, height 1.74 ± 0.09 m, mass 70.1 ± 10.3 kg, and BMI 23.2 ± 2.4 kg/m^2. The procedures of this study were approved by the College of Health and Human Services Human Subjects Review Committee at Eastern Michigan University. Participants were screened for medical contraindications and provided written informed consent prior to study participation.

Data collection

One triaxial wireless accelerometer node (G-Link model ADXL 210, ± 10 g [gravitational acceleration], LORD Microstrain Sensing Systems, Williston, VT, USA) was positioned dorsally, in line with the top of the iliac crest (McGregor, Busa, Yaggie, et al., 2009). This sensor consisted of internal circuitry enclosed in a 58 × 43 × 21 mm casing, plus an antenna extending a bit outside the dimensions and adding 18 mm to the thickness (mass = 47 g). The accelerometer was mounted to a semi-rigid strap, and secured with elastic wrap to

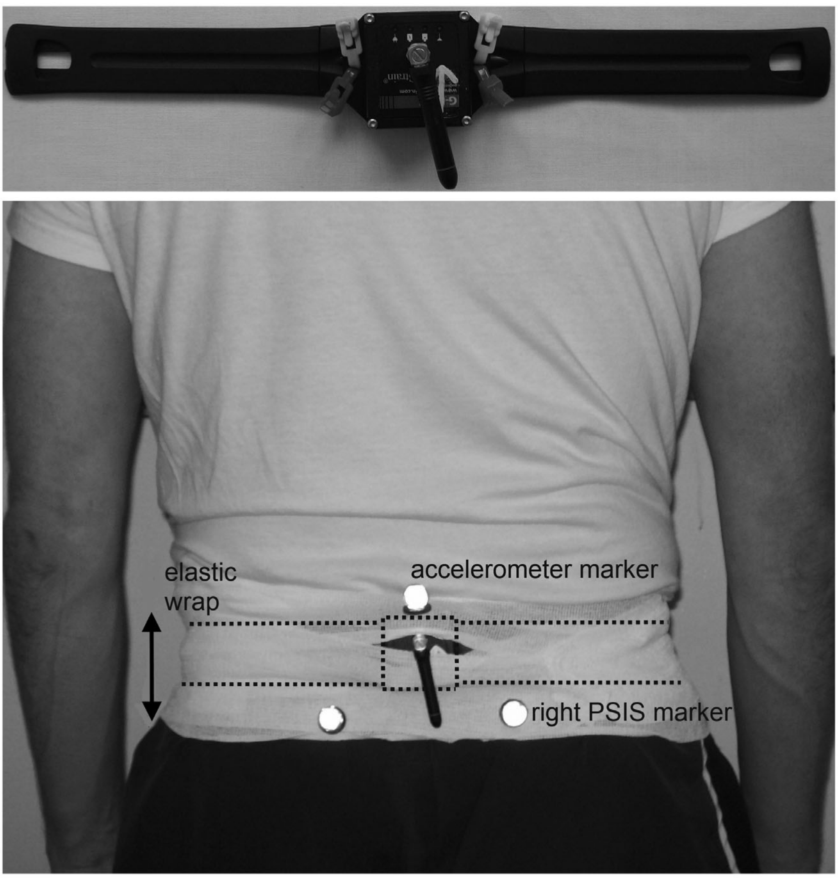

Figure 1. Participant set-up showing accelerometer/custom mounting strap (top), and location of elastic wrap, accelerometer, and reflective markers (bottom).

minimise extraneous movement of the device (Figure 1). Accelerometer data (units of g) were streamed wirelessly at 617 Hz to software (Agilelink, LORD Microstrain Sensing Systems, Williston, VT, USA), and stored for subsequent analysis.

A three-dimensional optical motion capture system (Vicon MX, Vicon, Centennial, CO, USA) was used to measure the trajectory of a reflective marker that was affixed to the superior surface of the accelerometer. Because of its availability as part of a 39-marker whole-body model (data not analysed for this paper), we also examined the marker pertaining to the right posterior superior iliac spine (PSIS) as an additional criterion standard (Figure 1). Seven cameras (Vicon T40 and T40 S) were placed roughly equidistant to the treadmill (maximum distance from camera to centre of treadmill was approximately 6 m). Motion capture data were captured at 200 Hz.

The running trials were conducted on a motorised treadmill (Woodway Pro, Woodway, Waukesha, WI, USA). Participants first completed one long trial at 2.78 m/s, sufficient to generate five 30-s epochs (150 s total), and then two sets of three short trials at 2.22, 2.78, and 3.33 m/s, sufficient to generate 60 s of data in each. The lowest speed was just above the walk–run gait transition, and the range of speeds would be considered moderate for this general sample of college-age participants. For the short trials, speeds were in random order for the first set and this order was duplicated in the second set. Participants were given as much rest between trials as they desired (typically 60–180 s). For technical reasons, it was not possible to collect five epochs worth of data in the long trial for one participant. Thus, data were analysed for 14 participants in the long trial and 15 participants in the short trials.

Data analyses

The motion capture system provided displacement data in units of mm, and acceleration data in units of mm/s^2 from doubly differentiated displacement data. Displacement data were first filtered with a fourth-order Butterworth filter with a low-pass cut-off at 10 Hz. Accelerometer data were converted into units of g, re-sampled at 200 Hz, and filtered similarly to correspond with the motion capture data.

Corrections needed to be made for the tilt of the accelerometer during running because the device is not perfectly aligned relative to the medio-lateral (ML), anterio-posterior (AP), and vertical (VT) axes of the global coordinate system (as opposed to the body coordinate system). Although it is not possible to determine the instantaneous orientation of the device, the average tilt over the entire trial can be estimated. The method assumes a constant angle between the accelerometer and the horizontal plane, and therefore a constant static gravity component (Moe-Nilssen, 1998a). For large datasets, the mean value of the acceleration vector ($\bar{\mathbf{a}}$) approaches the sine of that vector's angle (θ), so it is possible to make corrections in the following sequence according to the method of Moe-Nilssen (1998a):

$$\mathbf{a}_{\mathrm{APcorr}} = \mathbf{a}_{\mathrm{APmeas}} \cdot \cos\theta_{\mathrm{AP}} - \mathbf{a}_{\mathrm{VTmeas}} \cdot \sin\theta_{\mathrm{AP}} \tag{1}$$

$$\mathbf{a}_{\mathrm{VTprov}} = \mathbf{a}_{\mathrm{APmeas}} \cdot \sin\theta_{\mathrm{AP}} - \mathbf{a}_{\mathrm{VTmeas}} \cdot \cos\theta_{\mathrm{AP}} \tag{2}$$

$$\mathbf{a}_{\mathrm{MLcorr}} = \mathbf{a}_{\mathrm{MLmeas}} \cdot \cos\theta_{\mathrm{ML}} - \mathbf{a}_{\mathrm{VTprov}} \cdot \sin\theta_{\mathrm{ML}} \tag{3}$$

$$\mathbf{a}_{\mathrm{VTcorr}} = \mathbf{a}_{\mathrm{MLmeas}} \cdot \sin\theta_{\mathrm{ML}} + \mathbf{a}_{\mathrm{VTprov}} \cdot \cos\theta_{\mathrm{ML}} + 1 \tag{4}$$

where corr, meas, and prov refer to the corrected, measured, and provisional terms, respectively. The static component of gravity was also eliminated by adding 1 g to the vertical acceleration value.[1] The average acceleration after correction for all axes is zero, which is correct for constant velocity forward running.

RMS acceleration for the ML, AP, and VT axes was then calculated for each epoch from each trial (McGregor, Busa, Yaggie, et al., 2009):

$$|a_{\mathrm{RMS}}| = \sqrt{\frac{1}{N}\sum_{I}^{N}|a_i|^2} \tag{5}$$

where **a** is the acceleration vector in the given axis and N is the number of samples in the data-set. The resultant Euclidian scalar variable was also calculated to represent the overall magnitude of body acceleration, which was also used for analysis (McGregor, Busa, Yaggie, et al., 2009):

$$\mathrm{RES}_{\mathrm{RMS}} = \sqrt{|\mathrm{ML}_{\mathrm{RMS}}|^2+|\mathrm{AP}_{\mathrm{RMS}}|^2+|\mathrm{VT}_{\mathrm{RMS}}|^2} \tag{6}$$

Statistical analysis

The protocol was designed to test repeatability due to biological movement and device consistency as well as technical agreement between devices. These procedures tested: (1) between-trial repeatability for the two short trials, (2) within-trial repeatability across the five epochs of the long trial, and (3) criterion validity based upon agreement between the accelerometer and optical motion capture of the accelerometer and right PSIS marker (short trials). Intraclass correlation coefficient (ICC) (Shrout & Fleiss, 1979) was used to assess repeatability. The ICC(3,1) method is appropriate for a fixed set of raters (i.e. each trial) and was used to assess between-trial repeatability. Here, data from trial 1 and trial 2 were compared for each axis (ML, AP, VT, and RES) and method (accelerometer device, accelerometer marker, and right PSIS marker). For within-trial repeatability, the ICC(3,5) method holds the same assumptions as ICC(3,1), but assesses the mean of five measurements (i.e. each epoch) for each axis and method. ICC results were interpreted using the verbal classifications proposed by Hopkins (2006).

Device agreement was quantified using a Bland–Altman analysis (Bland & Altman, 1986). This analysis quantifies bias (mean difference between devices) and 95% limits of agreement (LOA), such that 95% of the data are within two SD of the mean difference. Absolute and relative errors were also calculated, using optical motion capture as the true value. Specifically, the accelerometer device was compared with the accelerometer marker and with the right PSIS marker, for each axis. All processing and analysis was done using custom designed code in a Matlab environment (version R2013b, Mathworks, Natick, MA, USA), except error calculations, which were done in Excel 2007 (Microsoft, Redmond, WA, USA).

Results

Between-trial and within-trial reliability

Between-trial ICCs (Table I) for the accelerometer ranged from 0.89 to 0.97, depending on the axis. ICCs were from 0.90 to 0.92 for the accelerometer marker and from 0.84 to 0.96 for the right PSIS marker. Within-trial ICCs (Table I) were from 0.99 to 1.00 for all methods. These reliability measurements indicate *nearly perfect* (ICC ≥ 0.9) or *very high* (0.7 ≤ ICC < 0.9) repeatability (Hopkins, 2006).

Table I. Repeatability of accelerometer and optical motion capture.

	Between-trial (2 trials)[a]			Within-trial (5 epochs)[b]		
Axis	Accelerometer	Accelerometer marker	Right PSIS marker	Accelerometer	Accelerometer marker	Right PSIS marker
ML	0.95	0.92	0.84	0.99	0.99	0.99
AP	0.97	0.92	0.96	1.00	1.00	1.00
VT	0.89	0.90	0.89	1.00	1.00	1.00
RES	0.90	0.90	0.90	1.00	1.00	1.00

Notes: ML, medio-lateral; AP, anterio-posterior; VT, vertical; RES, resultant Euclidean scalar. See methods section for further description of ICC calculations.
[a]ICC(3,1)
[b]ICC(3,5).

Device agreement

Measurements from the accelerometer device and optical motion capture of the accelerometer marker are presented as scatter plots (Figure 2) and Bland–Altman plots (Figure 3). Bias (the mean difference between the two devices) was −0.03 to 0.03 g, depending on the axis (Table II). LOA were the largest for the AP axis (±0.12 g) and the smallest for the VT axis (±0.03 g). Accelerometer bias relative to the right PSIS marker was smaller than bias relative to the accelerometer marker for AP and RES and larger for ML and VT. The LOA of the accelerometer device were smaller for the accelerometer marker than for the right PSIS. Using the accelerometer marker as the true value, accelerometer measurement

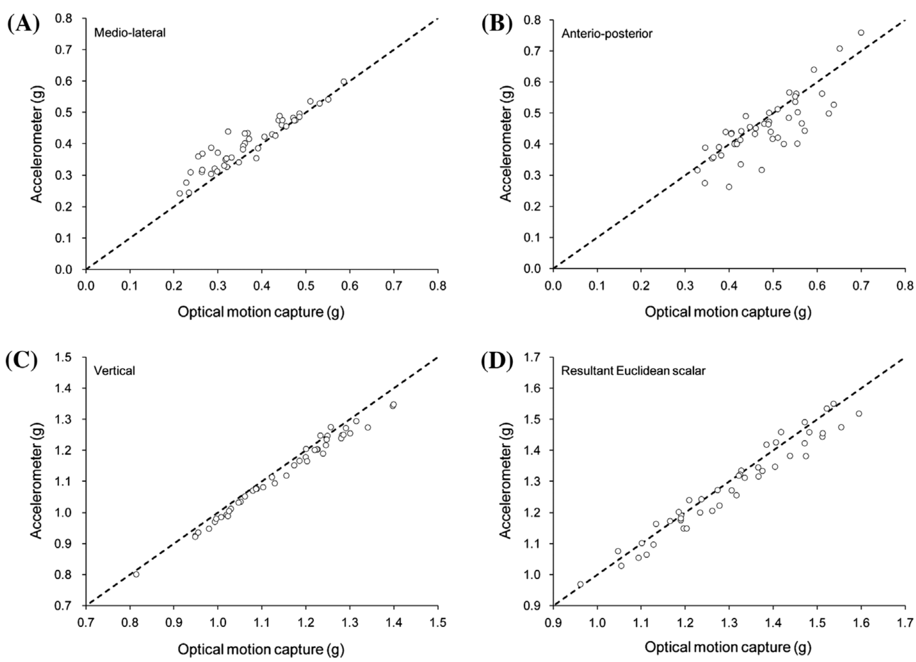

Figure 2. Accelerometer and optical motion capture of accelerometer marker for medio-lateral (A), anterio-posterior (B), vertical (C), and resultant Euclidean scalar (D). The line of equality is shown.

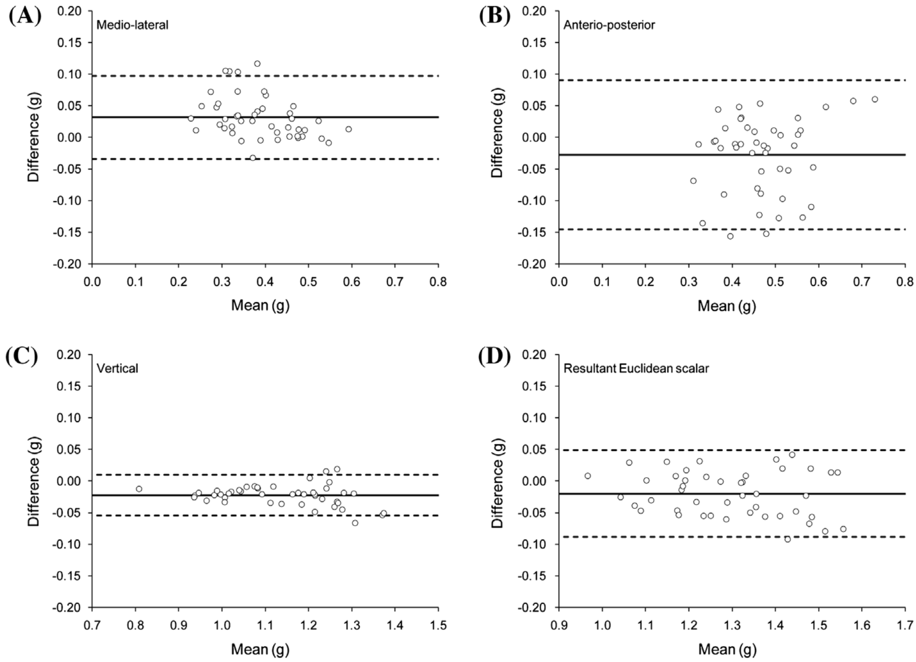

Figure 3. Bland–Altman plots representing agreement between accelerometer and optical motion capture of accelerometer marker for medio-lateral (A), anterio-posterior (B), vertical (C), and resultant Euclidean scalar (D). Lines indicate the mean difference (solid) and the 95% confidence interval of the LOA (dashed). *Difference* is accelerometer value minus optical motion capture value. *Mean* is mean value of the two devices. The scale is the same for each graph for ease of comparison.

Table II. Measures of accelerometer device agreement with optical motion capture.

	Agreement with accelerometer marker		Agreement with right PSIS marker	
Axis	Mean difference (g)	LOA (g)	Mean difference (g)	LOA (g)
ML	0.03	±0.07	0.09	±0.17
AP	−0.03	±0.12	0	±0.20
VT	−0.02	±0.03	−0.04	±0.09
RES	−0.02	±0.07	−0.01	±0.14

Notes: ML, medio-lateral; AP, anterio-posterior; VT, vertical; RES, resultant Euclidean scalar; LOA, 95% LOA. See methods section for further description of LOA.

had a mean absolute error from 0.02 to 0.05 g and a mean relative error from 2 to 12%, depending on the speed and axis (Table III). Error values were comparable when using the right PSIS marker as the true value, except for the medio-lateral axis, which showed greater error.

Discussion and implications

The use of accelerometers to assess human motion has grown tremendously in recent years. Although accelerometers have previously been validated against metabolic measures of

Table III. $M \pm SD$ acceleration RMS measurements by accelerometer and optical motion capture, with absolute and relative error.

		Measured RMS values			Accelerometer device error (vs. accelerometer marker)		Accelerometer device error (vs. right PSIS marker)	
Speed (m/s)	Axis	Accelerometer (g)	Accelerometer marker (g)	Right PSIS marker (g)	Absolute (g)	Relative (%)	Absolute (g)	Relative (%)
2.22	ML	0.34 ± 0.06	0.30 ± 0.07	0.25 ± 0.06	0.03 ± 0.03	12 ± 12	0.09 ± 0.04	38 ± 19
	AP	0.39 ± 0.06	0.41 ± 0.06	0.38 ± 0.04	0.04 ± 0.04	10 ± 10	0.03 ± 0.03	10 ± 7
	VT	1.07 ± 0.14	1.09 ± 0.15	1.10 ± 0.14	0.02 ± 0.01	2 ± 1	0.03 ± 0.02	3 ± 2
	RES	1.19 ± 0.14	1.21 ± 0.15	1.19 ± 0.14	0.03 ± 0.02	2 ± 2	0.02 ± 0.02	2 ± 1
2.78	ML	0.41 ± 0.06	0.37 ± 0.08	0.31 ± 0.07	0.04 ± 0.03	11 ± 13	0.10 ± 0.04	34 ± 17
	AP	0.46 ± 0.10	0.49 ± 0.08	0.46 ± 0.07	0.05 ± 0.05	10 ± 9	0.04 ± 0.03	9 ± 7
	VT	1.15 ± 0.12	1.17 ± 0.13	1.18 ± 0.12	0.02 ± 0.01	2 ± 1	0.04 ± 0.02	3 ± 2
	RES	1.30 ± 0.14	1.32 ± 0.14	1.31 ± 0.12	0.03 ± 0.02	2 ± 2	0.03 ± 0.02	2 ± 2
3.33	ML	0.46 ± 0.07	0.43 ± 0.09	0.36 ± 0.08	0.03 ± 0.03	9 ± 11	0.10 ± 0.05	31 ± 18
	AP	0.52 ± 0.09	0.55 ± 0.07	0.53 ± 0.07	0.05 ± 0.05	10 ± 8	0.05 ± 0.03	9 ± 6
	VT	1.16 ± 0.11	1.19 ± 0.12	1.21 ± 0.11	0.03 ± 0.01	2 ± 1	0.04 ± 0.03	4 ± 3
	RES	1.36 ± 0.13	1.38 ± 0.13	1.37 ± 0.12	0.04 ± 0.02	3 ± 2	0.03 ± 0.03	2 ± 2

Notes: Data from first trial; ML, medio-lateral; AP, anterio-posterior; VT, vertical; RES, resultant Euclidean scalar.

energy expenditure during running (Fudge et al., 2007; Halsey et al., 2008; McGregor, Busa, Yaggie, et al., 2009), this is the first study to establish the reliability and validity of a trunk-mounted high-resolution accelerometer against optical motion capture during running. In support of the hypotheses, the main findings of this study were: (1) the accelerometer demonstrated very high to nearly perfect repeatability, both between-trial and within-trial, and (2) the accelerometer showed good agreement with optical motion capture derived acceleration, when compared by axis.

The RMS acceleration data demonstrated very high to near perfect repeatability (Hopkins, 2006), both between two trials (separated by rest) and over five 30-s epochs within a single trial. This finding permits the following two conclusions. First, participant movement patterns and magnitudes were relatively stable over the time frames tested. Second, the accelerometer and motion capture methods both produced repeatable data (motion capture repeatability not shown). Thus, each method is internally consistent and may be used to track changes over time and between conditions.

The repeatability of the accelerometer signal now being established, the next consideration is whether the device is able to discriminate important differences in an experiment. This requires the bias or error to be smaller than real differences. We found that accelerometer bias and error was generally smaller than previously reported differences in overall movement magnitude between subject groups (Lin, Sung, Kuo, Kuo, & Chen, 2014; McGregor, Busa, Yaggie, et al., 2009). The mean difference between the accelerometer device and accelerometer marker (Table II) was –0.03 to 0.03 g, which is smaller than the measured increments in acceleration across speeds in the present study (at least 0.05 g, Table III) and those previously reported (at least 0.07 g) in trained and untrained runners (McGregor, Busa, Yaggie, et al., 2009). Mean absolute errors were of a similar magnitude.

The accelerometer bias relative to the right PSIS marker was slightly greater. The accelerometer marker was potentially subject to extraneous movement and vibration due to motion of the accelerometer device on the belt (even though efforts were made to minimise this). The right PSIS marker was not subject to as much potential extraneous movement because of the absence of accelerometer device momentum, but the movement of the skin still meant that the marker was not perfectly rigid with respect to the pelvis. Further, error between the accelerometer and right PSIS marker for the medio-lateral axis was higher than all other values, indicating that there was some side-to-side movement measured by the accelerometer that was not found for the right PSIS marker. This may be because the accelerometer is anatomically superior to the PSIS and is subject to greater effects of trunk rotation during running.

Our results were limited to a slower range of speeds that could be achieved by a general sample of participants largely untrained for running. The capability of young elite runners extends this range of speeds by 10 km/h or more, so future work should assess agreement and reliability in this range, especially given the increased error in peak acceleration measurement reported by Wundersitz et al. (2015) at speeds above the range we used. Additionally, there is a need for a more thorough investigation into RMS acceleration changes across this wider range of speeds and the accelerometer device resolution that would be required to discriminate each increment.

While accelerometers directly measure acceleration, motion capture systems measure marker trajectory displacement, which requires a *post hoc* calculation of acceleration. According to Giakas (2004), there is potential for increased error when displacement data are differentiated. Direct measurement by an accelerometer is not subject to such error. However, given the good agreement between the accelerometer and its associated reflective marker, we do not believe indirect measurement and subsequent differentiation imposes any significant error either. Thus, given this agreement, both methods are suitable for RMS acceleration measurement during running with appropriate filtering and geometric correction, where needed.

Acceleration peaks occurring each gait cycle contribute to the RMS value because they increase the spread of the data. The prominence of these peaks is affected by filtering. For example, a 10-Hz low-pass filter was shown to decrease peak acceleration by approximately 26% for running at 2.5–7.5 m/s and was ideal for comparison to peak ground reaction force values (Wundersitz, Netto, Aisbett, & Gastin, 2013). In the absence of established filter parameters for accelerometer–motion capture comparison, we applied a cut-off frequency of 10 Hz to both methods. This may not be ideal, since the two signals of not of the same type, so future work is needed to determine the ideal filter parameters for this comparison.

Correction of the accelerometer orientation is only possible for datasets large enough for the average acceleration value to converge (approximately 15 s for our data). The correction estimates the average tilt, so it is not possible to determine the device orientation at specific moments during the gait cycle. According to García-Pérez, Pérez-Soriano, Belloch, Lucas-Cuevas, and Sánchez-Zuriaga (2014), shock is attenuated by approximately 76% from the tibia to the head during unfatigued treadmill running at 4 m/s. Attenuation would be less at trunk level, so these peaks would contribute significantly to the RMS value. Accelerometer tilt thus affects the measured value of these peaks and optical motion capture is not subject to such limitations.

There are several practical benefits of accelerometer devices. The data-logging capability permits long duration field measurement, such as would be required for 10,000 m or marathon running races, and therefore is more likely to preserve ecological validity. Furthermore, triaxial accelerometers collect only three channels of data, instead of the trajectory of many more reflective markers. This focused data collection is more economical from a perspective of file size and computational expense. Consequently, while a comprehensive description of multiple body segments and joints is lost, what is gained is measurement of performance in real-world settings, which is useful for clinicians, coaches, and athletes alike. Data from only a few channels can also provide insight into integrative control mechanisms and constraints when analysed with non-linear methods (McGregor et al., 2011; McGregor, Busa, Skufca, et al., 2009; Parshad et al., 2012).

Conclusion

We are the first to examine the repeatability and validity of accelerometer measurement of RMS accelerations during running using optical motion capture as the criterion standard. For healthy college-age subjects, both biological movement patterns and technical measurements are stable and repeatable in treadmill running. The data suggest that the accelerometer device shows strong agreement with motion capture measurement of the device itself and is capable of discriminating real differences that have been previously reported. Measurements can be made with very little restriction to normal running movement. With the associated software, it is possible to provide real-time feedback about whole-body movement magnitude to the athlete or patient. Recent studies have established how acceleration is linked to economy of movement and gait characteristics; the above features of the device mean that these relationships may be assessed without the restrictions of a costly, lab-based measurement technique.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Note

1. We indicate an addition of 1 g to correct for gravity because the convention for the vertical axis is positive for up and negative for down. Moe-Nilssen (1998a) indicates a subtraction of 1 g to correct for gravity using the same axis convention, which we believe to be an oversight in that paper.

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References

Bassett, D. R., Mahar, M. T., Rowe, D. A., & Morrow, J. R. (2008). Walking and measurement. *Medicine and Science in Sports and Exercise, 40*(Suppl. 7), S529–36.

Bassett, D. R., Rowlands, A., & Trost, S. G. (2012). Calibration and validation of wearable monitors. *Medicine and Science in Sports and Exercise, 44*(Suppl. 1), S32–8.

Bland, J. M., & Altman, D. G. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *The Lancet, 327*, 307–10.

Butte, N. F., Ekelund, U., & Westerterp, K. R. (2012). Assessing physical activity using wearable monitors: Measures of physical activity. *Medicine and Science in Sports and Exercise, 44*(Suppl. 1), S5–S12.

Chapman, R. F., Laymon, A. S., Wilhite, D. P., Mckenzie, J. M., Tanner, D. A., & Stager, J. M. (2012). Ground contact time as an indicator of metabolic cost in elite distance runners. *Medicine and Science in Sports and Exercise, 44*, 917–25.

Chen, K. Y., & Bassett, D. R. (2005). The technology of accelerometry-based activity monitors: Current and future. *Medicine and Science in Sports and Exercise, 37*(Suppl. 11), S490–500.

Fudge, B. W., Wilson, J., Easton, C., Irwin, L., Clark, J., Haddow, O., … Pitsiladis, Y. P. (2007). Estimation of oxygen uptake during fast running using accelerometry and heart rate. *Medicine and Science in Sports and Exercise, 39*, 192–8.

García-Pérez, J. A., Pérez-Soriano, P., Belloch, S. L., Lucas-Cuevas, Á. G., & Sánchez-Zuriaga, D. (2014). Effects of treadmill running and fatigue on impact acceleration in distance running. *Sports Biomechanics, 13*, 259–66.

Giakas, G. (2004). Power spectrum analysis and filtering. In N. Stergiou (Ed.), *Innovative analyses of human movement* (pp. 223–58). Champaign, IL: Human Kinetics.

Halsey, L. G., Shepard, E. L. C., Hulston, C. J., Venables, M. C., White, C. R., Jeukendrup, A. E., & Wilson, R. P. (2008). Acceleration versus heart rate for estimating energy expenditure and speed during locomotion in animals: Tests with an easy model species, *Homo sapiens*. *Zoology, 111*, 231–41.

Henriksen, M., Lund, H., Moe-Nilssen, R., Bliddal, H., & Danneskiod-Samsøe, B. (2004). Test-retest reliability of trunk accelerometric gait analysis. *Gait & Posture, 19*, 288–97.

Holden, J. P., Selbie, W. S., & Stanhope, S. J. (2003). A proposed test to support the clinical movement analysis laboratory accreditation process. *Gait & Posture, 17*, 205–13.

Hopkins, W. G. (2006). A scale of magnitudes for effect statistics. Retrieved April 9, 2014, from www.sportsci.org/resource/stats/effectmag.html

Lin, S. -P., Sung, W. -H., Kuo, F. -C., Kuo, T. B. J., & Chen, J. -J. (2014). Impact of center-of-mass acceleration on the performance of ultramarathon runners. *Journal of Human Kinetics, 44*, 41–52.

McGregor, S. J., Busa, M. A., Skufca, J., Yaggie, J. A., & Bollt, E. M. (2009). Control entropy identifies differential changes in complexity of walking and running gait patterns with increasing speed in highly trained runners. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 19*, 026109.

McGregor, S. J., Busa, M. A., Parshad, R., Yaggie, J. A., & Bollt, E. (2011). Control entropy of gait: Does running fitness affect complexity of walking? *Clinical Kinesiology, 65*, 9–17.

McGregor, S. J., Busa, M. A., Yaggie, J. A., & Bollt, E. M. (2009). High resolution MEMS accelerometers to estimate VO2 and compare running mechanics between highly trained inter-collegiate and untrained runners. *PLoS ONE, 4*, e7355.

Moe-Nilssen, R. (1998a). A new method for evaluating motor control in gait under real-life environmental conditions. Part 1: The instrument. *Clinical Biomechanics, 13*, 320–7.

Moe-Nilssen, R. (1998b). A new method for evaluating motor control in gait under real-life environmental conditions. Part 2: Gait analysis. *Clinical Biomechanics, 13*, 328–35.

Moe-Nilssen, R. (1998c). Test-retest reliability of trunk accelerometry during standing and walking. *Archives of Physical Medicine and Rehabilitation, 79*, 1377–85.

Moe-Nilssen, R., & Helbostad, J. L. (2004). Estimation of gait cycle characteristics by trunk accelerometry. *Journal of Biomechanics, 37*, 121–6.

Parshad, R. D., Skufca, J. D., Bollt, E., McGregor, S. J., & Busa, M. A. (2012). A statistical approach to the use of control entropy identifies differences in constraints of gait in highly trained versus untrained runners. *Mathematical Biosciences and Engineering, 9*, 125–48.

Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin, 86*, 420–8.

Wundersitz, D. W. T., Gastin, P. B., Richter, C., Robertson, S. J., & Netto, K. J. (2015). Validity of a trunk-mounted accelerometer to assess peak accelerations during walking, jogging and running. *European Journal of Sport Science, 15*, 382–90.

Wundersitz, D. W. T., Netto, K. J., Aisbett, B., & Gastin, P. B. (2013). Validity of an upper-body-mounted accelerometer to measure peak vertical and resultant force during running and change-of-direction tasks. *Sports Biomechanics, 12*, 403–12.