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SlamTracker Accuracy under Static and Controlled Movement Conditions

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Accelerometry is the *de facto* standard in objective physical activity monitoring. However traditional accelerometer units undergo proprietary pre-processing, resulting in the 'black-box' phenomenon, where researchers are unaware of the processes and filters used on their data. Raw accelerometers where all frequencies related to human movement are included in the signal, would facilitate novel analyses, such as frequency domain analysis and pattern recognition. The aim of this study was to quantify the mean, standard deviation and variance of the SlamTracker raw accelerometer at a range of speeds. Four tri-axial accelerometers underwent a one minute static condition test nine movement condition tests. Accelerometers were assessed for mean, standard deviation, sample variance and coefficient of variation throughout in all axes for all experimental conditions. The sample variance was <0.001g across all speeds and axes during the movement condition tests. In conclusion, the SlamTracker is shown to be an accurate and reliable device for measuring the raw accelerations of movement.

Keywords: accelerometer, raw signal, accuracy, human movement, mechanical validation.

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Accelerometry is the most commonly applied method for objective assessment of physical activity in epidemiological studies (van Hees et al., 2012). Traditional accelerometer devices predominantly store a summary measure of the raw acceleration signal, termed an “activity count” (Corder et al., 2008). A count is a dimensionless unit aimed to be proportional to the average overall acceleration of the human body in a specified period of time, referred to as an “epoch” (Chen and Bassett, 2005). However, this relationship has been questioned due to the restrictive dynamic range of commercial accelerometers, the downstream signal processing and band-pass filtering (van Hees et al., 2012, Clark et al., 2016a). Such processing and filtering is designed to remove components of the signal unrelated to human movements (Brage, 2003, Rothney et al., 2008), however high frequency movement and noise information can escape the bandpass filter, which in turn adds unexplained variation in activity counts and incorrectly removes frequencies directly from human movement (Brond and Arvidson, 2015, Clark et al., 2016a).

There are a plethora of methods that exist to filter and summarise a raw acceleration signal, the choice of which has profound implications on the interpretation of the final output (Rowlands et al., 2007, van Hees et al., 2012). However, as traditional accelerometers are limited in memory and battery capacity to store raw signal data, data processing stages are performed on the device itself, and this process is irreversible once the count has been stored in local memory. This irretrievable conversion prevents re-analysis of the raw accelerometer signal using novel analytics and data processing techniques.

Although a detailed synopsis of the signal processing protocol employed would be vital to enable replication of empirical data, most manufacturers of accelerometer devices state that pre-processed raw data is proprietary information. This lack of transparency on the calculation of “activity counts” prevents a comparison between different accelerometer brands, or even between versions of the same brand (Corder et al., 2008, Rothney et al., 2008). On the other hand “activity counts” derived from a raw accelerometer have concordance with commercially developed devices ($r=0.93$, $P<0.05$), demonstrating the versatility of utilising the raw accelerometer signal (van Hees et al., 2012).

Using a raw accelerometer signal, where all frequencies related to human movement are included in the signal, would allow novel analyses, such as; pattern recognition, feature extraction, machine learning, cluster analysis, data mining to be undertaken, aided by the fact the Nyquist-Shannon sampling theorem is not violated (van Hees et al., 2012, Mannini and Sabatini, 2010). Further, given there is no hidden signal processing, researchers may maintain control and confidence in their outputs. So as raw accelerometers become more commonplace, it will be increasingly important to test their accuracy and variance during human movement, so device and human noise may be differentiated, and accuracy quantified (Clark et al., 2016a, Clark et al., 2016b).

The SlamTracker is a device that captures raw accelerometer signals without pre-processing the data, but has not been assessed in a controlled manner. Therefore, the aim of this study was to quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds.

Methods

Instruments and procedures

Four tri-axial accelerometers (ADXL345 sensor, Analog Devices) with a +/-16g dynamic range, 3.9mg point resolution and a 13 bit resolution underwent a one minute static condition test and were subsequently tested at nine movement conditions (three speeds at three radii), for one minute, on a motorised turntable (GPO Stylo, Manchester, UK), with speeds verified by digital tachometer (RS Digital Tachometer Model 445-9557, Corby, UK) (table 1).

	33.7 rpm	45.3 rpm	77.1 rpm
27 mm	0.09 $m{\cdot}s^{-1}$	0.13 $m{\cdot}s^{-1}$	0.22 $m{\cdot}s^{-1}$
56 mm	0.2 $m{\cdot}s^{-1}$	0.27 $m{\cdot}s^{-1}$	0.45 $m{\cdot}s^{-1}$
83 mm	0.29 $m{\cdot}s^{-1}$	0.39 $m{\cdot}s^{-1}$	0.67 $m{\cdot}s^{-1}$

Table 1. Movement test conditions

*27, 56, 83 denote the possible radii in millimetres, 33.7, 45.3, 77.1 denote the possible speed in revolutions per minute.

For the static condition each device was tested at 20, 40, 100 and 200 Hz, and only the sensitive axis (Z) was analysed due to the only force acting upon the accelerometer being gravity. All motorised turntable tests were performed at 40 Hz, with X, Y and Z axes being analysed. The decision to use 40 Hz was based on the results of the static condition test.

Data analysis

Raw acceleration data was uploaded into a comma separated values spreadsheet where all analyses took place. For the static condition, mean, standard deviation and coefficient of variation over the one-minute measurement were calculated for the Z axis amplitude, *g*.

For the movement test conditions; mean, standard deviation and coefficient of variation over each one minute test was assessed for all axes. Because axes can be subject to negative and positive *g* during movement, sample variance was calculated as the squared differences from the mean (equation 1).

Equation 1. Sample variance

$$\sigma^2 = \frac{\sum(X-\mu)^2}{N}$$

Where μ is the mean and N is the number of scores.

Results

Static condition

The static condition test demonstrated that the Z-axis amplitude coefficient of variation improved as recording frequency reduced (table 2). The mean Z-axis amplitude, offset to zero, across recording frequencies is shown in figure 1.

Frequency	Mean	SD	CV
200	0.918	0.009	0.01
100	0.923	0.004	0.005
40	0.904	0.004	0.004
20	0.913	0.004	0.004

Table 2. Static condition test

Mean (*g*), standard deviation and coefficient of variation (%) values for recording frequencies; 20, 40, 100 and 200 Hz, respectively.

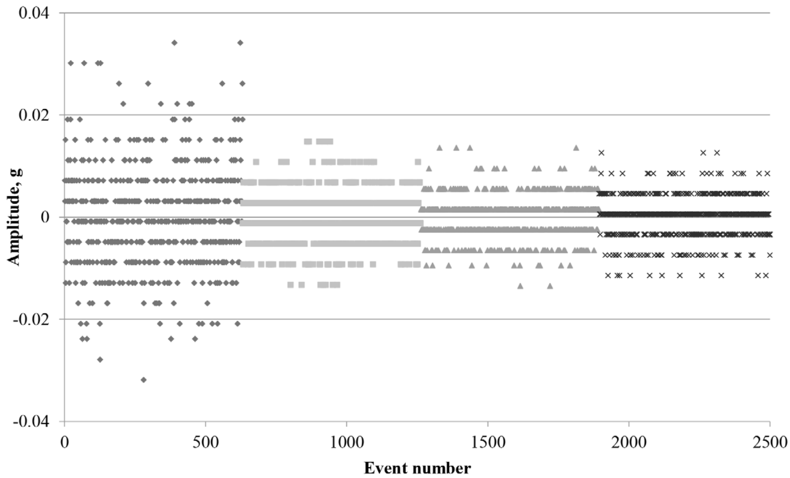

Figure 1. Amplitude for accelerometer Z-axis under no movement condition for different sampling frequencies.

Crosses denote device recordings at 20 Hz; closed triangles denote device recordings at 40 Hz, closed squares denote device recordings at100 Hz, closed diamonds denote device recordings at 200 Hz.

Movement conditions

The mean (SD) and sample variance for the X, Y and Z axes during all movement condition tests are detailed in table 3.

Axis	0.09 $m \cdot s^{-1}$	0.13 $m \cdot s^{-1}$	0.2 $m \cdot s^{-1}$	0.22 $m \cdot s^{-1}$	0.27 $m \cdot s^{-1}$	0.29 $m \cdot s^{-1}$	0.39 $m \cdot s^{-1}$	0.45 $m \cdot s^{-1}$	0.67 $m \cdot s^{-1}$
X (g)	-0.046 (0.02) <0.001	-0.025 (0.01) <0.001	-0.03 (0.01) <0.001	-0.001 (0.01) <0.001	-0.021 (0.01) <0.001	-0.028 (0.02) <0.001	-0.006 (0.02) <0.001	-0.007 (0.01) <0.001	-0.048 (0.02) <0.001
Y (g)	0.019 (0.01) <0.001	0.017 (0.01) <0.001	0.019 (0.01) <0.001	0.018 (0.02) <0.001	0.016 (0.01) <0.001	0.019 (0.01) <0.001	0.02 (0.03) 0.001	0.017 (0.02) <0.001	0.019 (0.01) <0.001
Z (g)	0.855 (0.02) <0.001	0.858 (0.02) <0.001	0.856 (0.02) <0.001	0.855 (0.02) <0.001	0.857 (0.02) <0.001	0.857 (0.02) <0.001	0.856 (0.02) <0.001	0.855 (0.02) <0.001	0.853 (0.02) <0.001

Table 3. Movement condition tests at nine speeds.

Mean accelerometer amplitude (g) (standard deviation) and sample variance (g) values are reported for all speeds and all axes.

Discussion

The aim of this study was to quantify the accuracy of the SlamTracker accelerometer at a range of speeds. This study found that during the static condition test 40 Hz had joint lowest CV and joint lowest SD (table 2). For the movement condition tests, the sample variance was <0.001g across all speeds and axes (table 3).

The static condition test was performed at a range of recording frequencies suitable for assessing physical activity (van Hees et al., 2012, Brage, 2003). It was found that as recording frequency was decreased, the coefficient of variation concomitantly improved, as did deviation from the mean. The highest recording frequency with the lowest coefficient of variation and lowest standard deviation was found at the 40 Hz recording frequency.

The movement condition tests found that, for all axes, the sample variance was less than 0.001 g across all speeds. This indicates that, irrelevant of speed, the SlamTracker accelerometer is reliably accurate and consistent, indicating no artefacts of the device are present during movement. This is an important finding as any artefacts or anomalies recorded during human movement assessment can be attributed to researcher error (i.e. affixing problems), tampering (i.e. participant moving device) or accidental damage (i.e. participant falling on device), as opposed to device error. Slaven et al. (2006) determined the quality of accelerometer data by applying *k*-means clustering to the raw acceleration signal mean and variance across specific, consecutive time points and reported data quality as 'good' or 'poor' by how the clustering algorithm grouped the data. Data were retained in the 'good' cluster if they were within ~6% of the cluster mean. The present study variance from the mean was under 1% for all axes and speeds, indicating all data points would be considered 'good'. Further, Tawk et al. (2013) reported accelerometer amplitude variance of <0.001 *g* during a static condition test, the present study, however, found similar low levels of variance in static and movement conditions.

This study comprehensively investigated the SlamTracker acceleration signal amplitude at predominantly slow speeds, ranging from static to slow ambulation. It has been suggested that in some previous studies with a mechanical calibration or validation component (i.e. (Brage, 2003, Ried-Larsen et al., 2012)), the mechanical device used only allowed very limited acceleration amplitude in the low frequency area (Brond, 2014). It was further suggested that utilising a device that can smoothly rotate at low speeds is of paramount importance when calibrating/validating accelerometers (Brond, 2014). The fact this study focussed predominantly on slow speeds is therefore a strength, as finding confidence in slow speeds demonstrates that subtle movements may be accurately attributed to human ambulation and not an artefact of device noise. It may be considered a limitation that the fastest speeds of human movement were not assessed in this study, however this device was subject to a broad band pass filter, up to 12 Hz, which has been vindicated by Wundersitz et al. (2015), who identified that filters at this frequency were most suitable to process accelerations in human running tasks, and filter out non-human motion. Further, although this is the first time the SlamTracker device has been mechanically validated, prior to human use, the SlamTracker has been extensively tested in biological tracking studies of multiple mammals, birds and ocean dwelling creatures of varying sizes (see; Wilson et al. (2007)).

Conclusion

This empirical investigation has quantified sample variance and deviation from mean values for the SlamTracker. This variance may be factored in to future analyses when using raw acceleration data. The SlamTracker demonstrates low variance and minimal deviation from mean values across an extensive range of slow speeds, and processes acceleration frequencies up to 12 Hz, and is therefore suitable for assessing human movement at very slow and fast speeds. Given the accuracy in static and movement tests for raw accelerometry, combined with its capability for novel analytics (Clark et al., 2016a), it is recommended that raw accelerometry be utilised over commercial devices that irretrievably pre-process data.

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Conflict of Interests

The authors declare that there are no conflict of interests regarding the publication of this paper.

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