Accelerometer wear-site detection: when one site does not suit all, all of the time

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Abstract

Objectives: Choice of accelerometer wear-site may facilitate greater compliance in research studies. We aimed to test whether a simple method could automatically discriminate whether an accelerometer was worn on the hip or wrist from free-living data. **Design:** Cross-sectional. **Methods:** Twenty-two 10-12 y old children wore a GENEActiv at the wrist and at the hip for 7-days. The angle between the forearm and the total acceleration vector for the wrist-worn monitor and between the pelvis and the total acceleration vector for the hip-worn monitor (i.e. the angle between the Y-axis component of the acceleration and the total acceleration vector) was calculated for each 5 s epoch. The standard deviation of this angle (SDangle) was calculated over time for the wrist-worn and hip-worn monitor for windows of varying lengths. We hypothesised that the wrist angle would be more variable than the hip angle. **Results:** Wear site could be discriminated based on SDangle; the shorter the time window the lower the optimal threshold and area under the receiver-operating-characteristic curve (AUROC) for discrimination of wear-site (AUROC = 0.833 (1 min) - 0.952 (12 h)). Classification accuracy was good for windows of 8 min (sensitivity = 90%, specificity = 87%, AUROC=0.92) and plateaued for windows of ≥ 60 min (sensitivity and specificity $>90\%$, AUROC = 0.95-0.96). **Conclusions:** We have presented a robust, computationally simple method that detects whether an accelerometer is being worn on the hip or wrist from 8-60 minutes of data. This facilitates the use of wear-site specific algorithms to analyse accelerometer data.

Keywords: hip, wrist, GENEActiv, activity monitor

Introduction

Over the past few years there has been a burgeoning market for consumer-level wearable physical activity monitors. In order to maximise usability, several manufacturers of consumer-level devices offer multiple wear locations. For example, the *Fitbit One* and *Zip*, the *Withings Pulse* and the *Striiv Smart* Pedometer all offer the hip and pocket as wear-site options; the *Misfit Shine* and *Flex* version of the *Fitbit* also offer the wrist as a further wear-site option.

Conversely, until recently, research-grade accelerometers were most commonly worn close to the centre of gravity of the body at a standardized location, usually at the hip, in order to reflect whole body movement and thus energy expenditure¹. Recently, concerns regarding low compliance to hip-wear in research studies have led to a shift to the wrist as the preferred site. Research-grade accelerometers designed to be worn at the wrist or hip are now widely available (e.g. *ActiGraph*, *GENEActiv* and *Axivity*) and large physical activity surveillance projects worldwide collect accelerometer data at the wrist, for example National Health and Nutrition Examination Survey (NHANES) in the USA,² Biobank in the UK (<http://www.ukbiobank.ac.uk/about-biobank-uk/>), Brazilian birth cohorts³ and the Growing up in Australia Checkpoint.⁴

Although most participants appear to prefer a wrist-worn monitor,^{5,6} there is evidence that some favour a hip-worn monitor⁵ and preference may sometimes depend on what people are doing. Offering participants a choice of wear-sites in research studies may facilitate greater compliance during a monitoring period. Although correlated,⁷ accelerometer output differs by wear-site with, for example, higher magnitudes generally found at the wrist.^{7,8,9} Therefore, to be able to offer research participants this option it would be necessary to be able to automatically detect wear site to enable wear-site specific analytical approaches to be applied to the data.^{10,11,12}

Auto-detection of wear-site would facilitate wear-site specific analysis of accelerometer data without having to rely on participant self-report. Because acceleration magnitudes at the hip and wrist are highly correlated, wear-site detection should be based on features other than magnitude. Several available methods depend on the detection of walking in order to determine wear-site¹³⁻¹⁵, as when a participant

is sedentary the variability in the accelerations recorded at different sites is low. Although walking is a prevalent activity, relying on the occurrence of free-living walking restricts when and how wear-site can be determined. Further, these methods have been developed in laboratory and or semi-structured conditions over relatively short periods of time and involve relatively sophisticated analytical methods, e.g. Support Vector Machine classifiers (SVM^{13,14,15}), and Random Forests.¹⁶ Development of methods using free-living participants is important as laboratory-based validity is typically not replicated when applied to free-living data.^{17,18} We hypothesised that variability in monitor orientation would be an effective and computationally inexpensive indicator of wear-site as, during a given time window, the wrist will likely undergo a wider and more variable range of orientations than the hip, irrespective of the activities undertaken.

The objective of this ‘proof of concept’ study was to develop a method for the automatic discrimination of hip and wrist wear-sites from accelerometer data and examine its accuracy in free-living data when applied to time windows of varying length. We proposed the two following hypotheses to test in free-living 10-12 y old children:

1. Across a given period of time, the wrist experiences a wider range of orientations than the hip. This difference in the variability of orientation will allow the determination of wear site from accelerometer data and facilitate the application of wear-site specific algorithms to the accelerometer data.
2. Accuracy of wear site detection will be highest for long time windows and will decrease as window size decreases.

Methods

Twenty-two boys (N = 12) and girls (N = 10), aged 10-12 y (age: 11.2 ± 0.6 y (mean $\pm$ SD), mass: 42.1 ± 14.5 kg, height: 1.48 ± 0.06 m) were recruited from schools in the Adelaide region of South Australia. The institutional ethics committee granted approval (Ethics Protocol 0000026929) and written informed consent and assent were obtained from the parents/guardians and children, respectively

Each participant wore two *GENEActiv* accelerometers, one at the hip and one at the wrist, for seven consecutive days. The hip monitor was worn on a belt worn round the waist positioned above the right hip, with its vertical axis (Y-axis) pointing down. The wrist monitor was worn on the non-dominant wrist (left wrist N = 19, Y-axis pointing towards the fingers; right wrist N = 3, Y-axis pointing towards the elbow). Children were instructed to wear both monitors continually day and night, but to remove the hip monitor for water-based activities to avoid the belt becoming soggy. Due to the wristband on the wrist monitor and taping of the hip monitor to the waist belt, the hip and wrist monitors were not interchangeable without it being apparent when the monitors were returned. Examination of the monitors and fittings on return confirmed no child switched the monitors.

The *GENEActiv* is a triaxial accelerometry-based activity monitor with a dynamic range of +/- 8g (Gravity Estimator of Normal Everyday Activity, ActivInsights Ltd, Cambridgeshire, UK). All monitors were time synchronised, and programmed to start collecting data at midnight on the day the child was given the monitors. Data were collected at 85.7 Hz, allowing over seven days of continuous recording, and uploaded using *GENEActiv* PC software version 2.2.

Accelerometer data processing: Raw acceleration data (85.7 Hz) expressed in g were averaged over 5 s epochs. The following metrics were computed for each epoch:

The magnitude of the acceleration vector, or Euclidian Norm EN:

$$EN = \sqrt{a_X^2 + a_Y^2 + a_Z^2};$$

The Euclidian Norm Minus One (ENMO), acceleration magnitude with gravity removed, with negative values set to 0:¹⁹

$$ENMO = \sqrt{a_X^2 + a_Y^2 + a_Z^2} - 1, ENMO(ENMO < 0) = 0;$$

The angle θ between the Y-axis component of the acceleration and the total acceleration vector:

$$\theta = \arccos\left(\frac{a_Y}{EN}\right);$$

Finally, the standard deviation SD_{θ} of θ over time windows of various lengths was calculated. Windows' lengths were 12 h, 4 h, 2 h, 1 h, 30 min, 15 min, 8 min, 4 min, 2 min and 1 min. Our pilot work indicated that SD_{θ} could discriminate between hip and wrist wear-site when applied to 12 h of data; these window sizes were selected to explore the change in accuracy as the window size was reduced.

The underlying hypotheses are that: 1. For the majority of epochs, gravity represents the largest part of the recorded acceleration, therefore, θ is an estimate of the angle between the Y-axis of the accelerometer and the vertical; and 2. Independently of activity levels, the upper limbs (and therefore, the monitors positioned on the wrist) experience wider ranges of orientations than the pelvis, and therefore, SD_{θ} will be higher for the wrist monitors.

Excess data beyond the seven days of wear were excluded and data between 9 pm and 9 am for each day were removed to focus the analyses on waking daytime wear, i.e. when wear-site may be switched. In order to remove periods of non-wear, 5-s epochs where $ENMO < 0.001$ (10^{-3} g) for both hip and wrist were excluded, leaving only periods where both monitors were worn concurrently. In the study by Phillips et al.,²⁰ the mean output from the wrist monitor for children during lying was equivalent to approximately 25 mg over a 1-s epoch, with 5 mg being greater than two standard deviations below the mean. A threshold of 10^{-3} g is therefore very unlikely to remove periods of sedentary activities.

All data processing was carried out in MATLAB R2012b (The MathWorks, Inc., Natick, Massachusetts, United States, code available in Supplementary material. (TO BE PROVIDED IF MANUSCRIPT ACCEPTED)).

Data analyses: Univariate binary logistic regression models were fitted with the wear-site as the dependent variable and SD_{θ} as the independent variable. Receiver-Operating-Characteristic (ROC) analyses were implemented to derive the optimum SD_{θ} thresholds for wear-site classification. Analyses were carried out for each time window (12 h, 4 h, 2 h, 1 h, 30 min, 15 min, 8 min, 4 min, 2 min, 1 min). Performances were summarised by calculating the area under the ROC curves (AUROC) and the thresholds were examined for validity by conducting a leave-one-out-cross-validation (LOOCV) - which assesses the performance of the model on unseen data.²¹ The optimal threshold for each time

window was defined as the threshold that maximised the sum of sensitivity (wrist-wear detected correctly) and specificity (hip-wear detected correctly).

Statistical analyses were carried out using Stata/IC V13.1 (Stata Corporation, College Station, Texas, USA).

Results

Participants had 6.7 ± 0.96 days of apparently continuous and equivalent wear of the hip- and wrist-worn monitors between 9 am and 9 pm. The standard deviation of the angle, SD_{θ} , for different time windows, is shown on Figure 1 (time windows = 1, 2, 4, 8, 15, 30, 60 and 120 min for one representative participant). As can be seen, SD_{θ} is higher overall at the wrist than at the hip, confirming our hypothesis that the wrist experiences a greater range of orientations than the hip during any given time window. Moreover, the longer the time window, the higher the optimal threshold is. The optimal threshold and corresponding sensitivity, specificity, AUROC and LOOCV results for differentiating between hip and wrist-wear are given for each time window in Table 1. Sensitivity increased as the duration of the time window increased, but specificity remained fairly constant. Overall, classification accuracy was good for time windows of 8 min (sensitivity = 90%, specificity = 87%, AUROC = 0.92) and very good for time windows of 60 min or more, with AUROC >0.95 and sensitivity and specificity >90% (except for the 720 min window where sensitivity was 100%, but specificity was 88%). The LOOCV procedure indicated robustness and stability as the high performance was maintained.

Discussion

We have presented a method for the automatic detection of accelerometer wear-site based on assessment of the variability in monitor orientation. The method is analytically very simple and results indicate it has a high level of accuracy for differentiating between hip- and wrist-wear. Auto-detection of accelerometer wear-site facilitates wear-site specific analysis of accelerometer data^{10,11,12} without the need for metadata. Furthermore, providing research participants with the option to choose and change

wear-site within a monitoring period, with the provision of appropriate waistbands and wrist straps, may reduce the frequency and duration of non-wear, particularly during sleep.

The variability in orientation of the device is greater at the wrist than the hip and this can be exploited to detect wear-site with high accuracy ($>90\%$ sensitivity and specificity, $AUC = 0.95$), when considering windows of 60 min or more. Unpublished data from our laboratory indicate the duration of monitor removal for sporting activities is often lower than 60 min (median 55 min, 25th-75th %ile 30-71 min), suggesting that the capture of windows as short as 15-30 minutes is desirable. Accuracy for an 8 min window was still acceptable (sensitivity 90%, specificity 87%, $AUC = 0.92$). The effect of the duration of the time window on the accuracy of wear-site detection across time was more notable for the wrist-site than the hip-site; accuracy of wrist-wear detection increased from 74% for a 1-min time window to 92% for a 15-min time window, while corresponding accuracy for hip-wear detection was 86% and 88%. The higher error rate for detecting true wrist-wear from short time windows makes sense; it is possible for the wrist to remain in one orientation over a given period of time, and the likelihood increases with shorter time windows. Conversely, it is unlikely that the orientation of the hip monitor will be highly variable over even short periods of time as the orientation of the pelvis is much more constrained.

The LOOCV indicated our results exhibited excellent robustness and stability for our population of 10-12 y old children. However, we acknowledge that this study is limited by a relatively small, homogenous sample and focused on daytime wear only; the proposed method should be cross-validated in external samples and tested in diverse populations to assess generalizability to other populations. It is likely that the optimal time window required for a given level of accuracy of wear-site detection will vary across populations. For example, a sedentary population may need different time windows to obtain the optimal balance of accuracy for both hip and wrist wear-site detection.

Strengths of the method proposed include its analytical simplicity and its development in a free-living sample over large amounts of data. Previous methods have shown the capability to distinguish between five wear-sites with high accuracy ($>90\%$) over shorter time windows, e.g. within one minute of

walking, using SVM.¹³ An advantage of the current method is it does not rely on the detection of walking first. Further, the method is robust across free-living data, and relatively independent of activity level. Previous methods have typically been developed using a range of specific activities performed for set durations under controlled conditions.^{13,14,16,22,23,24} From a practical perspective, monitor removal tends to occur for periods of 30 minutes or greater (unpublished data from our laboratory), so the ability to discriminate between hip and wrist wear-sites from 8 minute windows of data would appear to be more than sufficient.

Previous research has considered the detection of multiple wear-sites including the wrist, hip, waist, torso, arms, legs, trouser pockets and head.^{13,14,16,22,23,24} This study focused only on the wrist and the hip, as these wear-sites are widely used by research devices.

Conclusions

We present a simple method that can accurately discriminate between hip and wrist wear from 8-60 minutes of free-living data in 10-12 y old children. The method is robust, computationally very simple and facilitates the use of wear-site specific algorithms to analyse activity monitor data. The next steps are to test the performance of the method for detecting a change in wear-site within a monitoring period and assessing the accuracy of the method in other populations.

Practical Implications

- The hip and the wrist are the most widely used wear-sites for accelerometers
- As accelerometer output differs by wear-site it is necessary to know which wear-site is used prior to analysis
- Whether the monitor is worn at the hip or wrist can be determined automatically from the variability in the orientation of the monitor
- The method is computationally simple and, in children, can be used with similar accuracy on time windows of 8-60 min

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Figure legends

Figure 1: The variability in hip (black) and wrist (dashed) angle (angle SD) for a representative participant across one day assessed over 1 (a), 2 (b), 4 (c), 8 (d), 15 (e), 30 (f), 60 (g) and 120 (h) min windows with the optimal angle SD threshold for discriminating between hip- and wrist-wear marked in black.

Table 1. The optimal threshold and corresponding sensitivity, specificity, AUROC and LOOCV results for differentiating between hip and wrist-wear for each time window.

	Time window									
	12 h	4 h	2 h	1 h	30 min	15 min	8 min	4 min	2 min	1 min
Angle SD threshold	52.2	55.7	52.5	47.6	39.0	34.8	27.9	22.9	15.7	10.5
Sensitivity	100%	95%	94%	94%	95%	92%	90%	86%	80%	74%
Specificity	88%	93%	92%	90%	83%	88%	87%	88%	87%	86%
AUROC ^a (95% CI)	0.952 (0.916, 0.988)	0.960 (0.941, 0.977)	0.961 (0.949, 0.974)	0.951 (0.942, 0.961)	0.918 (0.910, 0.927)	0.930 (0.924, 0.937)	0.917 (0.9125, 0.922)	0.899 (0.895, 0.902)	0.870 (0.8673, 0.8727)	0.833 (0.8303, 0.8347)
LOOCV AUROC ^b	0.949 (0.912, 0.987)	0.959 (0.940, 0.977)	0.961 (0.948, 0.973)	0.951 (0.941, 0.961)	0.918 (0.909, 0.927)	0.930 (0.924, 0.936)	0.917 (0.912, 0.922)	0.899 (0.895, 0.902)	0.870 (0.867, 0.8726)	0.832 (0.830, 0.835)
Observations	206	640	1246	2492	4982	9948	18586	37248	74414	148230

^aArea under Receiver-Operating-Characteristic curve

^bLeave-One-Out-Cross-Validation Area under Receiver-Operating-Characteristic curve