**Title:** Reexamination of accelerometer data processing and calibration for the assessment of physical activity intensity

**Running head:** Accelerometer data processing and calibration

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## Abstract

This review reexamines use of accelerometer and oxygen uptake data for assessment of activity intensity. Accelerometers capture mechanical work, while oxygen uptake captures the energy cost of this work. Frequency filtering needs to be considered when processing acceleration data. A too restrictive filter attenuates the acceleration signal for walking and, to a higher degree, for running. This measurement error affects shorter (children) more than taller (adults) individuals due to their higher movement frequency. Less restrictive filtering includes more movement related signals and provide measures that better capture mechanical work, but may include more noise. An optimal filter cut-point is determined where most relevant acceleration signals are included. Further, accelerometer placement affects what part of mechanical work being captured. While the waist placement captures total mechanical work and therefore contributes to measures of activity intensity equivalent by age and stature, the thigh and wrist locations capture more internal work and do not provide equivalent measures. Value calibration of accelerometer measures is usually performed using measured oxygen uptake with the metabolic equivalent of task (MET) as reference measure of activity intensity. However, the use of MET is not stringent and is not a measure of activity intensity equivalent by age and stature. A candidate measure is the mass-specific net oxygen uptake, $VO_2net$ ($VO_2tot$ – $VO_2stand$). To improve measurement of physical activity intensity using accelerometers, research developments are suggested concerning processing of accelerometer data, use of energy expenditure as reference for activity intensity, and calibration procedure with absolute versus relative intensity.

**Key words:** Acceleration, counts, frequency filtering, mechanical work, energy expenditure

## Introduction

Accelerometer-based assessment of physical activity intensity is widely used in observation and intervention studies. It provides the opportunity to study intensity patterns continuously for long time-periods with high resolution. A crucial step of the assessment is the extraction of the useful part of the acceleration signal and transformation into meaningful measures. However, our comprehension of accelerometer-based assessments of physical activity has been negatively affected by previous non-optimal processing of accelerometer data on the one hand and how energy expenditure measures as reference of physical activity intensity have been calculated on the other hand. While the acceleration signal from sensors follows, in a complex way, the biomechanical rules determined by body dimensions, attachment position and movement efficiency, the corresponding energy cost is affected by physiological maturation and efficiency. The biomechanical and physiological measures of physical activity are not directly interchangeable, as the former determines the mechanical work performed while the later determines the energy cost of this work. Hence, they are not equal, which needs to be considered in processing of acceleration data and their calibration.

In 1996, Tryon and Williams introduced the fully proportional actigraphy developed by the Computer Science and Application (CSA) company, with detailed descriptions of the processing from raw acceleration data to counts.[1] The last processing step included the translation from gravity *g* to counts with the analogue-digital converter; the maximum acceleration of 2.13 g/sec was divided into 128 digital levels, providing a measure of 0.01664 g/sec/count. The integral by time results in g/count. The count is a unitless measure of the movement intensity of each time-period recorded called epoch (e.g. 10 sec or 60 sec). Since then, successive models of this accelerometer, now called the ActiGraph, have been developed. Today, the ActiGraph is the dominating accelerometer in research and the ActiGraph count has been established as a standard measure of physical activity intensity.[2,3] However, a plateau of the ActiGraph counts was demonstrated from recordings at the waist at an intensity corresponding to running at 10 $km \cdot h^{-1}$,[4,5] which indicates a measurement bias. Despite the detailed description provided by Tryon and Williams of the processing of raw acceleration data to ActiGraph counts,[1] this information and the consequence of the processing on the assessment of physical activity intensity have generally been overlooked. Partly because the processing information is not easily accessible or properly presented, but also because acceleration signal processing requires engineering competence which is not possessed by all users of accelerometers. Physical activity research has turned to the use of raw acceleration measures as a reaction against the incomplete information provided by many manufacturers of accelerometer methods.[6,7] A recent study provided detailed insight into current processing of raw acceleration into ActiGraph counts and demonstrated the inborn processing bias contributing to the plateau-effect, which is explained in details in the coming section of this work.[8] More importantly, the results emphasize the need for reexamination of acceleration data processing with respect to the acceleration measured at various body wear locations, whether it is the ActiGraph count or any other metric.

To facilitate interpretation of accelerometer data, value calibration has been performed using energy expenditure to obtain reference measures for absolute activity intensity, with the metabolic equivalent of task (MET) as the most commonly used. The MET is established by the quotient of total activity-specific energy expenditure (TEE) and resting energy expenditure (REE); both can be established by direct measurement of oxygen uptake but REE is often predicted from age- and sex-specific equations. Because of higher proportion of metabolic active tissue, the mass-specific (normalized by a measure of body mass) oxygen uptake during rest is higher in children compared to adults.[9] Consequently, the MET-values for specific activities increase from childhood to adulthood, which is especially apparent at moderate intensity or higher.[10-14] Still, cut-points for moderate physical activity (MPA; 3 METs) and vigorous physical activity (VPA; 6 METs) activity are used interchangeably between age-groups, but at the same time distinct values are applied (3 versus 4 METs for MPA).[2] Hence, we put higher demands on children and adults when determining their MPA and VPA. The use of MET as reference measure together with the ActiGraph count has resulted in a vast number of age-separated calibration algorithms with unknown comparability.[2]

This narrative review provides a reexamination of the assessment of physical activity intensity with accelerometers, approaching both the processing of acceleration data based on biomechanical theory and the use and calculation of energy expenditure to achieve a reference metric of activity intensity that is equivalent by age or stature.

## Processing of acceleration data

Freedson et al[15] and Trost et al[16] provided the first calibration studies of the ActiGraph counts generated from waist recordings. Figure 1 displays the counts generated for the walking and running speeds in their studies. It demonstrates lower values in children compared to in adults. In the same figure, waist data from the more recent study by Hildebrand et al are presented.[7] In contrast, the activity intensity metric Euclidian norm minus one (ENMO) based on raw ActiGraph acceleration data shows higher values in children compared to adults. Below we attempt to examine these contrasting results from a biomechanical perspective to provide an explanation.

An accelerometer can be considered to provide a measure of the mechanical work of moving a body as it registers acceleration. In classic physics, work (W) is simply calculated as the product of acceleration (a), body mass (m) and displacement (s), i.e. $W = a \cdot m \cdot s$. In addition, if acceleration is integrated by time, movement speed (v) is achieved and kinetic energy can be calculated as $E_k = (m \cdot v^2)/2$. Similarly, as the ActiGraph count is based on the integration of acceleration, this metric may represent movement speed. However, calculation of the work for moving the human body is more complex, as it involves the movement of different segments (trunk, legs, arms) in an interacting pattern typical for the activity performed. A biomechanical model of human movement describes total work ($W_{TOT}$) as divided into the external work for displacement of the center of mass relative to surrounding ($W_{EXT}$) and the internal work of moving the limbs to contribute to this displacement ($W_{INT}$) (Figure 2).[17-19] These parameters are calculated as mass-specific to be able to compare individuals or groups of different body size. By doing that, the work determined is the product of acceleration and displacement ($W = a \cdot s$). In humans, the biomechanical model is primarily applicable to explain physical activity intensity measurement from accelerometer recordings at the waist and leg (thigh), as the wrist has a more complex movement pattern not always related to the movement intensity of the rest of the body. Therefore, for example, discrepancies between the wrist and waist locations can occur for free-living measurements because their movements are being decoupled.[20] Due to the complexity of arm movements, machine-learning algorithms may be required to achieve the same level of accuracy for activity intensity as with the waist and thigh location.[21]

During walking, both the vertical ($W_{EXT\text{-}VERT}$) and the horizontal ($W_{EXT\text{-}HOR}$) components of $W_{EXT}$ increase with speed.[18,19] At the start of running there is a large increase of $W_{EXT\text{-}VERT}$, but it reaches a plateau with faster running speed, while $W_{EXT\text{-}HOR}$ continues to increase. $W_{INT}$ increases across walking and running. Therefore, $W_{EXT}$ (due to $W_{EXT-HOR}$) and $W_{INT}$ contribute both to the continuous increase of $W_{TOT}$ across running speeds. Altogether, $W_{TOT}$ forms a curvilinear relationship with movement speed. It has been demonstrated that the mass-specific $W_{TOT}$ is similar in children and adults for walking and running at the same absolute speed (at least within natural speed ranges), but $W_{EXT}$ is larger in adults due to larger vertical acceleration amplitude following larger step length, while $W_{INT}$ is larger in children due to higher step frequency.[17,18,22] $W_{EXT}$ has an inverse relationship with step frequency, while $W_{INT}$ shows a positive relationship with step frequency. From the biomechanical model, one would expect larger values from accelerometer recordings at the waist in adults compared to children as the mass-specific $W_{EXT}$ would be captured in this position, but that the opposite would occur for recordings at the thigh or wrist capturing more of $W_{INT}$. Further, the early observation of the plateau-effect of the ActiGraph counts would have been explained by that the ActiGraph accelerometer at that time recorded vertical accelerations only (uniaxial).[4]

However, the major explanation to the plateau-effect and age differences for waist data was found in the ActiGraph frequency band-pass filter.[4,5,8] The ActiGraph company made the ActiGraph raw acceleration data accessible with model GT3X+ that was released in 2010 and moved the processing to counts into their software ActiLife. This made it possible to investigate the frequency content of the measured acceleration as well as the processing into ActiGraph counts. Step frequency is the predominant frequency component due to the large acceleration generated with the ground contact of the foot and its propagation upwards through the leg to the waist. The ActiGraph filter algorithm allows full signal pass at a frequency of 0.75 Hz with successive attenuation of the signal at lower and higher frequencies (Figure 3).[8] Fifty percent of the signal remains at a signal frequency of 2.5 Hz, while total elimination occurs above 5 Hz.

Step frequency during walking may reach 2 Hz, while fast running can be performed up to 4 Hz.[5,17,18,22] The step frequency can be up to 1 Hz higher in children compared to in adults for the same absolute locomotion speed. Accordingly, the ActiGraph counts may underestimate the mechanical work performed at higher movement intensities and more in children than in adults. This is also demonstrated in Figure 4 displaying the ActiGraph counts generated during walking and running from several studies in children and adults.

When the filter is expanded allowing higher movement frequencies, the difference in activity counts generated from the waist between children and adults is diminished as well as the plateau-effect (Figure 5).[22] In addition, the curvilinear relationship between speed and counts appears more clearly, as expected from the biomechanical literature[17-19] and confirmed from other sources of acceleration data collected at the waist.[6,23] These results together with the results from Hildebrand et al[7] and in perspective of the biomechanical model of $W_{TOT}$, $W_{EXT}$ and $W_{INT}$[17-19] raise the principal question of what we actually measure with an accelerometer at the waist, as well as at other body placements, and the comparability between age-groups.

The narrow range of the ActiGraph band-pass filter imposes a more linear relationship between locomotion speed and acceleration amplitude from walking to running than it really is, by attenuating the acceleration amplitude to an increasing extent with higher speed and movement frequency (Figure3, Figure 5).[8,22] The acceleration captured corresponds to what is generated and propagated up to the waist by each ground contact by the foot for displacement of the center of mass, i.e. $W_{EXT}$, but with a reduced amplitude. By opening up the low-pass filter to 4 Hz, the full acceleration amplitude generated by the ground contact of the foot is captured across movement speeds. Still, the counts generated is mainly explained by $W_{EXT}$, as only frequencies corresponding to the foot ground contact frequency (i.e. step frequency) are included by the filter. ActiGraph counts and counts generated with the 4 Hz filter will therefore not be directly comparable between individuals of different age and stature. However, expanding the filter to 10 Hz may capture additional acceleration signals generated by locomotion, including leg movements that add to or modify the acceleration signal recorded at the waist, contributing to that a larger proportion of $W_{INT}$ explains the variation in counts.[22] Consequently, the wider filter would better capture the movement pattern due to age (step length and step frequency), getting closer to $W_{TOT}$. It would explain the more similar count values between children and adults observed using 10 Hz low-pass filter.[22]

Finally, total omission of a low-pass filter would contribute to capturing also more noise. An important question concerns whether the different results applying 10 Hz low-pass filter (similar values in children vs. adults) compared to the omission of a low-pass filter in the ENMO method applied in the study by Hildebrand et al[7] (higher values in children vs. adults) is explained by children truly generating more acceleration and therefore more work for similar activity due to a more inefficient movement pattern, or if there is a measurement error issue in processing acceleration data. The ENMO algorithms set all negative accelerations to zero after subtracting 1 *g* from the vector magnitude. This means that acceleration signals generated with larger amplitude but at lower frequency (as in adults) will be excluded to a larger extent compared to acceleration signals with lower amplitude but at higher frequency (as in children). In contrast, the generation of counts is the aggregation of both positive and rectified negative acceleration signals. The consequences of the ENMO processing versus the 10Hz low-pass filter method needs further investigation.

The ENMO[7] and the Mean Amplitude Deviation (MAD)[6] are two alternative measures of activity intensity generated from raw acceleration. Their metrics are expressed in m*g*. None of these approaches use a low-pass filter to attenuate irrelevant acceleration signals. The effect of low-pass frequency filtering on the accuracy of the acceleration data has been investigated for an accelerometer attached at the upper back during walking and running on a treadmill using a camera motion analysis system as criterion method for acceleration.[24] This study demonstrated large measurement error with unfiltered raw acceleration data, while the highest accuracy was achieved by applying 8-10 Hz low-pass filter. However, these results are not directly applicable to waist acceleration data and do not explain differences between children and adults. They do indicate that different outcomes are to be expected depending on filtering of acceleration data and an important goal is to explore accurate filter cut-points to capture the mechanical work actually performed and to minimize inclusion of noise. In the lab environment, the noise component of the registered acceleration signal can be controlled to be within a limited range, while in the free-living situation factors such as accelerometer position and attachment, and vibrations transferred from the environment for example during passive transportation may contribute to an important part of the acceleration information registered. Unfortunately, free-living investigations of the effect of frequency filtering are rare.

Recording acceleration signals at the thigh and wrist would contribute to different outcomes compared to at the waist. At the thigh placement, an accelerometer may capture more of the acceleration signal generated due to leg swing related to $W_{INT}$. It may be possible at this placement, that a 4 Hz low-pass filter would generate similar acceleration values in children and in adults as some of the relevant acceleration signals is still attenuated by the filter, while a 10 Hz low-pass filter contributes to higher acceleration values in children when all relevant acceleration signals are included. As with the thigh placement, it may well be that the wrist placement captures more of $W_{INT}$ and higher values would be observed in children than in adults if the 10Hz filter is applied. Altogether, recording location affects data processing and comparability between individuals of different age and stature.

Based on the rationale above, our statement is that improved processing of acceleration data may contribute to a measure of $W_{TOT}$ equivalent by age and stature for the same absolute movement speed with the waist placement, while more $W_{INT}$ may be captured at the thigh and wrist and therefore these placements would not be equivalent by age and stature. The recommended low-pass frequency filter cut-point would be 10 Hz, at least for the waist placement, to include all relevant acceleration signals. Further research is required to establish the optimal filter cut-point for all three body placements.

### Energy expenditure as reference for activity intensity

While most calibrations of accelerometers in adults have used the MET as criterion measure for activity intensity,[6,7,15,25-32] there has been a mixture between using the MET and the activity type (e.g. brisk walk, run) in children.[7,16,33-42] Several studies have demonstrated an increase in the MET-value with increasing age across childhood for walking and running at the same speed,[10-14] which can be explained by the decreasing mass-specific resting energy expenditure by age.[9] In one study, different measures of energy expenditure for walking and running and their relationships with age were investigated within an age-range of 5-18 years.[12] The MET-value showed a moderate positive relationship with age, while $VO_{2NET}$ ($ml \cdot kg^{-1} \cdot min^{-1}$) and $VO_{2ALLOM}$ ($ml \cdot kg^{-0.75} \cdot min^{-1}$) showed weak to moderate negative relationship with age. Hence, none of these measures of activity intensity are equivalent by age and stature.

The $VO_{2NET}$ measure in the study above was calculated by subtracting $VO_{2REST}$ from $VO_{2TOTAL}$. As accelerometers estimate the mechanical work performed during movement, this way of calculating $VO_{2NET}$ may not be optimal as it includes energy expenditure for standing. Biomechanical research has instead expressed $VO_{2NET}$ by subtracting $VO_{2STAND}$ from $VO_{2TOTAL}$. This measure of activity intensity (with the unit $ml \cdot kg^{-1} \cdot min^{-1}$) shows more similar values in children and adults for ambulatory movement, although some differences remain explained by stature.[17,18,43,44] One way to deal with differences in $VO_{2NET}$ due to age and stature may be to express it at kinematically equivalent speed determined by the Froude number. The Froude number (Fr) is calculated as: $Fr = V^2/gL$ (V=speed, g=acceleration due to gravity, L=stature). When individuals with different age and stature move at the same absolute speed, younger and shorter individuals have higher step frequency.[17,18] As the mass-specific energy expenditure per step is the same for individuals of different age and stature, younger and shorter individuals will have higher mass-specific energy expenditure.[17,18,45] However, at the kinematically equivalent speed, the mass-specific energy expenditure (and effort) is the same for individuals of different age and stature as they move at different absolute speeds.[45] Therefore, calibration studies with $VO_{2NET}$ may be employed if comparison between age-groups are of interest.

A related question concerns the establishment of cut-points for activity intensity to be able to determine time spent in, for example, MPA and VPA. Unfortunately, the literature provides a vast number of cut-points for children and adults to choose between, with a large variation in values both between age-groups and within age-groups. In calibration studies in children and adults, slow-comfortable walk has been selected to represent light activity, brisk-fast walk as moderate activity, and running as vigorous activity, but this has not been done consequently [6,7,15,16,25-42]. Central measures of intensity in these calibration studies have been 3 METs as reference cut-point for MPA and 6 METs for VPA. 4 METs has also been used as reference cut-point for MPA in children. This MET-value has been observed for movement speeds defined as being at moderate intensity, while 3 METs have been found for light activity (LPA).[11,12,14] Figure 6 displays walking and running speeds with the corresponding ActiGraph counts together with the range of cut-points for MPA and VPA in children, adolescents and adults based on the data published from the various calibration studies performed in these age-groups. These results emphasize an important issue concerning how MPA and VPA is defined. The cut-point for MPA generally falls on the walking speed of 4 $km \cdot h^{-1}$ in these studies, which is commonly defined as slow, casual or comfortable walk in children and adults. Therefore, the cut-point for MPA may be set too low and too easily classifies individuals as being sufficiently physically active.

There seems to be a conflict in physical activity research in the definition of MPA; either it should be distinguished by brisk walking, or also include lower intensities as comfortable walking. The early physical activity recommendations in adults exemplified the distinction of MPA from LPA as being equivalent to brisk walking at 4.8-6.4 $km \cdot h^{-1}$.[46,47] The Compendium of Physical Activities for adults includes walking at a moderate pace at 4.5-5.1 $km \cdot h^{-1}$ (3.5 METs) and at brisk pace at 5.6 $km \cdot h^{-1}$ (4.3 METs), compared to a slow pace at 3.2 $km \cdot h^{-1}$ (2.8 METs).[48] In youth, MPA in physical activity recommendations has been described as when their heart beats faster and when they breath faster, which would correspond to the brisk pace.[49] The Youth Compendium of Physical Activities includes self-paced brisk walking corresponding to 5.6 $km \cdot h^{-1}$ (6-9 yrs: 4.6 METs; ≥10 yrs: 5.0 METs), compared to self-paced casual walking at approximately 4-4.8 $km \cdot h^{-1}$ (6-9 yrs: 3.6 METs; ≥10 yrs: 3.9 METs).[50] The definition of VPA is more congruent in the calibration literature, often including running pace and with a cut-point of 6 METs in both children and adults. Still, 6 METs is reached at a different running speed in children compared to adults, due to different REE as well as that equal MET value does not reflect equivalent activity intensity.

We ask for more congruent definitions of MPA and VPA. We suggest the following standard activities in calibration studies as belonging to respective intensity category: self-paced casual walk as light activity, self-paced brisk walk as moderate activity and jog as vigorous activity. The next step would be to investigate the regression line of the Froude number (calculated from measured speed and body height) versus the mass-specific $VO_{2NET}$ ($VO_{2TOTAL}$ – $VO_{2STAND}$) and determine the $VO_2$net cut-points for MPA and VPA at the values achieved between the standard activities (Figure 7A). The final step would be to investigate the regression line of $VO_{2NET}$ versus the accelerometer metric (e.g. counts, m*g*) and to set the accelerometer cut-points corresponding to the defined $VO_{2NET}$ cut-points (Figure 7B). As the absolute speed corresponding to the equivalent speed is lower in children than in adults, the accelerometer cut-points will also be lower in children.

An additional factor that adds to the complexity of the determination of MPA and VPA is the influence of fitness level.[51] Two individuals with different fitness levels may perceive MPA and VPA at different equivalent speeds and $VO_2$net. Therefore, intensity cut-points relative to $VO_2$max (or $VO_2$net-max) may be determined (relative intensity), using data from calibration studies. $VO_2$net intensity cut-points (MPA, VPA) would be expressed as fixed proportions of various predetermined $VO_2$net-max levels representing very low, low, moderate and high fitness. However, the choice between absolute intensity cut-points or relative intensity cut-points needs to be carefully considered in relation to the investigation design performed, otherwise erroneous results may be achieved. For example, in an intervention study or implementing a training program in clinical setting to increase physical activity, two individuals with different $VO_2max$ who spend the same amount of time at their relative MPA level may experience similar health effect. This is because the individual with lower $VO_2max$ would require lower dose compared to the individual with higher $VO_2max$.[52,53] In this case, an association between MPA and health effect may be detected if relative intensity cut-points are used. Disregard of the $VO_2max$ may well explain the inter-individual variations frequently reported in training or intervention studies. On the other hand, in cross-sectional investigations when applying relative intensity cut-points, the amount of physical activity may be shifted so that the individual with lower $VO_2max$ may achieve more physical activity than the individual with higher $VO_2max$ compared to if absolute intensity cut-points had been used. In this case, a relationship between high physical activity and health might disappear or even show a reverse relationship because of the strong relationship between fitness and health.[54]

A practical issue with relative intensity is that, in many cases the $VO_2max$ is not directly measured but rather indirectly assessed using walk-tests, submax-tests or self-report. Therefore, a practical compromise would be to use these indirect measures to assign the individual into one of the $VO_2net$-max levels (very low, low, moderate, high) and thereafter apply the specific $VO_2net$ cut-points and corresponding accelerometer cut-points of respective level to determine time in, for example, moderate physical activity. Little has been investigated concerning the relative intensity cut-points. Therefore, this model of cut-points for accelerometer data needs to be further developed, refined and tested.

Our statement is that, to be able to directly compare physical activity intensity between individuals of different stature and age using accelerometers, and if energy expenditure is used as reference for activity intensity, accelerometer metrics could be calibrated against the mass-specific $VO_{2NET}$ calculated as $VO_{2TOTAL}$ subtracted by $VO_{2STAND}$. Relative intensity cut-points for accelerometer data may be developed and implemented to target differences in the perceived intensity level due to different $VO_2max$, but should be considered in relation to the investigation design performed.

## Summary and proposals

With this paper, we promote a reexamination of the use and processing of acceleration data in children and adults as well as of the energy expenditure reference measure of activity intensity. While an accelerometer at the waist could be used to estimate total mechanical work for the absolute speed that is equivalent age and stature, mass-specific net oxygen uptake ($VO_{2TOTAL}$ – $VO_{2STAND}$, $ml \cdot kg^{-1} \cdot min^{-1}$) may be used as a physiological measure of activity intensity that is equivalent by age and stature when expressed at equivalent speed. The thigh and wrist location can also be used to measure activity intensity but are not equivalent by age and stature. The wrist location may require more advanced data processing for an accurate measure of activity intensity. First, we need to decide whether mechanical work or energy expenditure is the measure of physical activity intensity as it affects the calibration method. We propose following future research needs to summarize the content of this paper:

- Examination of the optimal processing of acceleration data (e.g. frequency filtering) from accelerometers attached at the different body segments in different age and statures

- Assess the proportion of external and internal work recorded with accelerometers at the different body segments
- Further investigation of reference measures for activity intensity of ambulatory activities based on mechanical work or oxygen uptake
- Examination of the relationship between acceleration measure of activity intensity and reference measure of activity intensity (work or oxygen uptake)
- Establish standard activities in children and adults representing light, moderate and vigorous physical activity based on clear biomechanical or physiological definitions of target activity intensity, not based on MET-values
- Implement and evaluate relative intensity cut-points for accelerometers preferably in investigations with the design of intervention or training program to improve health; implementation and evaluation in cross-sectional investigations need to be done cautiously

## Perspectives

- Accelerometer data collected at the waist may represent total mechanical work and provide a measure of activity intensity equivalent by age and stature, while data collected at the thigh and wrist capture more internal mechanical work and therefore not equivalent
- Total mass-specific oxygen uptake subtracted by standing oxygen uptake ($VO_{2NET}$, ml·kg$^{-1}$) may be a reference measure of activity intensity equivalent by age and stature
- $VO_{2NET}$ may be used for accelerometer calibration and thereby allow comparison of time being physically active between individuals if different age and stature
- Improvements in measurement of physical needs to be verified in relation to various health outcomes to determine the clinical relevance

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## Figures

**Figure 1.** ActiGraph vertical counts and ActiGraph raw acceleration (ENMO) from data recorded at the waist in children and in adults during walking and running on a treadmill. Graph adapted from Trost et al[16] and Freedson et al[15], and from Hildebrand et al[7].

**Figure 2.** Mechanical work during walking and running, where total work ($W_{TOT}$) and its sub-components external work ($W_{EXT}$) and internal work ($W_{INT}$) are displayed. Graph adapted from Schepens et al.[17,18]

**Figure 3.** Replication of the ActiGraph frequrency band-pass filter, demonstrating the successive attenuation of the recorded acceleration signal with lower or higher movement frequencies than 0.75 Hz. Graph adapted from Brønd et al.[8]

**Figure 4.** ActiGraph counts (vertical axis) from walking and running in children and adults. Circles are values from walking and triangles from running. Graph adapted from several sources of published data.[4,5,15,16,23,25-32,34-42,55]

**Figure 5.** Original ActiGraph counts and activity counts generated with the low-pass filter expanded to a cut-point of 4 Hz or 10 Hz in children (dotted line), adolescents (dashed line) and adults (solid line) walking and running at the same speed on a treadmill. Graphs adapted from Fridolfsson et al.[22]

**Figure 6.** ActiGraph counts cut-points (vertical axis) for moderate (dashed lines) and vigorous (dotted lines) physical activity generated in calibration studies divided into different age categories. The two lines for each intensity level indicate the lowest and the highest cut-point generated from the included studies in each age category. Circles are values from walking and triangles from running. Graph adapted from several sources of published data.[4,5,15,16,23,25-32,34-42,55]

**Figure 7.** Conceptual proposal of calibration of accelerometers. **A** The first step of calibration by setting the mass-specific $VO_{2NET}$ cut-point at the equivalent speeds corresponding to the break-point between casual-comfortable walking and brisk walking (moderate), and between brisk walking and start of running (vigorous). **B** The second step of calibration by setting the corresponding accelerometer cut-points using the defined $VO_{2NET}$ for moderate and vigorous activity, here exemplified with activity counts generated using a 10Hz low-pass filter.[22]

Figure 1

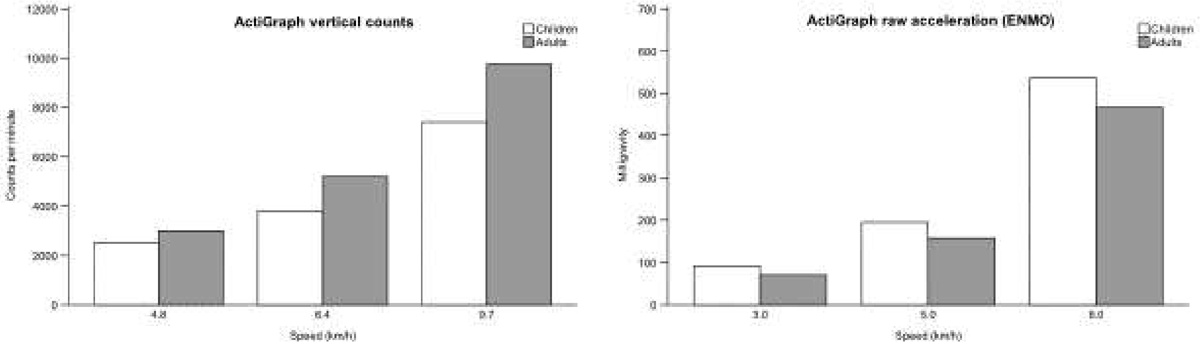



Figure 2

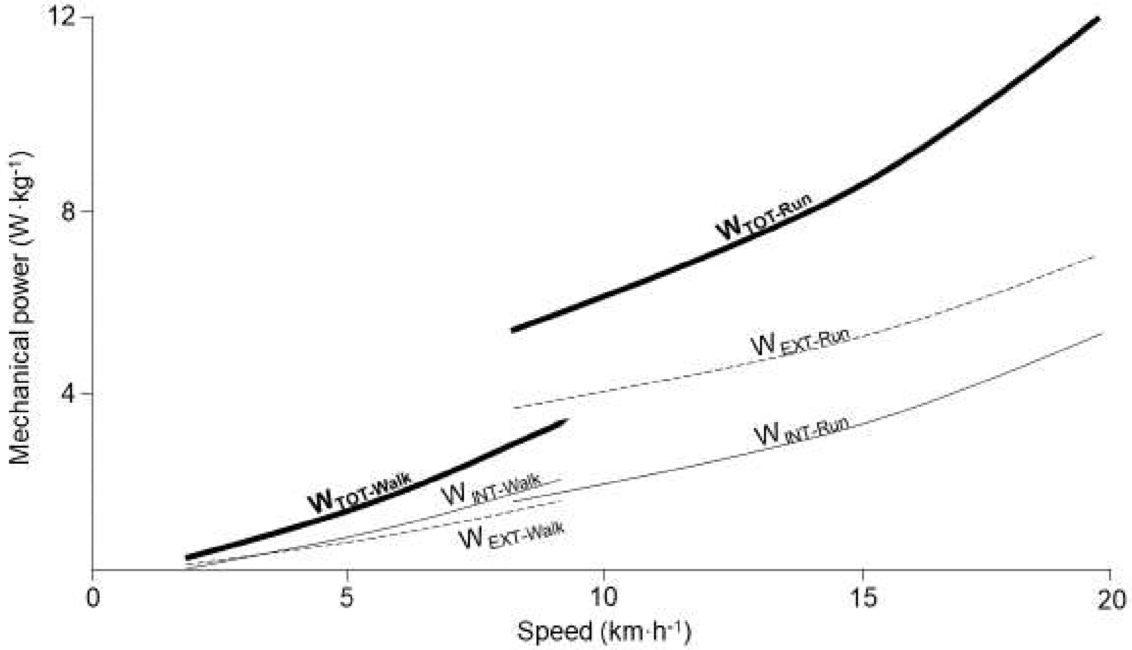


Figure 3

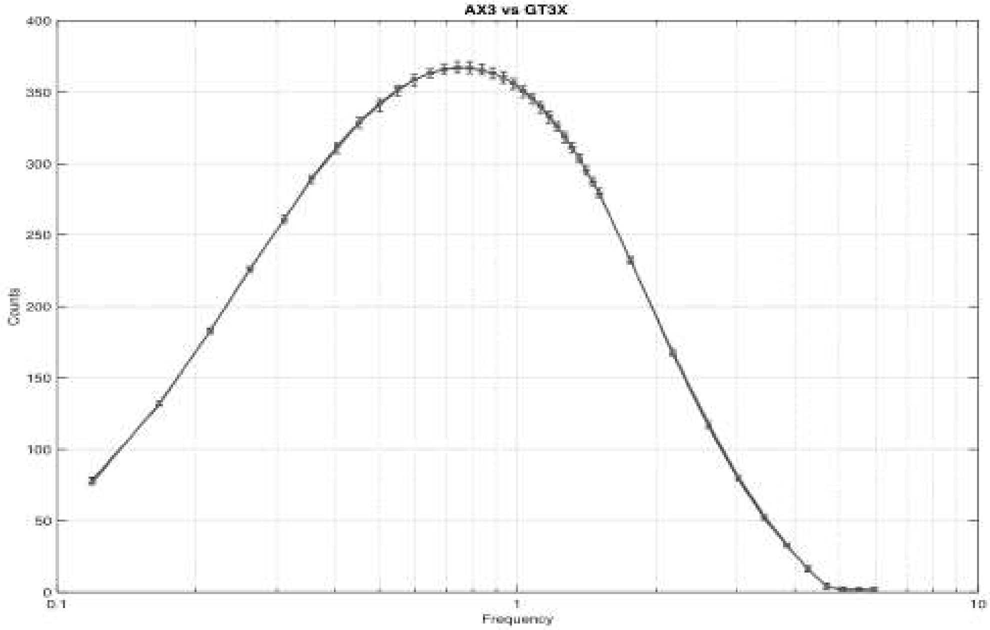



Figure 4

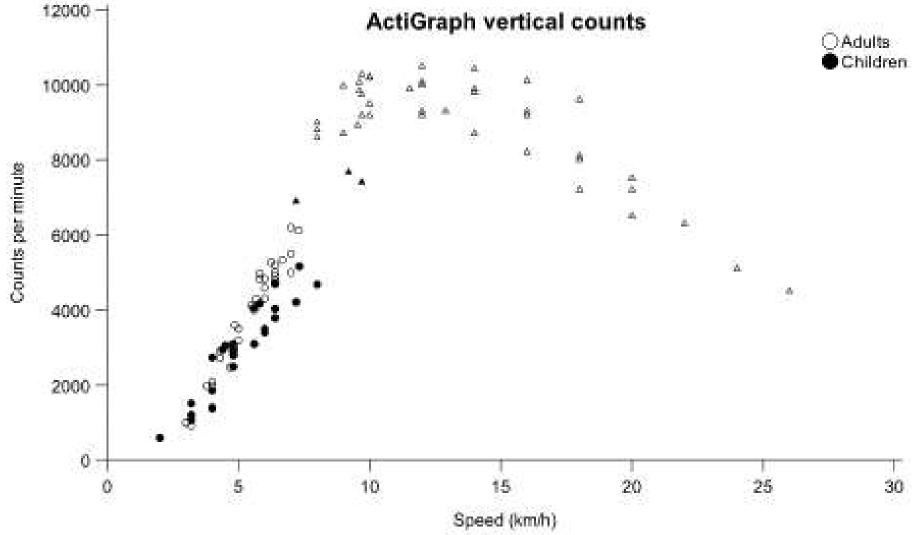


Figure 5

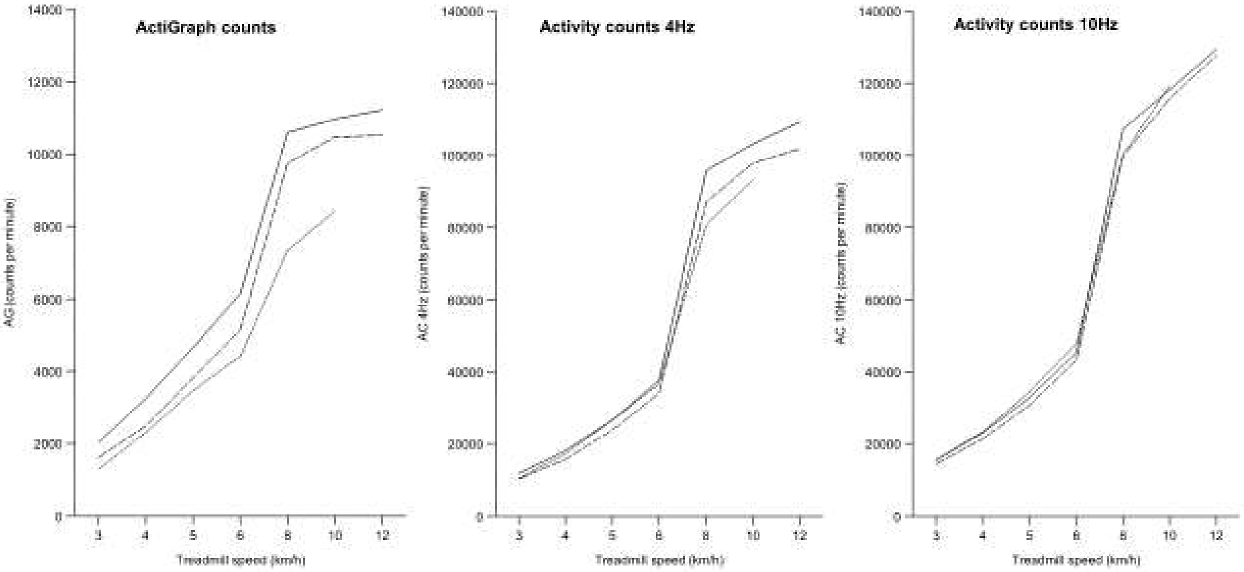



Figure 6

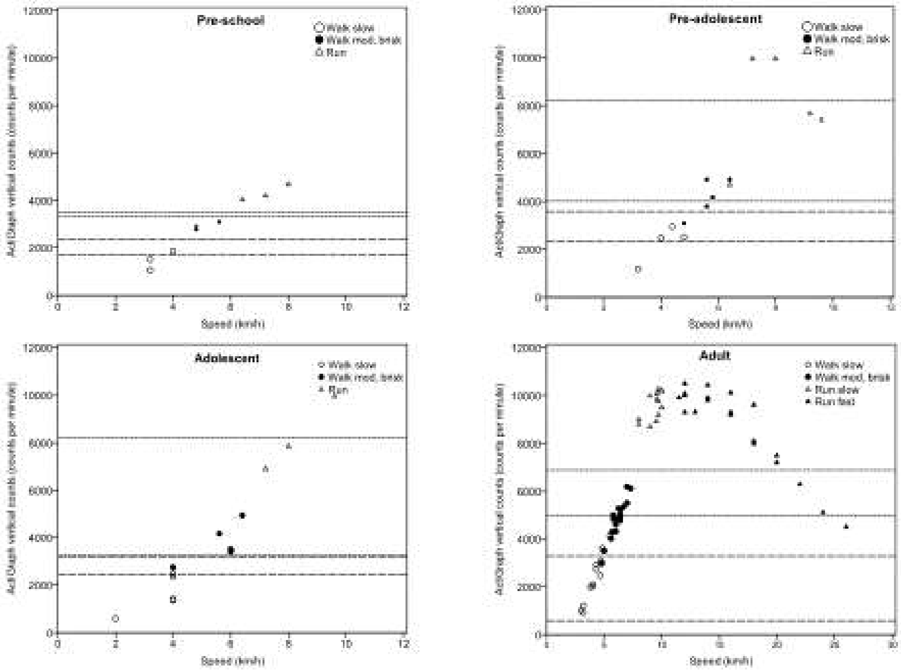
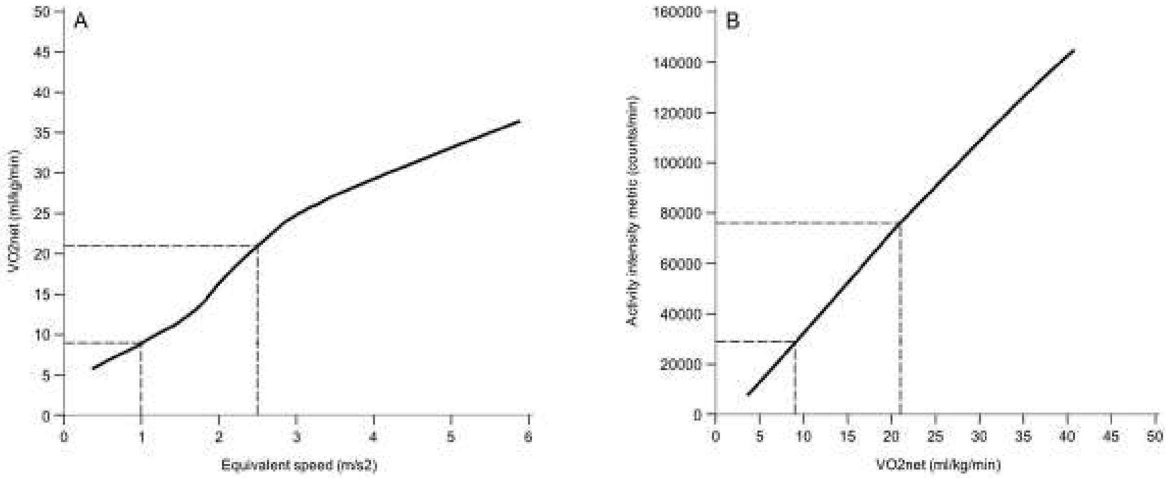


Figure 7


A
VO2net (ml/kg/min)
Equivalent speed (m/s2)
B
Activity intensity metric (counts/min)
VO2net (ml/kg/min)