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A Transparent Method for Step Detection using an Acceleration Threshold

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Abstract

Step-based metrics provide simple measures of ambulatory activity, yet device software either includes undisclosed proprietary step detection algorithms or simply do not compute step-based metrics. We aimed to develop and validate a simple algorithm to accurately detect steps across various ambulatory and non-ambulatory activities. Seventy-five adults (21–39 years) completed seven simulated activities of daily living (e.g., sitting, vacuuming, folding laundry) and an incremental treadmill protocol from 0.22–2.2ms^{-1}. Directly observed steps were hand-tallied. Participants wore GENEActiv and ActiGraph accelerometers, one of each on their waist and on their non-dominant wrist. Raw acceleration (g) signals from the anterior-posterior, medial-lateral, vertical, and vector magnitude (VM) directions were assessed separately for each device. Signals were demeaned across all activities and bandpass filtered [0.25, 2.5Hz]. Steps were detected via peak picking, with optimal thresholds (i.e., minimized absolute error from accumulated hand counted) determined by iterating minimum acceleration values to detect steps. Step counts

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were converted into cadence (steps/minute), and k-fold cross-validation quantified error (root mean squared error [RMSE]). We report optimal thresholds for use of either device on the waist (threshold=0.0267g) and wrist (threshold=0.0359g) using the VM signal. These thresholds yielded low error for the waist (RMSE<173 steps, ≤2.28 steps/minute) and wrist (RMSE<481 steps, ≤6.47 steps/minute) across all activities, and outperformed ActiLife's proprietary algorithm (RMSE=1312 and 2913 steps, 17.29 and 38.06 steps/minute for the waist and wrist, respectively). The thresholds reported herein provide a simple, transparent framework for step detection using accelerometers during treadmill ambulation and activities of daily living for waist- and wrist-worn locations.

Keywords

physical activity monitor; accelerometer; step algorithm; physical activity; wearable devices

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In recent decades, the technology underlying wearable activity monitor devices has surged in popularity and accessibility. For this reason, scientists regularly incorporate both research- and commercial-grade activity monitor devices into their physical activity (PA) research. The monitoring hardware varies in complexity from simple mechanical pedometers to piezo-electric or piezo-resistive accelerometers and microelectromechanical systems (MEMS). Accelerometry has gained the strongest foothold as the hardware of choice for quantifying PA.

In terms of PA activities, walking is the most commonly reported mode of exercise (Hulteen et al., 2017) and a functional part of daily mobility (Tudor-Locke & Rowe, 2012). Further, a step is the fundamental unit of walking in all its forms and purposes. Thus, step-based metrics (e.g., steps/day, steps/min) offer a simple, practical, and reliable measure of enacted ambulatory activity (Bassett Jr. et al., 2017) as well as various measures of health (Hall et al., 2020; Kraus et al., 2019). Accurate quantification of steps taken during human locomotion is an intuitive approach to quantifying accumulated ambulatory behaviors. Most consumer- and research-grade activity monitor devices and corresponding software offer step counting as a common measurement feature (e.g., ActiLife specific to ActiGraph™ Inc., Pensacola, FL, USA). Moreover, because step counts can be reported in epochs of 1 second to 1 minute, researchers can easily determine step rate (i.e., cadence or steps/minute). This feature is important because cadence is strongly associated with metabolic intensity (Tudor-Locke et al., 2019; Tudor-Locke & Rowe, 2012). Moreover, the 2018 Physical Activity Guidelines Advisory Committee (*2018 Physical Activity Guidelines Advisory Committee Scientific Report*, 2018) and subsequent follow-up studies (Kraus et al., 2019) recognized steps/day as a metric of growing importance to public health, but also urged increased study of cadence (steps/min), or what they called step frequency.

The predominant obstacles researchers face when attempting to use step-based metrics are that proprietary step detection algorithms are either inaccurate (e.g., ActiGraph step detection (Toth et al., 2018)), require *a priori* input of critical information such as acceleration thresholds (i.e., the minimum acceleration value that constitutes a step) and activity mode (e.g., R function 'stepCounter' from package GENEAclassify for use with

GENEActive monitors), or are simply not offered (e.g., GENEActiv software (Activinsights Ltd., Cambridgeshire, UK)). Additionally, most of the step detection literature is limited by the range of ambulation speeds measured. For example, some researchers have assessed walking only at participants' normal (Vaha-Ypya et al., 2018) or slow speeds (Munoz-Organero & Ruiz-Blazquez, 2017). Moreover, much of the literature has assessed walking for very brief periods of time, such as 25m overground walks and 30 sec treadmill bouts (Zijlstra & Hof, 2003), or simply 10m (Del Din et al., 2016), 12m (McCamley et al., 2012), 13.6m (Dijkstra et al., 2010), or 15m (Menz et al., 2003) overground walks. Thus, providing researchers with a versatile and transparent framework for detecting steps from accelerometer-based signals during prolonged walking bouts may support comparison between studies using different devices. Additionally, one challenging goal for physical activity researchers is to be able to quantify step detection during free-living behavior. Because free-living behavior entails various movements in addition to known bouts of ambulation, inclusion of activities that are not strictly ambulatory (e.g., sedentary seated, sedentary standing, sporadic stepping) are also recommended to more appropriately capture stepping behavior (Welk, 2019; Welk et al., 2019). Thus, the purpose of this study was to develop an acceleration threshold and an easily understood and transparent algorithm for use with two commonly used devices that provide raw acceleration data, GENEActiv and ActiGraph, to accurately detect steps across a range of treadmill walking speeds and simulated activities of daily living (SADLs).

Methods

Participants

The data reported herein were derived from the CADENCE-Adults Study (Tudor-Locke et al., 2019) (registered with Clinicaltrials.gov [NCT02650258]). Seventy-five healthy adults (49% men, mean ± SD age = 29.57 ± 5.56 [range 21–39] years, height =170.48 ± 9.25 cm, mass =72.39 ± 14.11 kg, BMI =24.77 ± 3.49 kg/m^2) provided written informed consent to participate. Procedures were approved by the University of Massachusetts Amherst's Institutional Review Board.

Protocol

Participants first performed seven SADLs including; seated rest, watching a movie, computer work, standing while folding laundry, vacuuming, stair pacing (ascent and descent of a single stair), and overground corridor walking at preferred speed. These SADLs were chosen to represent various general categories of physical activities, including sedentary sitting, sedentary standing, intermittent bouts of stepping and/or walking, and purposeful stepping and/or walking. Participants then performed a progressive treadmill protocol starting at 0.22 m*s^{-1} (i.e., 0.5 mph) and increasing in 0.22 m*s^{-1} increments until they: 1) chose to run; 2) reported a rating of perceived exertion (RPE; (Borg, 1982)) exceeding thirteen; 3) exceeded 75% of their age-predicted maximum heart rate (HRmax); or 4) completed the fastest included speed condition (2.68 m*s^{-1}, i.e., 6.0 mph). During treadmill bouts, participants were instructed to not hold the hand rails, and to swing their arms as they normally would during waking. Each SADL and treadmill bout lasted 5 minutes, followed by a 2-minute seated or standing rest.

Data Collection

Throughout each timed activity, steps were directly observed and hand-tallied. A step was defined as an event in a standing posture in which a foot is picked up off the ground and placed back on the ground in a different location (Bassett Jr. et al., 2017). A redundant video recording was collected to verify tallied step counts. Each participant wore a GENEActiv and ActiGraph GT9X accelerometer device on their waist near the right anterior superior iliac spine, as well as on their non-dominant wrist, with the ActiGraph placed medial and proximal to the GENEActiv at the waist and wrist, respectively. GENEActiv and ActiGraph data were collected at sample rates of 60 Hz and 80 Hz, respectively. The choice of 80 Hz sample rate for the ActiGraph was to align with national survey (National Health and Nutrition Examination Survey [NHANES] 2011–2014) data. In addition to exporting raw acceleration data for both devices, step data from the ActiGraph proprietary algorithm within ActiLife (Version 6, ActiGraph Inc., Pensacola, FL, USA) were exported in 1-second epochs.

Data Analysis: Step Detection Threshold (SDT)

The algorithm for determining the step detection threshold (SDT, i.e., the minimum acceleration value needed to be treated as a 'step'; see Figure 1) used raw acceleration data from ActiGraph and GENEActiv devices. Acceleration data are reported in gravity units or g's; one g is equivalent to 9.81 m*s^{-2}, i.e., the acceleration due to gravity. Data were assessed separately for each monitor and acceleration direction (i.e., vertical (V), anterior-posterior (AP), and medial-lateral (ML)), as well as vector magnitude (VM), as defined by:

$$VM = \sqrt{V^2 + AP^2 + ML^2} \qquad \text{Equation (1)}$$

Accelerometers are sensitive to device orientation. For example, an accelerometer's V signal will read −1 g when held perfectly parallel to the gravity vector. However, if the device is tilted at all, the signal value decreases in the V direction and increases in one or both other directions. Thus, to account for an accelerometer's dependence on device orientation, the mean acceleration value was first subtracted from the entire time series (i.e., all activities). Data were then band pass filtered at 0.25 and 2.5 Hz using a 4th order, zero-lag, dual-pass Butterworth filter. The choice of these filter thresholds was based on estimating ActiGraph's thresholds via reverse-processing acceleration outputs provided by ActiLife (unpublished), and because these thresholds intuitively make sense, as the 0.25 Hz high pass filter reduces signal drifts and the 2.5 Hz low pass filter removes frequencies that are less likely to occur. Peaks were identified from the detrended, filtered signal using a straight-forward peak picking algorithm that identified signal direction shifts of increasing acceleration followed by decreasing (i.e., positive peaks, defined if $a_i > a_{i-1}$ and $a_{i+1;}$ where a = acceleration signal at data point i); for more details and code using R-Notebook, see Supplemental Digital Content 1). Finally, an acceleration 'threshold' or minimum acceleration value was included with the goal of removing errant peaks. All peaks that occurred below this acceleration threshold were discarded and not counted as a step (Figure 1). To obtain the optimal threshold, acceleration threshold values were iteratively adjusted between 0.0 and

0.2g by 0.005g increments. This wide range was chosen to ensure the optimal threshold would be included and obtained. Step counts for each threshold iteration were compared to hand-tallied step totals across all activities. The threshold that yielded the lowest absolute error compared to hand-tallied step counts was obtained for each participant and then averaged across participants to obtain a single threshold value.

Previous acceleration-based studies have traditionally used either the V or VM signals (Migueles et al., 2017). As mentioned above, the main issue with using the V signal (or any single direction for that matter) is that it is sensitive to device orientation or position (Evenson et al., 2015). From a qualitative perspective, we confirmed this notion when visualizing the different signals; the values were dependent upon orientation. Overall, multi-axis accelerometers are believed to enhance the ability to detect PA movement compared to single axis analyses (Evenson et al., 2015). Moreover, tri-axial accelerometry is necessary to be sensitive enough to capture PA during sedentary activities such as sitting (Westerterp, 2009). Ultimately, we argue that the VM signal is the most robust because it is less sensitive to orientation and provides the most comprehensive representation of movement. Thus, we focus our analysis on the VM signal. For the sake of completeness and transparency though, we tested and report on the raw acceleration data from every direction (i.e., V, AP, ML, and VM).

Statistical Approach

We assessed and report both steps and cadence (steps/min). Cadence was included to account for different overall data lengths (e.g., some participants achieved 4.5 mph walking while others only achieved 2.5 mph before a termination criterion was met) and because it provides a scaled version of step count (i.e., rate of stepping error detection). We then calculated cadence error (BIAS), mean absolute percent error (MAPE), and root mean square error (RMSE) using the optimal thresholds (i.e., average of the best individual thresholds) for each device, wear location, and acceleration direction. We then averaged the device thresholds for the VM direction to provide a single value for each location (waist and wrist) and reassessed BIAS, MAPE, and RMSE. We also computed BIAS, MAPE, and RMSE from the step data provided by the ActiLife software.

To assess the accuracy of the candidate SDT, a repeated k-fold cross-validation was performed (k=5 with 10 repetitions). For this analysis, the data set (n=75) was divided into five equally-sized groups of participants (n=15). The mean optimal threshold across four of the groups (n=60) was treated as the 'training set', and the remaining group (n=15) served as the 'testing set.' The testing set yielded cadence error values (BIAS, MAPE, and RMSE). The error and training thresholds were averaged across the five iterations (folds) for each repetition, and then averaged across the 10 repetitions to obtain a single mean and standard deviation. The same k-fold cross-validation assessment was performed on the step data from the ActiLife software. Considering the data that is not cross-validated may be influenced by 'overfitting' (Staudenmayer et al., 2012), RMSE (steps/min) for each device and wear location are reported from these k-fold cross-validated results.

Results

The results of the optimal acceleration SDTs for the waist and wrist using the VM direction are presented in Table 1. The waist SDTs for the GENEActiv and ActiGraph, respectively, were (mean ± SD) 0.0314 ± 0.0121 g and 0.0220 ± 0.008 g. The wrist SDTs for the GENEActiv and ActiGraph, respectively, were 0.0372 ± 0.018 g and 0.0345 ± 0.019 g. The complete list of results across all directions, wear locations, and devices are reported in Supplemental Digital Content 2. Based on the results of the k-fold cross validation analysis (Table 2), the SDT for the waist yielded RMSE of 172.28±2.54 steps and 2.28±0.03 steps/min for the GENEActiv, and 145.59±2.77 steps and 1.92±0.04 steps/min for the ActiGraph. RMSE for the wrist was 392.34 ±2.09 steps and 5.25± 0.03 steps/min for the GENEActiv and 480.30± 2.93 steps and 6.47± 0.04 steps/min for the ActiGraph. For comparison, the ActiGraph proprietary algorithm yielded 1,311.94±1.06 steps and 17.29±0.01 steps/min for the waist location, and 2,913.37±1.25 steps and 38.06±0.01 steps/min for the wrist location.

When averaging the thresholds into a single value for each location, RMSE values for the waist (SDT = 0.0267g) were 207.92 steps and 2.74 steps/min for the GENEActiv, and 163.16 steps and 2.15 steps/min for the ActiGraph. For the wrist (SDT = 0.0359g), RMSE values were 384.23 steps and 5.11 steps/min for the GENEActiv, and 405.66 steps and 5.38 steps/min for the ActiGraph (Table 1).

Activity-specific BIAS step and cadence errors are presented in Figure 2 and Tables 3 and 4, with positive and negative numbers representing overestimation and underestimation of steps, respectively. For the waist, the SDTs outperformed the ActiGraph proprietary algorithm for the active SADLs (i.e., vacuuming, stair pacing, and corridor walking displayed, respectively, ≥ 172, 203, and 31.3 steps and ≥ 34.4, 40.6, and 6.12 steps/min error with ActiGraph proprietary compared to the SDTs using either device) and the very slow (i.e., 0.5–2.0 mph ranged from 34.9–255 steps and 6.98–55.9 steps/min greater error) and fast (i.e., 4.5 mph > 18.23 steps and > 3.64 steps/minute greater error) treadmill speeds (Figure 2, Table 3). Moreover, the SDTs displayed comparable error values for sedentary activities (i.e., seated, computer work, and watching a movie ranged from 0.19–3.14 steps and 0.04–0.62 steps/minute lower error with ActiGraph proprietary) and common walking speeds (e.g., between 2.5–4.0 mph ranged from 2.4–7.4 steps and 0.48–1.49 steps/minute greater error;). Compared to the ActiGraph proprietary algorithm, the best performance from the waist SDT was during vacuuming, stair pacing, and treadmill walking at 0.5, 1.0, and 1.5 mph (BIAS error = −1.86, −7.90, −0.24, 0.50, 4.85, and 0.39 steps/minute, respectively, for the SDT using the ActiGraph device, compared to the ActiGraph proprietary BIAS error = −38.01, −48.51, −6.50, −44.33, −55.91, and −45.00 steps/minute, respectively).

For the wrist, the SDT using either device outperformed the ActiGraph proprietary algorithm for all treadmill bouts (BIAS error ranged from 87.9–303.1 steps and 17.59–60.97 steps/minute greater error), stair pacing (≥ 255.4 steps and ≥ 55.6 steps/minute error), and corridor walking (≥ 271.1 steps and ≥ 54.2 steps/minute error, Figure 2, Table 4). Comparable error scores were observed for vacuuming (1.93 steps/minute less and 9.37 steps/minute greater error compared to the SDT using the ActiGraph and GENEActiv devices, respectively). The only activity in which the ActiGraph proprietary algorithm outperformed the SDT for both devices was during laundry (204.4 and 187.1 steps and 40.88 and 37.41 steps/minute less error compared to the SDT using the ActiGraph and GENEActiv devices, respectively).

Discussion

The purpose of this study was to develop an acceleration threshold and an easily understood and usable algorithm for use with GENEActiv and ActiGraph devices to detect steps during treadmill walking and various SADLs on both the waist and wrist. While all of the thresholds (i.e., each unique combination of device, wear location, and acceleration direction) and their corresponding error performance can be found in Supplemental Digital Content 2, we focus on a single SDT for the waist (SDT = 0.0267g, RMSE ~ 2.4 steps/min), and wrist (SDT = 0.0359g, RMSE ~ 5.2 steps/min) using the VM signal. These waist SDTs produced more accurate step counting than the ActiGraph proprietary algorithm during the active SADL bouts (> 200 steps and 40.6 steps/min greater accuracy) and very slow or fast walking speeds (< 2.5 and > 4.0 mph, respectively, > 250 steps and > 50 steps/min accuracy). Similar error scores were obtained for all algorithms during the sedentary SADLs and normal walking speeds. For the wrist, the SDTs outperformed the ActiGraph proprietary algorithm in every SADL and treadmill walking speed except laundry folding. Overall, The SDTs herein represent a straight-forward, computationally efficient measure to calculate step counts in laboratory-based measurements of treadmill walking and SADLs. The acceleration thresholds reported can be implemented by executing the script in the included Supplemental Digital Content 1 to obtain a total step count. In addition, ActivInsights currently offers a step counting function called ‘stepCounter’ within the R package GENEAclassify. This function could also be used for step detection using the parameters reported herein (i.e., acceleration threshold, filter boundaries, or filter method).

The reported SDTs clearly outperformed ActiGraph’s proprietary algorithm. The high error observed with the ActiGraph wrist (RMSE = 27.18 steps/minute, MAPE = 44.0%) aligns with a recent study reporting a mean percentage error score of ~ 41% (Chow et al., 2017), as well as a recent scoping review of the literature, (MAPE range of 21.8–47.25% across treadmill speeds of 1.0–3.5 mph) (Moore et al., 2020) . For ActiGraph proprietary algorithm waist accuracy, our findings (RMSE = 11.15 steps/minute, MAPE = 13.37%) generally agree with previous reports. Hickey and colleagues (Hickey et al., 2016) reported 8% step counting bias error during rhythmic activities (i.e., walking between ~1.5–4.5 mph and running at ~6.0 mph), and 38% and 57.5% error during non-rhythmic and sedentary activities, respectively. Chow et al. (2017) reported low bias error values at around −0.3% during walking and running treadmill speeds between ~3.1–7.5 mph. Figure 2 and Table 3 illustrate that the ActiGraph waist proprietary algorithm performed poorly at very slow (BIAS error between −44.33 and −45.00 steps/minute from 0.5–1.5 mph) and fast (BIAS error −4.17 steps/minute at 4.5mph) speeds, as well as during SADLs such as vacuuming (BIAS error −38.01 steps/minute) and stair pacing BIAS error −48.51 steps/minute). These treadmill speed-based findings align with recent reports of ActiGraph performance (Moore et al., 2020).

This study was certainly not the first to attempt to use raw acceleration signals to detect steps. Among the various approaches, a common method used is continuous wavelet transform (Del Din et al., 2016; Godfrey et al., 2015; Hickey et al., 2017; McCamley et al., 2012; Pham et al., 2017), which is a financial expense if using MATLAB, as it requires an additional toolbox ('Wavelet toolbox, $500/year, https://www.mathworks.com/pricing-licensing.html?prodcode=WA) in addition to the annual MATLAB fees (Education license = $250/year, https://www.mathworks.com/pricing-licensing.html?prodcode=ML&intendeduse=edu). It should be noted that ~ 80% of colleges and universities do not offer MATLAB to faculty or students free of charge. van Hees and colleagues argued that one important approach to enhance harmonization of physical activity research methodologies is to reduce costs associated with the methods used (van Hees et al., 2016). Additionally, the continuous wavelet transform method is commonly not described in detail, leaving naïve researchers to work from a 'black box' mentality. The benefit of the simple, open-source method proposed herein is that it does not require signal processing savvy to understand how step detection is being determined.

Another important limitation in the step algorithm literature mentioned earlier is that most studies detected steps only during known bouts of ambulation (Fortune et al., 2014; Fortune et al., 2015), with some studies further restricting activities to specific walking speed ranges (e.g., slow (Munoz-Organero & Ruiz-Blazquez, 2017) or 'normal' (Vaha-Ypya et al., 2018) walking speeds). Furthermore, most studies only capture short bouts of ambulation. For example, Ziljstra and Hof (2003) developed their algorithm using accelerometer data during a 25m overground walk and six treadmill walking bouts of 30 seconds each. Godfrey et al (2015) evaluated 2 minutes of walking, averaging ~ 240 total steps, while Del Din et al (2016) assessed four 10-meter walks at preferred walking speed. Dijkstra et al (2010) instructed participants to follow a 13.6m course, as well as various 15m walks. Menz and colleagues (2003) evaluated two 15m walking trials, while McCamley et al (2012) assessed three 12m trials. Purposeful, rhythmic movements such as continuous walking represent only a small portion of one's overall (or even ambulatory) PA throughout a day (Tudor-Locke et al., 2011). For an algorithm to be able to accurately determine accumulated steps over the course of an entire day, it must have the sensitivity to detect steps during other, less well-defined, sporadic and incidental movements, and the specificity to minimize false positive detection. Developing thresholds based on 'normal' walking speeds (e.g., 0.89–1.34 $m*s^{-1}$ (2–3 mph)) will likely underestimate step counts performed during activities of daily living or slow walking. Conversely, developing an algorithm that accurately detects steps during SADLs, especially those involving sedentary or light intensity behavior, will likely overestimate ambulatory movement. To more accurately capture overall steps, the method should be sensitive to minor changes in accelerations observed during slow walking or non-rhythmic stepping, such as those observed during vacuuming, yet not too sensitive to inaccurately flag noise components as steps. The threshold developed to produce the least overall error in this study was determined from a wide range of activities, including sedentary and light-intensity SADLs and light- and moderate-intensity treadmill walking. This type of approach was recently recommended as the most appropriate way to sample one's general PA, and that assessing only known ambulation do not take into account all other motion during SADLs that occur throughout the day (Welk, 2019).

A recent study investigating the use of an accelerometer to determine postural orientation also reported a step detection algorithm (Vaha-Ypya et al., 2018). The algorithm developed in that study performed different signal processing methods than those reported herein. Briefly, data in that study were first low-pass filtered at 0.5 Hz using a 2nd order Butterworth filter, then the scalar product was used to obtain the vertical acceleration, which was band-pass filtered using 1 and 4 Hz cutoffs again using a 2nd order Butterworth filter, and finally integrated to estimate the impulse. Step detection was based on the integrated signal in gravity seconds (gs). The gs value selected to detect a step was 0.03 gs within 0.5 seconds. It was not clear how the researchers arrived at this threshold, but it is notable that this value was similar to the V direction (reported in Supplemental File 2; 0.0321 and 0.0319 for GENEActiv and ActiGraph, respectively), especially considering the between-study methodological differences. While it may be of interest to explore this threshold value of ~ 0.03 as being ubiquitous for step counting, further knowledge of the methods used to obtain their utilized threshold are first needed.

We acknowledge that the SDTs for the wrist still underestimate steps across various ambulation speeds (e.g., cadence error range 8.25–25.69 steps/minute underestimation between 2.5–4.5 mph; Table 3) and largely overestimated the laundry folding condition (cadence error >73 steps/minute, Table 3). Wrist-based device error has been consistently reported previously. For example, Toth and colleagues (2018) reported MAPE values ranging from 25.1–30.4% when comparing the ActiGraph proprietary algorithm to the criterion measure of video recording. For this reason, we recommend a continued effort by researchers to either use waist-based technologies or continue to develop and establish more accurate wrist-based step detection. Nonetheless, it should be noted that the wrist-based SDTs offered herein still greatly improved upon ActiGraph's proprietary algorithm (e.g., cadence error > 60 steps/minute walking at 1.5–4.0 mph, Table 3, Figure 2).

Limitations

The reported SDTs were tested using a specific set of scripted SADLs and treadmill-based activities. This laboratory-based design requires further evaluation under free-living conditions. However, the inclusion of SADLs extends our understanding of step detection algorithms beyond those based simply on brief and intentional walking bouts alone. While the study by Hickey and colleagues (2017) valiantly evaluated simulated free living context, only ~ 600 steps per participant on average were assessed. Future studies should follow the direction of Toth and colleagues (2018) by assessing this and other step detection algorithms relative to criterion measures such as video or an ankle-worn StepWatch in the free-living setting.

These thresholds were also determined using GENEActiv's and ActiGraph's 'raw' acceleration data. We compared raw accelerometer data from two devices, presuming that the two devices have similar or identical hardware (and, thus, corresponding raw data). Although the outputs are similarly labeled as 'raw' accelerations with the same units (g), this statement is likely inaccurate (John & Freedson, 2012; John et al., 2013; Okely et al., 2018). For example, as of 2012, ActiGraph's GT3X model restricted all accelerations (including those labeled as raw outputs) to those greater than 0.05 g and less than 2 g

(John & Freedson, 2012). Assuming the GT9X retained its acceleration range and reduction from the previous model, the output signals may not be raw but rather represent ‘clipped’ data. As a result, the acceleration thresholds reported herein may only be applicable to the specific devices used in this study. However, it’s worth noting that ultimately the thresholds were similar between devices, and thus the average threshold reported herein may still be generalizable to other scenarios.

Conclusion

Using device-labeled raw acceleration data, we determined waist- and wrist-specific acceleration thresholds that can be used with an open-source, intuitive algorithm to determine step events from numerous SADLs and treadmill walking bouts at various speeds in adults aged 21–39 years. The thresholds performed well (cross-validated RMSEs ~158 and 436 steps and ~2.1 and 5.8 steps/minute for the waist and wrist, respectively) and performed better than the proprietary step detection algorithm provided by ActiGraph (RMSE ~1312 and 2913 steps and 17 and 38 steps/minute for the waist and wrist, respectively). Researchers may choose to utilize the reported optimal thresholds specific to the ActiGraph and GENEActiv devices, or they may use the average threshold across devices. In either case, the differences in error are negligible. In any case, these thresholds reported herein will allow researchers collecting acceleration data to incorporate step-based metrics with considerably better accuracy than what is currently available from device manufacturers.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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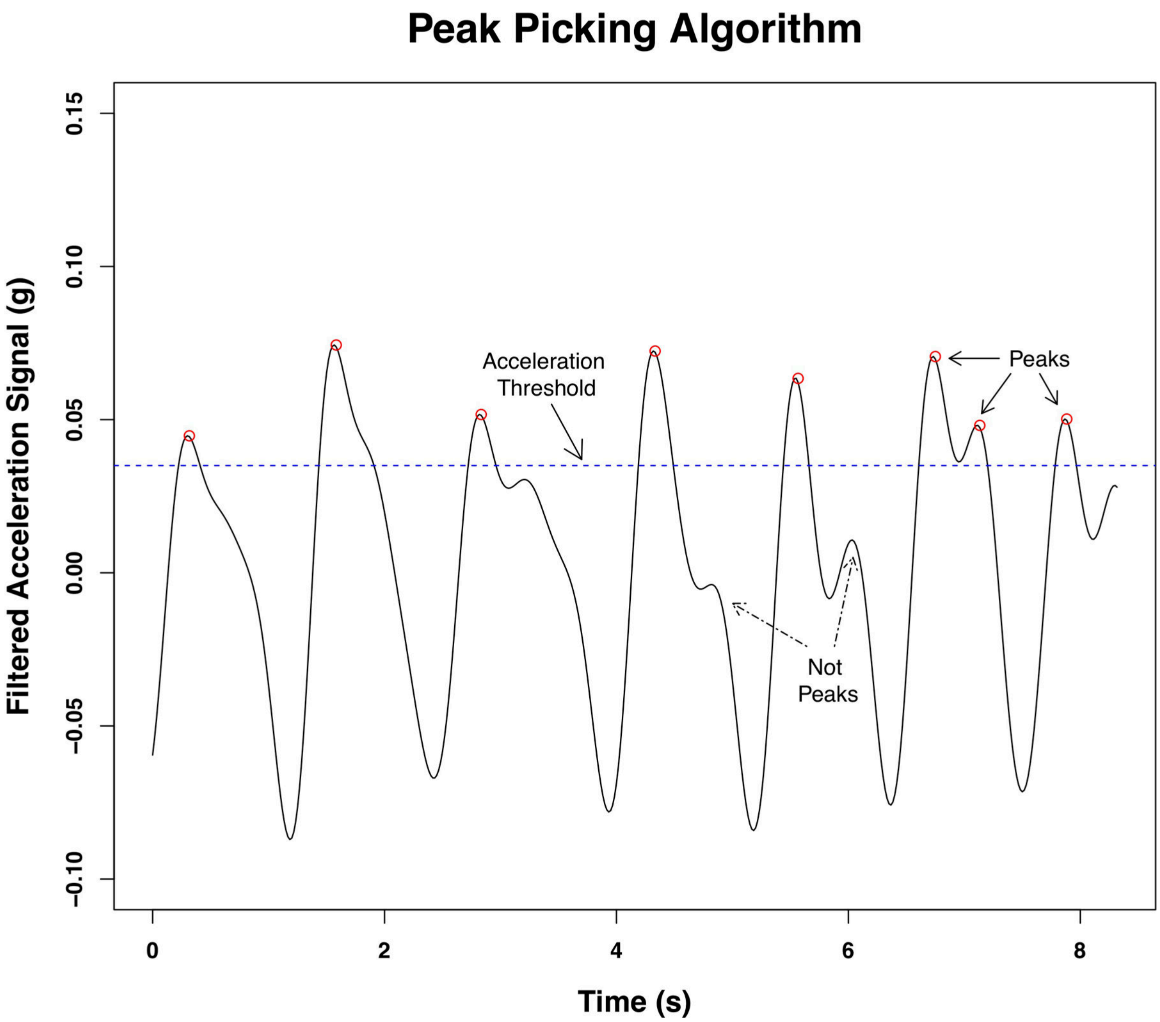

Figure 1:

Peak picking algorithm using time series acceleration signals. Peaks (red circles) were identified by definitive characteristics of the signal whereby the acceleration value is lower than the data point immediately preceding and following the point. Moreover, only peaks that occurred above a predefined value (i.e., acceleration threshold, represented here by the blue dashed horizontal line at an arbitrary value of y = 0.035 g) were accepted as peaks

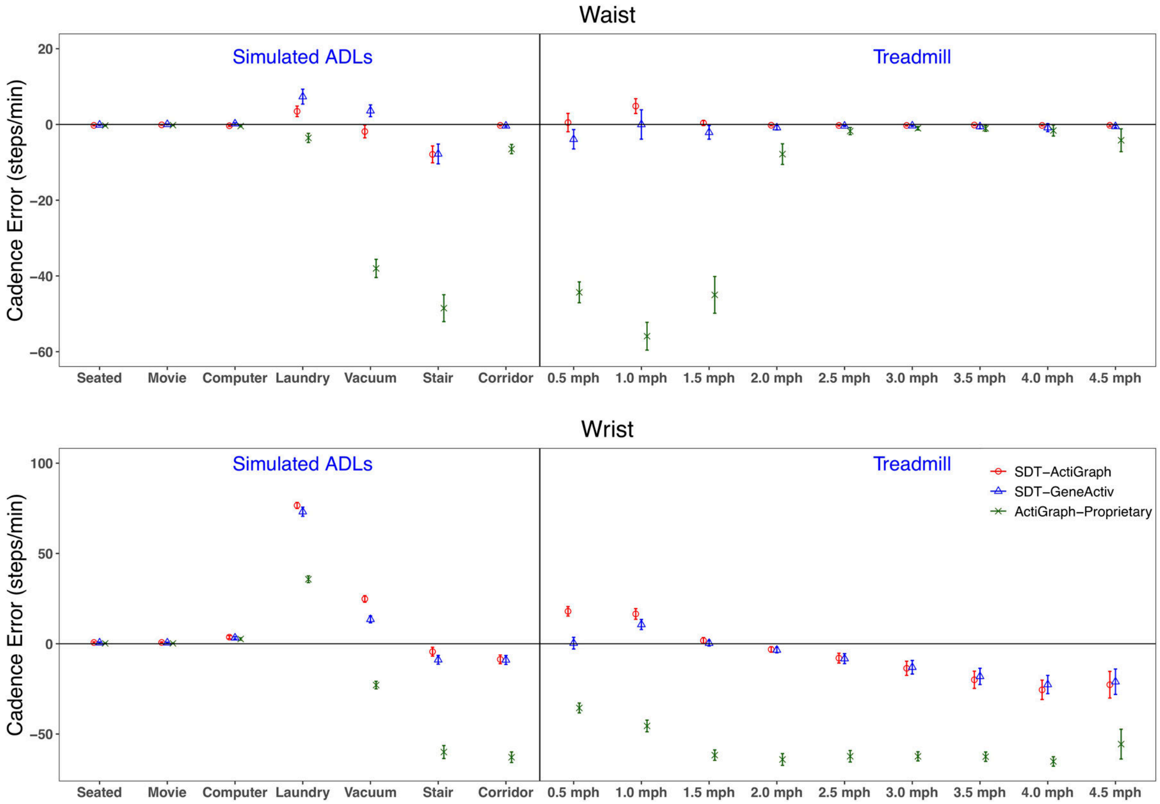

Figure 2:

Bias (cadence error; steps/minute) values across activities for the waist (top) and wrist (bottom) using the SDT from the VM direction for the ActiGraph (red circles) and GENEActiv (blue triangles) acceleration signals compared to ActiGraph proprietary algorithm (green x's). Data are mean ± CI$^{95\%}$.

Table 1:

Error values (mean ± SD) for best (top) vector magnitude thresholds and ActiGraph proprietary algorithm, and for the mean of the best thresholds (bottom) for the waist and wrist.

Location	Monitor	Threshold	BIAS (Steps)	BIAS (Cadence)	MAPE (%)	RMSE (Steps)	RMSE (Cadence)
Waist	**SDT-GENEActiv**	0.0314 (0.012)	24.89 ± 173.17	0.321 ± 2.29	2.67 ± 2.03	173.80	2.30
	SDT-ActiGraph	0.0220 (0.008)	24.44 ± 144.34	0.33 ± 1.90	2.16 ± 1.80	145.44	1.92
	AG Proprietary	--------	−311.92 ± 694.90	-4.74 ± 10.16	13.37 ± 11.19	757.46	11.15
Wrist	**GENEActiv**	0.0372 (0.018)	−10.21 ± 389.46	−0.07 ± 5.17	6.07 ± 4.58	386.98	5.14
	ActiGraph	0.0345 (0.019)	−8.24 ± 401.02	−0.04 ± 5.34	6.17 ± 4.89	398.42	5.30
	AG Proprietary	--------	−1916.97 ± 583.15	−25.55 ± 9.33	44.00 ± 13.38	2002.58	27.18
		Average Threshold					
Waist	**SDT-GENEActiv**	0.0267	129.39 ± 163.86	1.70 ± 2.17	3.30 ± 2.46	207.92	2.74
	SDT-ActiGraph		−89.29 ± 137.48	−1.18 ± 1.81	2.47 ± 1.86	163.16	2.15
Wrist	**SDT-GENEActiv**	0.0359	−22.20 ± 386.17	−0.36 ± 5.13	6.12 ± 4.54	384.23	5.11
	SDT-ActiGraph		−41.79 ± 406.22	−0.48 ± 5.40	6.20 ± 4.95	405.66	5.38

Note: Threshold in g; BIAS = constant error in steps or cadence (steps/min); MAPE = mean absolute percent error (%); RMSE = root mean square error in steps or cadence (steps/min);

Table 2:

K-fold cross-validation (k=5) of the step detection threshold (SDT) for the GENEActiv and ActiGraph devices, and for the ActiGraph proprietary algorithm.

Location	Monitor	BIAS (Steps)	BIAS (Cadence)	MAPE (%)	RMSE (Steps)	RMSE (Cadence)
Waist	**SDT-GENEActiv**	24.86 ± 0.67	−0.33 ± 0.01	2.68 ± 0.03	172.28 ± 2.54	2.28 ± 0.03
	SDT-ActiGraph	24.82 ± 0.58	0.34 ± 0.01	2.20 ± 0.04	145.59 ± 2.77	1.92 ± 0.04
	AG Proprietary	−1284.23 ± 0.00	−16.92 ± 0.00	24.62 ± 0.00	1311.94 ± 1.06	17.29 ± 0.01
Wrist	**SDT-GENEActiv**	134.64 ± 0.50	1.84 ± 0.01	6.59 ± 0.04	392.34 ± 2.09	5.25 ± 0.03
	SDT-ActiGraph	309.20 ± 0.55	4.16 ± 0.01	8.41 ± 0.02	480.30 ± 2.93	6.47 ± 0.04
	AG Proprietary	−2875.01 ± 0.00	−37.69 ± 0.00	54.86 ± 0.00	2913.37 ± 1.25	38.06 ± 0.01

Note: BIAS = steps error or cadence error (steps/min); MAPE = mean absolute percent error (%); RMSE = root mean square error in steps or cadence (steps/min).

Table 3:

Actual steps taken (hand counted steps) compared to waist-worn device-detected steps, as well as step and cadence (steps/min) bias error across activities and devices using the vector magnitude acceleration step detection thresholds (SDTs) and ActiGraph's proprietary algorithm.

			SDT -ActiGraph			SDT-GENEActiv			ActiGraph Proprietary		
Activity	**n**	**Hand Counted Steps**	**Detected Steps**	**Step Error**	**Cadence Error**	**Detected Steps**	**Step Error**	**Cadence Error**	**Detected Steps**	**Step Error**	**Cadence Error**
Seated	75	0	0.24±0.93	0.24±0.93	0.05±0.19	0.84±1.75	0.84±1.75	0.17±0.35	0.05±0.28	0.05±0.28	0.01±0.06
Movie	75	0	0.54±1.45	0.54±1.45	0.11±0.29	1.22±2.39	1.22±2.39	0.24±0.48	0.14±0.45	0.14±0.45	0.03±0.09
Computer	75	0	0.62±1.71	0.62±1.71	0.12±0.34	3.32±4.26	3.32±4.26	0.66±0.85	0.18±0.58	0.18±0.58	0.04±0.12
Laundry	75	22.03±28.11	39.38±30.67	17.35±29.98	3.47±5.60	58.76±51.68	36.72±42.46	7.35±8.49	4.26±6.49	−17.77±26.17	−3.55±5.21
Vacuum	75	230.23±48.67	220.95±57.92	−9.28±36.36	−1.86±7.27	248.39±44.85	18.07±33.45	3.61±6.89	40.16±30.14	−190.07±51.95	−38.01±10.34
Stair	75	467.58±85.19	428.08±78.46	−39.50±48.07	−7.90±9.61	428.66±62.89	−38.92±56.46	−7.78±11.29	225.04±70.96	−242.54±76.76	−48.51±15.27
Corridor	75	541.68±38.94	540.47±38.49	−1.20±2.72	−0.24±0.54	539.78±37.17	−1.89±5.26	−0.38±1.05	509.16±46.20	−32.51±26.50	−6.50±5.27
0.5 mph	75	224.74±60.21	227.24±65.46	2.50.±52.29	0.50±10.46	205.19±71.25	−19.55±55.13	−3.91±11.03	3.11±6.96	−221.64±59.50	−44.33±11.84
1.0 mph	75	338.11±45.28	362.35±48.35	24.24±42.14	4.85±8.43	338.07±80.69	−0.04±83.71	−0.01±16.74	58.55±61.45	−279.55±79.13	−55.91±15.75
1.5 mph	75	419.58±39.98	421.55±41.34	1.97±14.21	0.39±2.84	409.15±48.62	−10.43±39.02	−2.09±7.80	194.57±99.15	−225.01±104.77	−45.00±20.85
2.0 mph	75	482.05±32.38	481.00±31.81	−1.05±3.36	−0.21±0.67	477.81±32.18	−4.24±12.30	−0.85±2.46	442.91±56.49	−39.15±58.85	−7.83±11.71
2.5 mph	73	530.88±29.81	529.56±29.27	−1.32±2.96	−0.26±0.59	528.92±29.43	−1.96±3.34	−0.39±0.67	522.11±32.40	−8.77±20.17	−1.75±4.01
3.0 mph	73	569.55±30.41	568.25±29.76	−1.30±3.00	−0.26±0.60	567.82±30.096	−1.73±3.79	−0.35±0.76	564.51±31.13	−5.04±9.76	−1.01±1.94
3.5 mph	70	608.30±35.12	607.53±34.77	−0.77±2.90	−0.16±0.58	605.50±36.96	−2.80±11.75	−0.56±2.35	603.10±38.07	−5.20±16.00	−1.04±3.18
4.0 mph	61	645.95±38.59	644.64±38.75	−1.31±2.29	−0.26±0.46	641.72±43.91	−4.23±20.47	−0.85±4.09	637.93±48.38	−8.02±28.34	−1.60±5.63
4.5 mph	35	706.77±51.94	705.63±52.02	−1.14±3.48	−0.26±0.68	704.14±51.59	−2.63±4.90	−0.53±0.98	685.91±64.79	−20.86±43.92	−4.17±8.69

Note: All data reported as mean ± SD. Seated = seated rest; Movie = watching a movie; Computer = performing basic computer work with mouse and keyboard; Laundry = folding towels while standing; Vacuum = vacuuming throughout a carpeted room; Stair = self-paced ascent and descent of a single stair; Corridor = self-paced walking overground; 0.5–5.0 mph = walking on treadmill at that speed in miles per hour

Table 4:

Actual steps taken (hand counted steps) compared to wrist-worn device-detected steps, as well as step and cadence (steps/min) error across activities and devices using the vector magnitude acceleration step detection thresholds (SDTs) and ActiGraph's proprietary algorithm.

			SDT -ActiGraph			SDT-GENEActiv			ActiGraph Proprietary		
Activity	**n**	**Hand Counted Steps**	**Detected Steps**	**Step Error**	**Cadence Error**	**Detected Steps**	**Step Error**	**Cadence Error**	**Detected Steps**	**Step Error**	**Cadence Error**
Seated	75	0	4.92±9.34	4.92±9.34	0.94±1.87	4.26±8.02	4.26±8.02	0.85±1.60	2.59±4.53	2.59±4.53	0.52±0.91
Movie	75	0	4.64±8.01	4.64±8.01	0.93±1.62	3.86±6.67	3.86±6.67	0.77±1.33	2.22±4.14	2.22±4.14	0.44±0.83
Computer	75	0	20.66±19.01	20.66±19.01	4.13±3.80	18.69±15.67	18.69±15.67	3.74±3.13	15.54±13.40	15.54±13.40	3.11±2.68
Laundry	75	22.03±28.11	405.03±27.81	383.00±35.65	76.60±7.13	387.66±50.61	365.65.±54.40	73.13±10.88	200.62±29.06	178.60.±39.95	35.72±7.99
Vacuum	75	230.23±48.67	354.35±32.54	124.10.±39.35	24.82±7.87	297.81±46.52	67.60±41.30	13.52±8.26	115.78±33.49	−114.45±45.20	−22.89±9.04
Stair	75	467.58±85.19	445.59±58.05	−22.00±5.26	−4.40±10.51	423.18±72.09	−44.40±52.30	−8.88±10.46	167.73±52.25	−299.85±77.60	−59.97±15.52
Corridor	75	541.68±38.94	498.46±46.19	−43.20±51.90	−8.64±10.38	496.78±48.78	−44.90±53.35	−8.98±10.67	227.39±74.04	−314.30±63.15	−62.86±12.63
0.5 mph	75	224.74±60.21	314.59±63.90	89.85.±56.60	17.97±11.32	226.45±77.55	1.70±69.65	0.34±13.93	46.96±38.08	−177.80±58.80	−35.56±11.76
1.0 mph	75	338.11±45.28	420.68±54.20	82.55±63.65	16.51±12.73	391.41±52.71	53.30±60.05	10.66±12.01	110.47±52.13	−227.65±69.75	−45.53±13.95
1.5 mph	75	419.58±39.98	428.41±28.54	8.8±35.50	1.76±7.10	421.19±28.62	1.60±33.9	0.32±6.78	111.14±62.01	−308.45±62.10	−61.69±12.42
2.0 mph	75	482.05±32.38	466.39±30.77	−15.65±32.05	−3.13±6.41	464.66±32.24	−17.40±33.35	−3.48±6.67	161.55±81.81	−39.15±58.85	−64.10±14.06
2.5 mph	73	530.88±29.81	491.08±48.99	−39.80±58.15	−7.96±11.63	489.64±51.70	−41.25±59.15	−8.25±11.83	219.27±72.72	−8.77±20.17	−62.32±13.59
3.0 mph	73	569.55±30.41	501.55±73.12	−68.±84.20	−13.60±16.84	504.49±71.14	−65.05±80.40	−13.01±16.08	257.78±55.17	−5.04±9.76	−62.35±10.83
3.5 mph	70	608.30±35.12	508.51±91.92	−99.80±99.85	−19.96±19.97	517.91±88.83	−90.40±94.45	−18.08±18.89	295.54±63.50	−5.20±16.00	−62.55±10.85
4.0 mph	61	645.95±38.59	518.38±102.74	−127.55±104.80	−25.51±20.96	533.07±98.93	−112.90±98.75	−22.58±19.75	320.03±67.46	−8.02±28.34	−65.18±10.20
4.5 mph	35	706.77±51.94	593.34±135.87	−113.45±107.35	−22.69±21.47	601.63±129.66	−105.15±102.30	−21.03±20.46	428.83±152.83	−20.86±43.92	−55.59±24.00

Note: All data reported as mean ± SD. Seated = seated rest; Movie = watching a movie; Computer = performing basic computer work with mouse and keyboard; Laundry = folding towels while standing; Vacuum = vacuuming throughout a carpeted room; Stair = self-paced ascent and descent of a single stair; Corridor = self-paced walking overground; 0.5–5.0 mph = walking on treadmill at that speed in miles per hour