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The ActiGraph counts processing and the assessment of vigorous activity

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Summary

The purpose of this study was to investigate the effect of different band-pass filters on the measurement bias with ActiGraph counts during high speed running and for estimating free-living vigorous physical activity (VPA). Two alternative band-pass filters were designed, extending the original frequency range from 0·29 to 1·66 Hz (AG) to 0·29–4 Hz (AC4) and 0·29–10 Hz (AC10). Sixty-two subjects in three age groups participated in a structured locomotion protocol consisting of multiple walking and running speeds. The time spent in free-living VPA using the three different band-pass filters were evaluated in 1121 children. Band-pass filter specific intensity cut-points from both linear regression and ROC analysis was identified from a calibration experiment using indirect calorimetry. The ActiGraph GT3X+ device recording raw acceleration at 30 Hz was used in all experiments. The linear association between counts and running speed was negative for AG but positive for AC4 and AC10 across all age groups. The time spent in free-living VPA was similar for all band-pass filters. Considering higher frequency information in the generation of ActiGraph counts with a hip/waist worn device reduces the measurement bias with running above 10 km·h^{-1}. However, additional developments are required to accurately capture all VPA, including intermittent activities.

Introduction

The accelerometer devices manufactured by ActiGraph Inc. are widely used for the objective assessment of physical activity (PA) in epidemiological research (Migueles *et al.*, 2017). The output commonly used is named 'counts' and is the result of several consecutive processing steps of acceleration (Tryon & Williams, 1996). Counts are linearly associated with energy expenditure (EE) during locomotion activities (Freedson *et al.*, 1998) although studies have identified a plateau effect or even an inverted-U phenomenon at speeds above 10 km·h^{-1} (Brage *et al.*, 2003). This measurement bias is proposed to originate from intrinsic properties of movement and placement of the activity monitor but also the narrow frequency band-pass filter included in the counts processing method (John *et al.*, 2012). A measurement bias with running above 10 km·h^{-1} has important implications for the assessment of vigorous physical activity (VPA) and consequently what intensities researchers recommend important for healthy behaviour.

The band-pass filter implemented in the ActiLife counts processing method allows acceleration in a frequency range of 0·29–1·66 Hz resulting in an amplitude attenuation of 50% at 0·25 and 2·5 Hz. The mean averaged deviation (MAD), Euclidian norm minus one (ENMO) and Activity Index (AI) have been proposed as alternative measures to AG counts not restricting the frequency range (van Hees *et al.*, 2013; Aittasalo *et al.*, 2015; Bai *et al.*, 2016). However, omitting noise reduction or error correction in the acceleration measurements seems to challenge the validity of measuring free-living PA in a noisy environment. Machine learning and multiple regression models have also been proposed to accommodate various measurement biases observed with the ActiGraph counts, although the plateau/inverted-U has not been specifically addressed (Crouter *et al.*, 2006; Crouter & Bassett, 2008; Staudenmayer *et al.*, 2009).

The AG counts processing implementation in ActiLife is proprietary information, and currently, researchers are not provided an option to consider alternative band-pass filters in order to reduce the measurement bias with locomotion at speeds above 10 km·h^{-1} and thus to improve the assessment of VPA with population studies. However, the limitation with ActiLife has been addressed in a recent study generating AG counts from raw acceleration measured with the activity monitor Axivity AX3 (Brond *et al.*, 2017). The accuracy obtained clearly suggests a valid method for investigating the effect of using alternative band-pass filters with AG counts.

The purpose of this study is to investigate the generation of ActiGraph counts and the option to consider higher frequency information for reducing the measurement bias at running speeds above 10 km h^{-1} and the effect on estimating free-living VPA. We also hypothesize an increase in VPA with higher frequency filters in free-living physical activity.

Methods

Study design and experiments

The objectives of this study were to design two alternative band-pass filters, extending the original frequency range of 0·29–1·66 Hz (AG) to 0·29–4 Hz (AC4) and 0·29–10 Hz (AC10), and to evaluate the counts generated with locomotion at different speeds in addition to a population study. A locomotion, calibration and population experiment are required to investigate the proposed objectives. The locomotion experiment evaluates the AG, AC4 and AC10 counts during walking and running at different speeds and across three age groups and provides the option to evaluate the effect of using alternative band-pass filters with AG counts on the measurement bias with running above 10 km·h^{-1}. The population experiment is used to evaluate free-living VPA using PA collected in a large population study of children. The currently available cut-points to evaluate the time spent in different intensity domains are not applicable to AC4 and AC10 counts. Thus, the calibration experiment is used to establish AG, AC4 and AC10 harmonized cut-points for the classification of light, moderate and vigorous intensity domains identified by indirect calorimetry.

Instrumentation and counts processing

All participants in the three experiments were fitted with an ActiGraph GT3X+ activity monitor (ActiGraph LLC, Pensacola, FL) over the right hip at the level of the iliac crest using an elastic belt. All monitors were initialized using the ActiLife software (version 6.11.7) to record raw acceleration data at 30 Hz sampling frequency. The raw acceleration data were loaded into Matlab (R2016 64bit) for processing into counts using the method described in (Brond *et al.*, 2017) and using the original band-pass filter (AG) in addition to the two alternative band-pass filters (AC4 and AC10). Only the vertical axis was considered in the analysis, and an epoch length of 10 s was used. Before executing the locomotion and calibration protocol, it was ensured that the devices position and orientation were similar for all subjects. The participants enrolled in the population study were asked to wear the ActiGraph GT3X+ for seven consecutive days during waken hours except during water activities (e.g. bathing, swimming, showering). An examiner supervised the participants face-to-face to attach the monitor over the right hip in an elastic belt around their waist.

Locomotion experiment

A convenient sample of 62 subjects divided into three age groups was invited to participate: (i) a children group with a mean (SD) age of 10·3 (0·3) included 22 participants (14 females) from the fourth grade of a local municipality school in Svendborg, Denmark, (ii) an adolescent group aged 15·7 (0·3) had 20 participants (8 females) from the ninth grade of a municipality school in Malmö, Sweden and (iii) an adult group aged 24·7 (2·7) included 20 participants (5 females) from the institute of sports and biomechanics at the University of Southern Denmark, Denmark. An indoor 25 m gym hall was used for children's group, an indoor 200 m athletics track for the adolescent group and an outdoor 400 m athletics track for the adult group. The adult group followed a protocol consisting of two walking speeds, running at a comfortable speed at which all participants could follow the pace and one fast running. The adolescents performed three walking speeds and the same two running activities as the adult group. The children protocol included three walking speeds, a slow running in addition to the same two running speeds as used with the adults and adolescents. For the children activity, duration was fixed, whereas for the adolescent's and adult activity distance was fixed. The children performed walking and running for 120 s, and fast running was sustained for 30 s. The adult and adolescent group performed walking and running activity for 400 m and the fast running for 200 m. The start of all activities was initiated by an instructor, and subjects were required to use the same group-pace during walking and running at speeds below fast running. For the final fast running activity, the pace was individually selected. All activities were separated by a 5-min break. The individual average locomotion speed for each activity was calculated from the distance and time. For the children, distance was estimated using the raw acceleration counting the number of number laps and estimating the distance for the last lap based on the relative time from last turn to stop. For the adults and adolescents, the time to perform the known activity distance was estimated from the raw acceleration. The walking–running experiment did not require approval by an ethics committee. The participants received detailed information about the study protocol and verbally agreed to participate in the study.

Calibration experiment

Thirty-six children (third and fourth grade) were recruited from a local school in the Odense municipality. The children were recruited by email through the school office and word of mouth, and informed consent was received from their parents. The children engaged in the experiment participated in a structured activity protocol consisting of three sedentary activities (sitting quietly, sitting playing tablet games and standing playing tablet games), two walking activities (preferred speed and brisk), a running activity (self-selected running speed), an intermittent basketball activity, biking and a playground activity. The activity protocol was performed inside a classroom (sedentary activities) and outside and around the school area (all other activities). Oxygen consumption was measured in the calibration experiment using the lightweight Metamax 3X (CORTEX Biophysik GmbH, Leipzig Germany) portable metabolic analyser (Medbo *et al.*, 2002). The metabolic analyser was worn on the back during execution of all activities. The measurements started after an adaption period of 10 min. The walking, brisk walking and running activities were performed consecutively in the order of intensity without breaks. A 2- to 5-min natural break was used between all other activities. The intensity of each activity was self-selected but subjects were also encouraged to adapt to an intensity they could complete the full duration of each activity. A log was used to record activity start times and to extract the individual activities from the raw data. The duration of each activity was 5 min, and total energy expenditure (TEE) was calculated as the average ($ml \cdot kg^{-1} \cdot min^{-1}$), although omitting the first 60 s. Resting energy expenditure (REE) was estimated using age and weight adjusted Schofield prediction equations and used to calculate the MET value of each activity as the quotient TEE/REE (Hermann *et al.*, 2017). The Ethics Committee of the Region of Southern Denmark approved the calibration study.

Cut-points

A total of six sets of cut-points were generated. Linear regression was used with four sets (REGI-IV), and receiver operating characteristics (ROC) analysis was used with two sets (ROCI and ROCII). The REGI cut-points were determined by evaluating the linear association between counts (AG, AC4 and AC10) and EE (METs) using the data collected during standing, preferred walk, brisk walk and running. The REGII is similar to REGI although including the basketball activity. The REGIII is similar to REGI, although a squared term is added in the regression model to account for a potential curvilinear association. The REGIV cut-points were determined by evaluating the association between counts and METs during walking and running independently. This approach is inspired by the 2-regression model used by Crouter *et al.* (Crouter & Bassett, 2008). The moderate and vigorous intensity thresholds were predicted using the 3 and 6 METs absolute intensities for all methods using regression (Garber *et al.*, 2011). The ROCI cut-points were determined as the optimal detection of the brisk walk activity with respect to preferred walk activity and vigorous intensity threshold as the optimal detection of the running activity with respect to the brisk walking activity (Jago *et al.*, 2007). The moderate cut-point threshold used with ROCII was determined by estimating the 95% upper confidence limit of the intensity generated during the walking at preferred speed activity, whereas the 95% upper confidence limit of the intensity generated during brisk walking was used to define the vigorous intensity threshold cut-point. The same sedentary cut-point was used with all methods and determined as the maximum count value for the activities sitting, sitting playing tablet game and standing playing tablet games activities.

Population study

Evaluation of free-living PA was based on a large population sample of Norwegian fifth-grade children from the Active Smarter Kids (ASK)-study (Resaland *et al.*, 2015), conducted in Sogn og Fjordane county, Norway during 2014–2015. Sixty schools, encompassing 1202 children, fulfilled the inclusion criteria and agreed to participate. This sample represented 86·2% of the population of 10-year-olds in the county, and 95·2% of those eligible for recruitment. Later, three schools encompassing a total of 27 children declined to participate. Thus, 1145 (97·4%) of 1175 available children from 57 schools agreed to participate in the study. Of these children, 1121 (97·7%) children provided at least 1 day of valid accelerometer data at baseline and were included in the study. The South-East Regional Committee for Medical Research Ethics in Norway approved the study protocol. We obtained written informed consent from each child's parents or legal guardian and from the responsible school authorities prior to all testing. The ASK study is registered in Clinicaltrials.gov with identification number: NCT02132494. Data reduction, assessment of time spent at different intensity domains and statistical analysis were done in Matlab (R2016 64bit). A non-wear criterion of 60 min consecutive zeros not allowing for any sporadic activity was used (Aadland *et al.*, 2018), and daytime was restricted from 6 am to 11 pm in addition to requiring 10-h wear time to provide a valid measurement day. One-way ANOVA and Tukey–Kramer multiple comparisons (post hoc analysis) were used to statistically test differences in time spent in the different intensity domains.

Results

Figure 1 presents the frequency response of the original ActiGraph filter (AG), and the AC4 and AC10 filters estimated using the freqz function available with Matlab. The frequency response of AC4 and AC10 as compared to the AG clearly demonstrates that higher frequency components are considered. Below 0·75 Hz, there is a minor difference in the attenuation as frequency decrease.

Locomotion experiment

Figure 2 presents the counts generated with AG, AC4 and AC10 during walking and running at selected speeds and

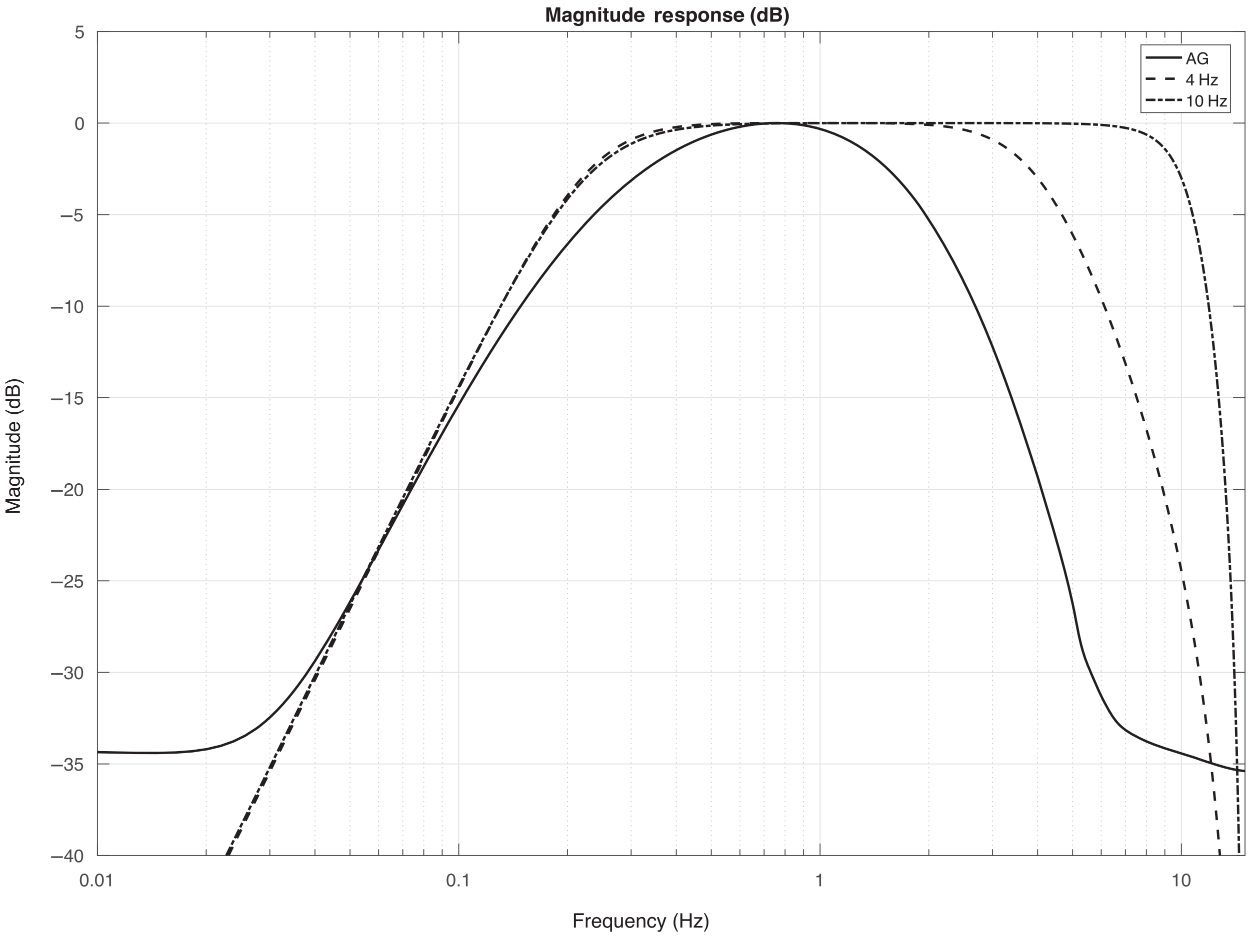

Figure 1 The AG, AC4 and AC10 band-pass filter frequency response indicated by the spectral density power (Decibel). The frequency response is estimated with the freqz function available with Matlab using 4096 points.

across the three age groups. The association between counts and locomotion below 10 km·h^{-1} seem linear with AG and for all age groups. The counts generated with both AC4 and AC10 during running as compared to walking are slightly elevated which seems to demonstrate a curvilinear association with locomotion speed below 10 km·h^{-1}. In all age groups, there was a significant positive association between walking speed and counts for all three aggregation methods (all $P<0{\cdot}01$). There was a significant negative association between running speed and AG counts in all age groups (all $P<0{\cdot}01$). In contrast, there was a significant positive association between running speed and counts for both the AC4 and AC10 in adults and adolescents (all $P<0{\cdot}01$), and a non-significant positive association for the AC10 aggregation in children ($P = 0{\cdot}46$). The association between running speed and AC4 counts in children was negative and borderline significant ($P = 0{\cdot}054$).

Calibration experiment

The predicted REE of the children was 5·16 (SD: 0·57) ml·kg^{-1}·min^{-1}, and the measured intensity of the four activities preferred walk, brisk walk, basketball and running was 3·6 (0·44), 4·4 (0·5), 6·8 (0·96) and 7·3 (0·99) METs. The intensity range of all sedentary activities was 1·1–1·7 METs. The moderate and vigorous intensity cut-points estimated for each band-pass filter (AG, AC4 and AC10) and with the six methods used to estimate the cut-points (REGI-IV, ROCI-ROCII) are presented in Table 1. The sedentary cut-points for AG, AC4 and AC10 were 115, 576 and 768 counts per minute, respectively. Regression model performance and sensitivity and specificity of the ROC analysis are presented in the Appendix S1.

Population experiment

Twenty-two subjects failed to provide at least 1 day with 10 h of PA and were thus excluded from the analysis. The mean number of valid days for the 1121 subjects was 7 (SD: 1·5) and with a mean wear time of 13·1 (SD: 2·00) hours per day. The time spent sedentary, light, moderate and vigorously across the six analytical methods and aggregation methods (AG, AC4 and AC10) are presented in Table 2. The time spent sedentary is significantly ($P<0{\cdot}05$) higher with AG than AC4 and AC10. The time spent within the light intensity

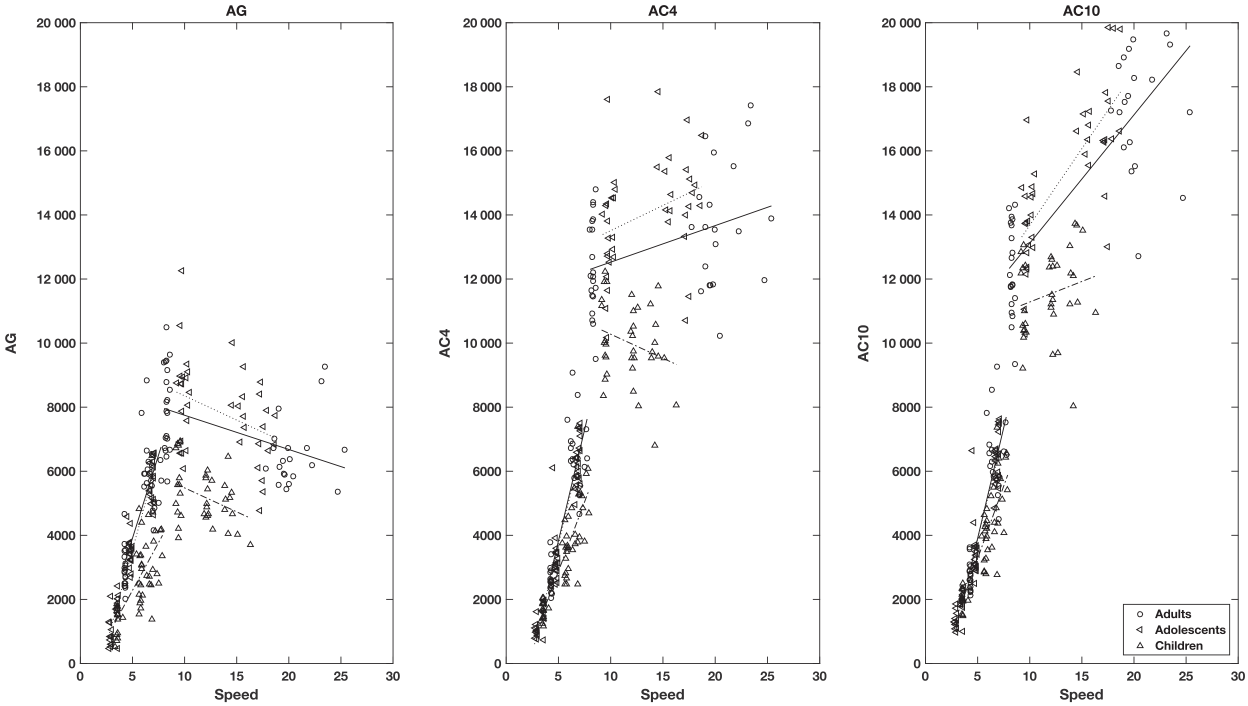

Figure 2 Results from the locomotion experiment. Linear regression analysis of the relationship between speed and AG, AC4 and AC10 counts during walking and running and with adults (solid line), adolescents (dashed line) and children (dashed-dotted line).

Table 1 Band-pass filter specific cut-points determined from both ROC and regression analysis using the measurements conducted in the calibration experiment

	Moderate			Vigorous		
	AG	AC4	AC10	AG	AC4	AC10
REGI	2051	15 211	17 491	5783	57 627	66 708
REGII	1972	13 996	16 645	4900	43 663	51 242
REGIII	2161	14 737	17 511	6018	56 609	65 782
REGIV	2016	14 059	16 591	6250	43 967	51 767
ROCI	3648	24 403	28 623	5765	51 525	58 963
ROCII	4288	26 121	29 817	6309	44 195	49 152

domain is significantly ($P<0{\cdot}05$) increased with both AC4 and AC10 as compared to AG and, this is consistent across both regression and ROC based cut-points. The time spent within the moderate intensity domain estimated with the ROC generated cut-points (ROCI and ROCII) is substantially lower than estimated with the cut-points generated with regression. There is a small but significant ($P<0{\cdot}05$) increase of the moderate intensity domain with AG as compared to AC4 and AC10 with three of the cut-points. Only the REGIII cut-points provide a time within moderate that demonstrates a similar or increased time with AC4 and AC10 as compared to AG. The time spent vigorously range from 7·2 to 18·1 min. There is a significant ($P<0{\cdot}05$) increased time spent in VPA with AG as compared to AC4 and AC10 with four of the six cut-points (REGI, REGII, REGIII and ROCI), while a significant ($P<0{\cdot}05$) increased time spent vigorously with AC4 and AC10 as compared to AG with REGIV and ROCII.

Discussion

This is the first study to investigate the measurement bias with AG counts and effect of alternative band-pass filters during walking and running and during free-living. The counts output with all band-pass filters demonstrate a positive linear association during walking for all age groups and negative during running for AG, whereas positive associations were found with AC10. A positive association during running was also observed with AC4 although not with children. This could be attributed to the use of a small indoor gym and the consequence of increased number of turns with running speed, but also a lack of the children to sustain high speed running. The AG counts obtained in this study during locomotion is consistent with previous studies demonstrating the plateau effect or inverted-U phenomenon above 10 km·h^{-1} (Brage *et al.*, 2003). Considering higher frequency information in the generation of counts reduce the measurement bias with running at speeds above 10 km·h^{-1} for all age groups and thus independent from stature and gait maturation. These findings support the proposed hypothesis that the plateau phenomenon is caused by the narrow band-pass filter (John *et al.*, 2012). However, the estimated free-living VPA was similar or lower with AC4 and AC10 as compared to AG with four of the six generated cut-point sets. This finding was not expected and in strong contrast to the proposed hypothesis.

Table 2 Estimated minutes spent in different intensity domains for the subjects enrolled in the population study by band-pass filter and analytical method used to determine the cut-point thresholds

	Sedentary	Light	Moderate	>Vigorous
REGI				
AG	507·8 (59·6)	197·6 (35·3)	65·9 (21·0)	12·3 (9·7)
AC4	467·1 (59·3)*	251·7 (43·8)*	60·5 (20·7)*	7·2 (5·9)*
AC10	463·7 (59·6)*	256·2 (44·4)**	63·2 (21·2)**	7·9 (5·7)*
REGII				
AG		194·5 (34·7)	63·2 (19·3)	18·1 (11·6)
AC4		245·2 (42·6)*	61·1 (19·6)*	13·0 (8·6)*
AC10		249·9 (43·3)**	63·6 (20·1)***	13·9 (8·6)*
REGIII				
AG		202·0 (36·1)	62·7 (20·6)	11·2 (9·3)
AC4		249·2 (43·4)*	62·6 (21·1)	7·5 (6·1)*
AC10		254·2 (44·0)**	65·0 (21·5)***	8·2 (5·9)*
REGIV				
AG		196·2 (35·0)	69·4 (22·2)	10·3 (9·0)
AC4		245·6 (42·7)*	60·9 (19·6)*	12·9 (8·6)*
AC10		249·6 (43·3)**	64·2 (20·2)**	13·6 (8·5)*
ROCI				
AG		241·8 (43·9)	21·7 (9·4)	12·4 (9·7)
AC4		283·7 (49·2)*	26·3 (11·1)*	9·3 (6·9)*
AC10		290·4 (50·1)**	26·5 (10·8)*	10·5 (7·0)**
ROCII				
AG		251·4 (45·9)	14·4 (7·0)	10·1 (8·9)
AC4		287·4 (49·9)*	19·2 (8·1)*	12·7 (8·5)*
AC10		292·7 (50·5)**	19·7 (7·9)*	15·0 (9·1)**

*Significant different from AG ($P<0.05$).
**Significant different from AG and AC4 ($P<0.05$).
***Significant different from AC4 ($P<0.05$).

Different analytical methods have been used in the literature to derive cut-point that define the light, moderate and vigorous intensity domains from ActiGraph counts, and the receiver operating characteristics (ROC) curves and linear regression analysis are commonly used (Freedson *et al.*, 1998; Jago *et al.*, 2007). There are different strengths and limitations to these methods, and other more advanced methods using machine learning have been suggested as alternatives. However, with no consensus to the most optimal method it was decided in this study to evaluate the time spent in VPA with cut-points generated from six different methods. The REGIV and ROCII cut-points were the only to demonstrate an increased free-living VPA with AC4 and AC10 counts as compared to AG counts. The brisk walking activity was the only activity defines the vigorous cut-point with ROCII, and only the stand, normal walking and brisk walking activities were used with REGIV cut-point sets. Thus, the running activity was not used to define the vigorous cut-point with any of these two cut-points sets. The requirement to not include the running activity in order obtain an increased VPA with AC4 and AC10 as compared to AG seems to be required by the elevated counts output with AC4 and AC10 during running as compared to walking, which is not demonstrated with AG counts. Increasing the frequency information from 1·66 Hz to >4 Hz in the generation of counts tend to favour running more than walking, which is caused by the difference in step frequency with the two locomotion types. The step frequency of walking is below 2 Hz, whereas step frequency for running is above 3 Hz (Schepens *et al.*, 1998, 2004). This seems to indicate that extending the consideration of frequencies provides a counts output during locomotion that tend to be more in line with biomechanics per se, and specifically, the substantial higher peak ground reaction force observed with running as compared to walking (Keller *et al.*, 1996).

The purpose of the narrow band-pass filter originally implemented in the AG counts processing was to reduce the influence of external noise (Tryon & Williams, 1996). However, considering the counts generated using the AC4 and AC10 band-pass filters during running as compared to walking it seems to suggest that the original band-pass filter is also implemented as an important prerequisite. The effect of the original band-pass filter clearly reduce the influence of locomotion type with the association between locomotion speed and AG counts and thus demonstrates the same association as EE (METs) with locomotion speeds (Ainsworth *et al.*, 2011).

The strong focus on cyclic movements and specifically running with the inclusion of higher frequency information could potentially have a negative consequence for the accurate identification of intermittent activities as VPA. Most intermittent game-based activities performed by children and adolescents are considered VPA (Butte *et al.*, 2018), and the proportion of the basketball activity performed in the calibration experiment to be identified as VPA from the different cut-points is almost non-existing with AC4 (<1·4%) and AC10 (<3·5%) as compared to AG (<23%). Thus, the increased time identified in VPA with AG counts as compared to AC4 and AC10 counts is most likely explained by an increased identification of intermittent activities as VPA even though it has been demonstrated that the estimated intensity of these activities from hip worn accelerometry using AG counts is biased (Staudenmayer et al., 2012). Therefore, an improved assessment of free-living VPA needs to consider the accurate intensity estimation of intermittent activities rather than the measurement bias with high speed running. Importantly, improving the assessment of VPA from acceleration measurement at the hip by only reducing the measurement bias with running at speeds above 10 km·h^{-1} is not an optimal solution per se.

Conclusions

Extending the frequency range with the generation of ActiGraph counts reduces the measurement bias with running activities above 10 km·h^{-1}. However, contrary to our expectations, there was no increase in free-living VPA compared to the original ActiGraph method. The original band-pass filter implemented with AG counts still provides the most optimal solution for the assessment of VPA when using cut-points predicted from ROC and regression analysis. The processing of raw acceleration into counts also needs to be developed to capture intermittent activity for an increase in vigorous activity would be detectable compared with the original ActiGraph counts.

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Conflict of interest

The authors have no conflict of interests that have influenced the work.

References

Aadland E, Andersen LB, Anderssen SA, *et al.* A comparison of 10 accelerometer non-wear time criteria and logbooks in children. *BMC Public Health* (2018); **18**: 323.

Ainsworth BE, Haskell WL, Herrmann SD, *et al.* 2011 compendium of physical activities: a second update of codes and MET values. *Med Sci Sports Exerc* (2011); **43**: 1575–1581.

Aittasalo M, Vähä-Ypyä H, Vasankari T, *et al.* Mean amplitude deviation calculated from raw acceleration data: a novel method for classifying the intensity of adolescents' physical activity irrespective of accelerometer brand. *BMC Sports Sci Med Rehabil* (2015); **7**: 18.

Bai J, Di C, Xiao L, *et al.* An activity index for raw accelerometry data and its comparison with other activity metrics. *PLoS ONE* (2016); **11**: e0160644.

Brage S, Wedderkopp N, Franks PW, *et al.* Reexamination of validity and reliability of the CSA monitor in walking and running. *Med Sci Sports Exerc* (2003); **35**: 1447–1454.

Brond JC, Andersen LB, Arvidsson D. Generating ActiGraph counts from raw acceleration recorded by an alternative monitor. *Med Sci Sports Exerc* (2017); **49**: 2351–2360.

Butte NF, Watson KB, Ridley K, *et al.* A youth compendium of physical activities: activity codes and metabolic intensities. *Med Sci Sports Exerc* (2018); **50**: 246–256.

Crouter SE, Bassett DR Jr. A new 2-regression model for the Actical accelerometer. *Br J Sports Med* (2008); **42**: 217–224.

Crouter SE, Clowers KG, Bassett DR Jr. A novel method for using accelerometer data to predict energy expenditure. *J Appl Physiol* (2006); **100**: 1324–1331.

Freedson PS, Melanson E, Sirard J. Calibration of the Computer Science and Applications, Inc. accelerometer. *Med Sci Sports Exerc* (1998); **30**: 777–781.

Garber CE, Blissmer B, Deschenes MR, *et al.* American College of Sports Medicine position stand. Quantity and quality of exercise for developing and maintaining cardiorespiratory, musculoskeletal, and neuromotor fitness in apparently healthy adults: guidance for prescribing exercise. *Med Sci Sports Exerc* (2011); **43**: 1334–1359.

van Hees VT, Gorzelniak L, Dean Leon EC, *et al.* Separating movement and gravity components in an acceleration signal and implications for the assessment of human daily physical activity. *PLoS ONE* (2013); **8**: e61691.

Herrmann SD, McMurray RG, Kim Y, *et al.* The influence of physical characteristics on the resting energy expenditure of youth: a meta-analysis. *Am J Hum Biol* (2017); **29**. https://doi.org/10.1002/ajhb.22944

Jago R, Zakeri I, Baranowski T, *et al.* Decision boundaries and receiver operating characteristic curves: new methods for determining accelerometer cutpoints. *J Sports Sci* (2007); **25**: 937–944.

John D, Miller R, Kozey-Keadle S, *et al.* Biomechanical examination of the 'plateau phenomenon' in ActiGraph vertical activity counts. *Physiol Meas* (2012); **33**: 219–230.

Keller TS, Weisberger AM, Ray JL, *et al.* Relationship between vertical ground reaction force and speed during walking, slow jogging, and running. *Clin Biomech (Bristol, Avon)* (1996); **11**: 253–259.

Medbo JI, Mamen A, Welde B, *et al.* Examination of the Metamax I and II oxygen analysers during exercise studies in the laboratory. *Scand J Clin Lab Invest* (2002); **62**: 585–598.

Migueles JH, Cadenas-Sanchez C, Ekelund U, *et al.* Accelerometer data collection and processing criteria to assess physical activity and other outcomes: a systematic review and practical considerations. *Sports Med* (2017); **47**: 1821–1845.

Resaland GK, Moe VF, Aadland E, *et al.* Active Smarter Kids (ASK): rationale and design of a cluster-randomized controlled trial investigating the effects of daily physical activity on children's academic performance and risk factors for non-communicable diseases. *BMC Public Health* (2015); **15**: 709.

Schepens B, Willems PA, Cavagna GA. The mechanics of running in children. *J Physiol* (1998); **509**(Pt 3): 927–940.

Schepens B, Bastien GJ, Heglund NC, *et al.* Mechanical work and muscular efficiency in walking children. *J Exp Biol* (2004); **207**: 587–596.

Staudenmayer J, Pober D, Crouter S, *et al.* An artificial neural network to estimate physical activity energy expenditure and identify physical activity type from an accelerometer. *J Appl Physiol* (2009); **107**: 1300–1307.

Staudenmayer J, Zhu W, Catellier DJ. Statistical considerations in the analysis of accelerometry-based activity monitor data. *Med Sci Sports Exerc* (2012); **44**: S61–S67.

Tryon W, Williams R. Fully proportional actigraphy: a new instrument. *Behav Res Methods Instrum Comput* (1996); **28**: 392–403.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Regression analysis – model performance & ROC analysis – sensitivity and specificity.