Published in final edited form as:

J Meas Phys Behav. 2018 September ; 1(3): 136–142. doi:10.1123/jmpb.2018-0007.

Use of Objective Measures to Estimate Sedentary Time in Youth

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Abstract

The purpose of the study was to conduct a comprehensive evaluation of the ActiGraph GT3X+ (AG) and activPAL (AP) for assessing time spent in sedentary behaviors (SB) in youth using structured and free-living activities. Forty-four participants (mean±SD; age, 12.7±0.8 yrs) completed up to 8 structured activities and approximately 2-hrs of free-living activity while wearing an AG (right hip) and AP (right thigh). A Cosmed K4b² was used for measured energy expenditure (MET_y; activity VO₂ divided by resting VO₂). Direct observation was used during the structured activities. SB time was estimated using the inclinometer function of the AP and AG, and count thresholds with AG (<75 vector magnitude (VM) counts/10-s, < 25 vertical axis (VA) counts/10-s, and <50, 100, 150, and 200 VA counts/min). For the structured activities, the AG inclinometer and AP correctly classified supine rest about 45% of the time, seated activities 54.6% and 65.1% of the time, respectively, and walking and running >96% of the time. For the free-living measurement, the VA <25 counts/10-s has the lowest RMSE (20.6 min), while the VM <75 counts/10-s had the lowest MAPE (69.2%). The AG inclinometer was within 0.2 minutes of measured time, but had the highest MAPE (107.1%). The AP was within 1.6 minutes of measured time, but had the highest RMSE (28.5 minutes). Compared to measured SB time, the VA <25 counts/10-s and VM <75 counts/10-s provided the most precise estimates of SB during free-living activity. Further refinement is needed to improve the AP and AG posture estimates.

Keywords

Accelerometer; activity counts; free-living activity; structured activity; direct observation; indirect calorimetry

INTRODUCTION

Sedentary behavior (SB) is a known contributor to poor health, and is particularly concerning as a contributing factor to obesity and its comorbidities. However, the exact nature of its health impact is unclear, owing largely to the absence of a standardized definition of SB (Gibbs, Hergenroeder, Katzmarzyk, Lee, & Jakicic, 2015). Typical definitions of SB emphasize energy expenditure (EE), posture (i.e. sitting time), or both. There are a variety of ways to measure SB depending on the definition being used (Ridley,

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Ridgers, & Salmon, 2016), but regardless of how SB is defined, objective measures (primarily accelerometers and inclinometers) have generally taken preference over self-reported measures (Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011). A consensus definition of SB was recently created by the Sedentary Behavior Research Network (SBRN). Their definition includes any waking behavior with an EE <1.5 metabolic units (METs), while in a sitting, reclining, or lying posture (Tremblay et al., 2017). A limitation to this definition is that assessing both posture and EE in a free-living setting is difficult to capture and can increase participant burden. Because of this, researchers typically only capture a single component of SB (posture or EE) with a gold standard, while the other component is weakly assessed, if at all. In these studies, satisfying both EE and posture criteria of the definition is often not possible, and estimation is necessary. Thus, a distinct priority is to improve measurement of the individual components of SB, with the goal of eventually developing streamlined methods for combining posture and EE measurement to adhere with the consensus definition of SB. To that end, this paper seeks to understand objective measurement of posture and EE as it pertains to assessments of SB in youth.

The widespread adoption of objective measures of SB has occurred rapidly, and posture measurement has been advanced through the use of accelerometer-based devices, such as the ActiGraph GT3X+ (AG) and activPAL (AP). However, information about the validity of these tools remains sparse, particularly for youth populations (Atkin et al., 2012). At the fundamental level, the AG and AP both use a triaxial accelerometer to measure acceleration, but how the data are used to assess SB is different between devices. With the AG, count-based cut-points are commonly used to identify SB, with <100 vertical axis (VA) counts/min (Treuth et al., 2004) being the most commonly used cut-point. The use of a count cut-point results in assessing SB on the basis of EE without taking into account posture, although it is assumed the individual is in a sitting or lying position. While the 100 count/min cut-point is commonly referred to as the Matthews cut-point (Matthews et al., 2008), it was originally developed based on a calibration study in adolescent girls by Treuth and colleagues (2004). Alternatively, an inclinometer can be used to identify posture and predict SB without the use of the EE part of the SB definition. Inclinometers are present in both the AG and AP.

Inclinometers estimate posture based on how gravitational acceleration is distributed among the three axes of an accelerometer. For example, when an individual is standing, the y-axis (VA) of the AG, when worn on the hip, should contain the total acceleration due to gravity. However, as the individual tilts at the waist, acceleration due to gravity will be dispersed across the other axes and off of the y-axis allowing for determination of posture based on the redistribution of acceleration due to gravity and the inclination angle of the y-axis. When using the AG inclinometer function, counts are also used to help distinguish standing versus sitting (ActiGraph Corp., 2016), since a hip-worn monitor is in a similar orientation for sitting and standing. Specifically, when counts are > 6 counts/sec, the AG assumes the person is standing and inclination angle is ignored. In contrast, the AP is not as susceptible to confusing sitting and standing, because it is worn on the thigh, meaning the device will experience a change in incline of about 90 degrees between sitting and standing. However, the AP does not distinguish between lying and sitting due to the thigh being in the same position. Due to differences in wear locations, the interpretation of the inclinometer data from the AP and AG is different, making direct comparisons difficult.

Currently, there is limited information about how the AG and AP estimates of SB compare in youth. In addition, studies that have compared both monitors have tended to not use a criterion measure of direct observation or indirect calorimetry. Three studies have compared the AP inclinometer function to AG count-based estimates of SB in youth, and have found the best agreement between AP and AG estimates when using cut-points of <75 counts/15s (Ridley et al., 2016) and < 100 counts/min (Dowd, Harrington, & Donnelly, 2012; Ridgers et al., 2012). Other studies in youth have compared the AP to the Actical (Van Cauwenberghe, Wooller, Mackay, Cardon, & Oliver, 2012) or have compared only the AP (Aminian & Hinckson, 2012; Davies et al., 2012) or AG (Fischer, Yildirim, Salmon, & Chinapaw, 2012; Hänggi, Phillips, & Rowlands, 2013) estimates of SB to direct observation or indirect calorimetry. Thus, there is a need for a comprehensive study comparing SB estimates from the AG and AP to criterion measures in both structured and free-living settings. To date, most previous studies have used structured activities or short bouts in a specific setting (e.g. classroom) and measured posture through direct observation. EE has often been overlooked and if measured it has typically only been done in a structured laboratory setting. Therefore, the purpose of this study was to conduct a comprehensive evaluation of the AG and AP for assessing youth SB using both structured and free-living activities with criterion measures of direct observation and indirect calorimetry, respectively. A secondary purpose was to examine the relationship between estimates of posture and EE from the monitors, to better understand the potential implications of measuring and reporting on different aspects of SB.

METHODS

Participants

Participants between 11 and 15 years of age were recruited from Boston Public Schools. Participants were given a written assent form to sign, and parents of participants were given an informed consent form along with a health history questionnaire, all of which were signed and returned to the researchers before enrollment in the study. Exclusion criteria included contraindications to exercise, physical inability to perform the planned activities, and stimulant medicine that may influence metabolism such as Concerta or Ritalin. Recruitment procedures were reviewed and approved by the respective Institutional Review Boards of the University of Massachusetts Boston and Boston Public Schools.

Procedures

This was part of a larger study using the same participants and physical activity protocols (Crouter, Flynn, & Bassett, 2015; Crouter, Horton, & Bassett, 2013). The data collection was structured into three separate days with structured and unstructured free-living activities being completed on separate days. At each visit, participants concurrently wore an AG, AP, and a Cosmed K4b². The AG was positioned on the waist at the right anterior axillary line, and the AP was affixed to the anterior surface of the right mid-thigh.

All activities took place at GoKids Boston, located on the University of Massachusetts Boston campus, or at a local Boston Public School. On day 1, anthropometrics (height and weight) and demographics (age, gender, race and ethnicity) were acquired. Resting

metabolic rate (RMR) was then measured using a Cosmed K4b² during 30 minutes of supine rest on a table in a quiet room.

During the day 2 visit, participants performed up to seven structured activities for 8 minutes each, with up to a 3-min break between each activity. Each participant completed the activities in order from lowest to highest intensity: 1) Using a desktop computer to search the internet or play games (n=40); 2) Playing board games or cards (n=40); 3) Light cleaning (e.g., sweeping, dusting, wiping down equipment; n=40); 4) Jackie Chan video game, an interactive activity where participants ran in place on a mat in order to move the character in the game (n=41); 5) Wall ball, a variation of handball (n=40); 6) Walking a designated route that included stairs, variable terrain, and crossing roads, at a self-selected pace (n=45); 7) Running the same designated route as the walking activity, at a self-selected pace (n=44).

On day 3, the participants completed approximately two hours of self-selected unstructured activity (i.e. free-living simulation), limited to the university or school campus where collection took place. A researcher supervised the participant at all times, but did not interfere with the tasks being performed. Example activities performed during the unstructured measurement included SB (e.g., playing computer games, reading, and doing homework), sporting activities (e.g., basketball, lifting weights, soccer, and playing catch), active video games (e.g., Dance Dance Revolution), and walking and running around the property.

Instrumentation

Each participant wore an AG and an AP. The AG GT3X+ (ActiGraph, LLC, Pensacola, FL, USA) is a lightweight, rechargeable, triaxial accelerometer-based activity monitor. The monitor's software is equipped with an inclinometer function that can estimate posture (lying, sitting, standing, or non-wear) when the monitor is worn on the waist. The AG data were sampled at 30 Hz and were converted to counts/10-s and counts/60-s, with the low frequency extension applied, for both the VA and vector magnitude (VM). Using the count/10-s file posture classification from the inclinometer was determined for each 10-s epoch, which was then summarized into 1-min values.

The AP (activPAL³, PAL Technologies, Glasgow, Scotland, UK) is a lightweight, rechargeable, triaxial accelerometer-based activity monitor that is worn on the thigh. It determines daily activity in terms of time spent in different postures (lying/sitting, upright, and stepping). The user can select the epoch length for data collection, and sampling frequency is set at 20 Hz. In order to match the AG inclinometer data, the AP 20 Hz data were converted to 15-s epochs after download, which were then summarized into 1-min values.

The Cosmed K4b² (COSMED, Rome, Italy) portable indirect calorimeter was concurrently used to gather respiratory gas exchange data as a criterion measure of EE. Prior to each test the oxygen (O₂) and carbon dioxide (CO₂) analyzers were calibrated according to the manufacturer's instructions. This consisted of performing a room air calibration, and a reference gas calibration using 15.93% O₂ and 4.92% CO₂. The flow turbine was then calibrated using a 3.00 L syringe (Hans-Rudolph). Finally, a delay calibration was

performed to adjust for the lag time that occurs between the expiratory flow measurement and the gas analyzers. The relative timestamps from the K4b² were aligned to a digital clock so that the data could be synchronized with the absolute timestamps recorded by the AG and AP. To account for the additional weight of the K4b², AG, AP, and additional devices, 2 kg were added to the child's body weight for all weight bearing structured activities and the entire free-living measurement.

Data Analysis and Statistical Treatment

The analyses focused on SB defined by posture classification (structured activities) or EE (free-living). Supine rest from visit one was included in the posture-based analysis, for a total of eight activities. Each activity was assigned a criterion postural label (lying down = lying; board games and computer games = sitting; cleaning, Jackie Chan game, and wall ball = standing; walking and running = stepping). Posture labels were based on direct observation of the activity during minutes 5–7 of each activity. Posture allocation was a secondary focus within the larger study, thus we chose to only collect posture data for a short period when the activity was most stable. Data from minutes 5–7 of each activity were included in the analysis and the outcome variable was estimated time (in seconds) spent in each posture category. Classification accuracy was assessed by examining percent of time the AG and AP classified each activity compared to direct observation.

For the free-living EE analysis, the K4b² served as the criterion measure. The oxygen consumption (VO₂) data were averaged over one-minute periods and converted to EE (MET_y = activity VO₂ divided by measured RMR). A cutoff of <1.5 MET_y was used to identify minutes of SB. All minutes of the free-living measurement were used, except when the mask was removed for water breaks.

Eight comparison measures were assessed for agreement with the criterion measure of total time spent in SB. First, six incremental cut-points for the AG VM and VA were used, similar to the approach used by Ridgers et al. (2012). Two cut-points used data in 10-s epochs [VM: <75 counts/10-s (Crouter, Horton, & Bassett, 2012); VA: <25 counts/10-s (Crouter et al., 2012)], and the remaining four used VA 60-s epochs [(i.e. <50, <100 (Treuth et al., 2004), <150, and <200 counts/60-s)]. The other two measures were derived from the posture estimates of the AG inclinometer and AP. These were treated in the same fashion as the estimates from the structured activities, such that total time spent sitting/lying was equated to an estimate of total time spent in SB.

For the free-living assessment, a one-way Repeated Measures ANOVA with Bonferroni-corrected post hoc tests was used to test differences between measured time spent in SB (time spent at < 1.5 MET_y) and estimated time spent in SB from the AG and AP. Agreement was further assessed using Bland-Altman plots, root mean square error (RMSE), and mean absolute percent error (MAPE). Significance was set at an alpha level of 0.05, and statistical analyses were carried out jointly in R and SPSS (SPSS Inc., Chicago, IL, USA).

RESULTS

Data for two girls and six boys were excluded due to missing AP data or download error leaving a final sample of 44 participants. Participant characteristics, for those included in the analysis, are summarized in table 1. The males and females were similar overall, with a slightly higher proportion of overweight and obese in males, and greater racial and ethnic diversity in females.

Structured Activities: Posture Classification

Table 2 shows the percent of time classified in each activity category for the AG inclinometer and AP. All posture classifications are based on comparison to direct observation. In general, both devices classified supine rest correctly about 45% of the time. The AP performed slightly better than the AG for correctly identifying sitting activities and mixed posture activities. During mixed posture activities, the AG misclassified the activities as sitting 25.3% of the time. For walking and running, the AG and AP both correctly identified the activity greater than 96% of the time.

Free-living Activities: Time Spent in Sedentary Behaviors

Forty-two participants completed the free-living protocol. Data from another two participants were lost, due to AP malfunction. Results from the free-living analysis are shown in table 3 and figure 1. Overall, the best performing method based on the lowest RMSE was the VA <25 counts/10-s while the VM <75 counts/10-s had the lowest MAPE. The AG inclinometer had the closest mean estimate of time spent in SB compared to the K4b² (within 0.2 minutes of measured minutes); however, it had the highest MAPE (107.1%) and second highest RMSE (26.5 minutes). The AP was within 1.6 minutes of measured SB time, but had the highest RMSE (28.5 minutes) and one of the higher MAPE (85.0%). The only method to differ significantly from the criterion measure of total time spent in SB was the VA <200 counts/60-s cut-point (mean difference = -9.25 min, $p=0.046$). The 60-s cut-points tended to perform progressively worse as the thresholds increased, moving from a MAPE and RMSE of 77.1% and 21.0 min, respectively, for the VA <50 counts/60-s cut-point, to a MAPE and RMSE of 91.0% and 24.7 min, respectively, for the VA <200 counts/60-s cut-point. Additionally, most methods had positive relationships between the measured time spent in SB and the prediction errors. Only VA <100 counts/60-s, VA <150 counts/60-s, and VA <200 counts/60-s had r values less than 0.36, while all other methods had r values ranging from 0.48 (VA <50 counts/60-s) to 0.66 (AG inclinometer) indicating that most methods tended to overestimate lower measured SB times and underestimate higher measured SB times.

The Bland-Altman plots (Figure 1) showed mean biases near zero minutes; however, there was large individual error with 95% limits of agreement that were consistently near ± 50 minutes. All methods, except for VA <150 counts/60-s and VA <200 counts/60-s, tended to underestimate total time spent in SB when there were more measured SB minutes, and overestimate when there were fewer measured SB minutes. The VA <25 counts/10-s and <50 counts/60-s cut-points had the narrowest limits of agreement.

DISCUSSION

This study used structured and free-living protocols to conduct a comprehensive evaluation of the AG inclinometer and cut-points and AP inclinometer for estimating time spent in SB, based on posture (structured activities) or EE (free-living measurement), in youth. For the structured activities, the AP and AG worked best for detecting ambulation and classified SB postures correctly less than 50% of the time. For free-living measurement, the VA cut-point of <25 counts/10-s showed the strongest agreement, with the lowest RMSE, second lowest MAPE, and was within 0.6 minutes of measured SB time.

To our knowledge, only one study has examined posture classification in youth using the AG inclinometer (Hänggi et al., 2013). That study involved semi-structured activities similar to the present study, and showed that the inclinometer in the first triaxial AG monitor (GT3X) correctly classified lying, sitting, and standing, 15%, 94%, and 20% of the time, respectively. It is unclear why the results of the present study contrast with Hänggi et al. (2013), especially since the sample populations and study protocols were similar in both studies. The differences between the GT3X and GT3X+ models could be a factor, but this seems unlikely since there are no differences in filters or algorithms between the devices. The authors do note, based on communication with ActiGraph, that when using the inclinometer, counts >100 counts/min classify the activity as standing (Hänggi et al., 2013). This is different than the current approach published on the ActiGraph website where if the counts are >6 counts/1-s the wearer is assumed to be standing and the inclination angles are ignored (ActiGraph Corp., 2016).

To date, the performance of the AP inclinometer for posture recognition has been studied more than the AG inclinometer. Aminian and Hinckson (2012) found the AP to be 100% accurate in youth for posture classification during structured activities. Additionally, in a group of preschool children performing usual activity in a nursery, Davies et al. (2012) found the AP to have sensitivities of 86.7%, 91.8%, and 80.3% for detecting time in sitting/lying, standing, and walking, respectively, compared to 1 hour of direct observation. While the AP classification for stepping for the current study (>97%) is in line with previous studies, the classification of lying/sitting and standing are lower than what others have found. One potential source of error is that lying is misclassified as standing if the knees are bent greater than 20° from horizontal (Bassett et al., 2014). In the current study, the participants were not instructed on how to lie on the table; rather they were instructed to lie still on their backs in a comfortable fashion like they were watching television at home. A second source of error, is that youth do not always sit in a standardized way, as adults do. For example, youth will often sit with knees to their chest or take a half sitting and half kneeling position. Thus, the change in angle could result in misclassification of seated activities as standing.

To further the comparison between the AG inclinometer and AP for classifying posture during structured activities, we combined the “lying” and “sitting” positions classified by the AG inclinometer into a single category for a direct comparison to what the AP reports (table 3). Combining the two AG categories led to correct classification of 74.6% of the structured activities designated as SB (i.e., seated or lying). However, the individual positions were

only classified correctly about 50% of the time when examined separately. This has implications for researchers and what questions they are asking. If the goal is to classify time in SB, which by definition are in the lying or sitting position, then combining the two categories into a single group will provide a reasonable estimate that outperformed the AP in this study. However, if the goal is to classify specific activities then other approaches should be explored. Recent work has shown success at classifying activities such as lying and sitting using machine learning approaches. Trost, Zheng, and Wong (2014) found that, when using a regularized logistic regression model, sitting, standing, and walking were classified correctly greater than 91% of the time using a hip worn monitor in youth. Chowdhury, Tjondronegoro, Chandran, and Trost (2017) found that, when using an ensemble approach with machine learning algorithms, lying, sitting and standing could be classified correctly greater than 85% of the time using a wrist worn monitor in youth and adults. A limitation to these findings is that they are based on structured activities, and it is unclear how these findings will translate to real world conditions. Additionally, implementation of these models in free-living is limited at this time. Thus, current approaches using the AG inclinometer or AP continue to be the most practical approaches for measuring posture in free-living settings.

During the free-living measurement, the proportion of time spent in SB varied widely depending on the prediction method (range, 21.8 – 40.8 minutes). All AG cut-points had lower RMSE than the AP and the AG inclinometer, but the inclinometers tended to have lower mean biases. In general, use of the VA <25 counts/10-s and VM <75 counts/10-s cut-points resulted in the best agreement with measured time spent in SB from the K4b². These results also highlight the potential importance of shorter epoch lengths (Freedson, Pober, & Janz, 2005), which for SB estimates has been overshadowed by the continued use of the <100 counts/min cut-point. The current convention is to apply linear scaling to this cut-point for shorter epochs but it cannot be assumed that, for example, 10 counts/6-s is the same as 100 counts/60-s.

A key limitation of this study is that there was no criterion measure of posture during the free-living portion of the study. Thus, all activities below 1.5 METs were considered SB, whether or not they were performed in a seated or lying posture as posture was unknown. Alternatively, as others have previously done (Pavey, Gilson, Gomersall, Clark, & Trost, 2017) the AP could be used as the referent method for time spent in SB in the free-living portion. Neither approach is ideal since both are only capturing part of the definition of SB which includes both posture and EE. For this study we chose to examine SB during free-living based on the EE part of the definition, due in part, to how the AP classified position during the structured activities in this study. However, as shown in table 3, when the AP is used as the referent method similar results are seen as when the K4B² is used as the referent method with no improvements in the individual error. This highlights the importance of being able to capture both the posture and EE of an activity when measuring SB. Currently, the best available method to deal with this problem is to simultaneously measure EE and perform direct observation of posture throughout the study protocol. However, this is not practical for many applications due to the added burden during data collection, and the difficulty of aligning posture records to high frequency output from the monitors. Additionally, while there is promise for using machine learning algorithms to classify

activities such as lying and sitting, this work has been limited to structured activities (Chowdhury et al., 2017; Trost et al., 2014) and it is not clear how well they will work in free-living environments.

Challenges specific to identifying SB postures have important implications for free-living studies, in which accounting for both the metabolic and postural elements of SB is both a key need and a major challenge. A monitor that can correctly detect posture without increasing the burden on the participant would allow these types of studies to progress more rapidly and accurately. However, the results of the present study suggest no such monitor currently exists. As such, researchers should use caution before combining cut-points with objective posture classification to estimate SB, which is not yet a common practice. The AP and the AG inclinometer show promise for classifying posture, but need further refinement and validation before they can be appropriately used as criteria for classifying posture in free-living studies as they are comparatively worse than cut-points as indicators of time spent in SB. Cut-points based on 10-s epochs tended to provide the most precise estimates of time spent in SB, thus it is suggested that a cut-point of <25 VA counts/10-s or <75 VM counts/10-s be used when estimating SB time in youth at the group level, however caution should be used when interpreting at the individual level.

Acknowledgments

Disclosure: This research was supported by NIH Grant R21HL093407. There are no declared conflicts of interest for any of the authors.

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Figure 1.

Bland-Altman plots depicting error scores (measured minus estimation) for time spent in sedentary behavior (SB) during a 2 hour free-living measurement using the (A) activPal (AP) inclinometer, (B) ActiGraph (AG) inclinometer, (C) AG<75 vector magnitude counts/10-s, (D) AG<25 vertical axis (VA) counts/10-s, (E) AG<50 VA counts/60-s, (F) AG<100 VA counts/60-s, (G) AG<150 VA counts/60-s, and (H) AG<200 VA counts/60-s.

The solid line represents the mean, and dashed lines represent the 95% confidence interval of the observations.

Table 1.

Descriptive characteristics of the participants.

	Males (n=23)	Females (n=21)	All Participants (N=44)
Age (yrs) $\pm$ SD (range)	12.8 $\pm$ 0.9 (11–14)	12.5 $\pm$ 0.7 (11–14)	12.7 $\pm$ 0.8 (11–14)
Height (cm) $\pm$ SD (range)	160.1 $\pm$ 10.4 (142–188)	152.1 $\pm$ 9.2 (128–168)	156.4 $\pm$ 10.5 (128–188)
Weight (kg) $\pm$ SD (range)	62.0 $\pm$ 16.8 (37–98)	54.2 $\pm$ 19.0 (32–103)	58.3 $\pm$ 18.1 (32–103)
BMI Classification			
Normal Weight (5 th to <85 th percentile)	34.8%	44.2%	39.5%
Overweight (85 th to <95 th percentile)	30.4%	25.4%	27.9%
Obese ($\geq$ 95 th percentile)	34.8%	30.4%	32.6%
Race/Ethnicity			
Hispanic	26.1%	33.0%	29.6%
Black/African American	65.2%	61.9%	63.6%
Asian	8.7%	14.2%	11.4%
White	26.1%	23.9%	25.0%

Table 2.

Classification accuracy for ActiGraph inclinometer and activPAL data for each structured activity. Values represent percent of time classified in each category.

Activities	Assigned Position	ActiGraph GT3X+				activPAL			
		Lying	Sitting	Lying/ Sitting *	Standing	“non-wear”	Lying/ Sitting	Standing	Stepping
Sedentary									Standing and Stepping #
Supine Rest	Lying	48.0	41.6	89.6	3.0	7.3	45.0	54.7	0.3
Playing on a desktop computer	Sitting	3.4	53.6	57.0	39.8	3.2	62.5	37.2	0.3
Playing board games/cards	Sitting	3.9	55.6	59.5	38.4	2.1	67.6	31.5	0.9
All lying/sitting activities		26.8	47.8	74.6	20.3	5.1	54.7	44.9	0.5
Mixed Posture									
Light cleaning	Standing/Stepping	2.9	43.6	46.5	53.5	0.0	1.6	55.5	42.9
Jackie Chan	Standing/Stepping	1.1	14.0	15.1	84.9	0.0	2.8	6.3	90.9
Wall Ball	Standing/Stepping	0.6	18.5	19.1	80.9	0.0	2.5	16.1	81.4
All mixed posture activities		1.5	25.3	26.8	73.2	0.0	2.3	25.8	71.9
Ambulation									
Walking	Stepping	0.0	0.6	0.6	99.4	0.0	0.0	2.5	97.5
Running	Stepping	0.0	0.5	0.5	99.5	0.0	0.3	2.9	96.9
All walk/run activities		0.0	0.5	0.5	99.5	0.0	0.1	2.7	97.2

* Lying and sitting as a single category is presented for comparison to the activPAL, but is not reported by ActiGraph inclinometer.

standing and stepping as a single category is presented for comparison to the ActiGraph inclinometer “standing”, but is not reported by the activPAL.

Table 3.

Group- and individual-level agreement for each method during the free living measurement.

Method	Total Sedentary Minutes (mean±SD)	Referent Measure: Cosmed K4b ²		Referent Measure: activPAL	
		RMSE (minutes)	MAPE (%) [#]	RMSE (minutes)	MAPE (%) ^{##}
Cosmed K4b ²	28.8±30.9	--	--	--	--
activPAL	27.2±25.5	28.5	85.0	--	--
GT3X+ Inclinometer	29.0±25.3	26.3	107.1	22.1	106
GT3X+ <75 VM counts/10 s	21.8±23.2	22.7	69.2	21.7	82.6
GT3X+ <25 VA counts/10 s	28.2±26.2	20.6	75.3	19.1	92.0
GT3X+ <50 VA counts/min	30.1±27.8	21.0	77.1	19.4	94.3
GT3X+ <100 VA counts/min	34.8±30.9	21.7	85.7	21.2	106.8
GT3X+ <150 VA counts/min	38.0±32.8	22.9	84.4	23.8	121.1
GT3X+ <200 VA counts/min	40.8±34.7 ^{*A}	24.7	91.0	26.2	138.7

VM, vector magnitude; VA, vertical axis; RMSE, root mean squared error; MAPE, mean absolute percent error; sedentary time from activPAL and GT3X+ inclinometer based on labelling all seated/lying as sedentary.

* significant difference from Cosmed K4b² (p<0.05)

^A significant difference from activPAL (p<0.05)

[#] Calculated after excluding 11 cases with zero minutes of sedentary time measured by the K4b²

^{##} Calculated after excluding 3 cases with zero minutes of sedentary time estimated by the activPAL.