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Generating ActiGraph counts from raw acceleration recorded by an alternative monitor

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Abstract

Purpose: To implement an aggregation method in Matlab for generating ActiGraph counts from raw acceleration recorded with an alternative accelerometer device and to investigate the validity of the method. **Methods:** The aggregation method including the frequency band-pass filter was implemented and optimized based on standardized sinusoidal acceleration signals generated in Matlab and processed in the ActiLife software. Evaluating the validity of the aggregation method was approached using a mechanical setup and with a 24-hour free-living recording using a convenient sample of nine subjects. Counts generated with the aggregation method applied to Axivity AX3 raw acceleration data were compared to counts generated with ActiLife from ActiGraph GT3X+ data. **Results:** An optimal band-pass filter was fitted resulting in a root mean squared error (RMSE) of 25.7 counts per 10 second and mean absolute error (MAE) of 15.0 counts per second across the full frequency range. The mechanical evaluation of the proposed aggregation method resulted in an absolute mean (sd) difference of -0.11 (0.97) counts per 10 second across all rotational frequencies compared to the original ActiGraph method. Applying the aggregation method to the 24-hour free-living recordings resulted in an epoch level bias ranging from -16.2 to 0.9 counts per 10 second, a relative difference in the averaged physical activity (counts per minute) ranging from -0.5% to 4.7% with a group mean (sd) of 2.2% (1.7%) and a Cohen's Kappa of 0.945 indicating almost a perfect agreement in the intensity classification. **Conclusion:** The proposed band-pass filter and aggregation method is highly valid for generating ActiGraph counts from raw acceleration data recorded with alternative devices. It would facilitate comparability between studies using different devices collecting raw acceleration data.

Keywords: GT3X+, physical activity, filtering, algorithms, validation

Introduction

Estimating physical activity (PA) in large-scale epidemiological projects is nowadays commonly performed using objective methods, which are widely accepted to have higher validity than self-report in the assessment of energy expenditure (17, 32). Accelerometry is a feasible objective method, with the ActiGraph as the most widely used brand and typically attached to the hip, although wrist, thigh and ankle are also used. The main output from the ActiGraph is called counts and is generated through several processing steps of the original raw acceleration signal recorded (28). The validity of the ActiGraph monitors for the assessment of physical activity in a population has been extensively studied across many different age groups, gender and patient groups.

Today, alternative brands of accelerometers, smaller size, water resistant, lower cost and full transparency of hardware and software information are available. However, these brands do not share the number of calibration and validation studies available with the ActiGraph, which would otherwise facilitate their use. The direct application of these calibration and validation studies would require an accurate generation of ActiGraph counts from raw acceleration data collected with the alternative accelerometer brands, which also would facilitate comparability across previous and new studies. In addition, a transparent and open implementation of the ActiGraph counts generation would enable and simplify large-scale data handling and processing as well as methodological development using alternative platforms like OSX or Linux and in any programming language or statistical software.

Only a few attempts have been made to enable comparability of ActiGraph counts with the output of alternative brands. Paul et al (20) and Straker et al (26) used simple linear regression to relate mean daily Actical counts to ActiGraph counts. Although high correlation between brands could be achieved, there were large individual differences. None of these studies investigated the validity of intensity classification, which has been shown to have important impact on health related outcomes (1). In addition, the scattergrams and Bland-Altman plots in the study by Straker et al (26) demonstrated that the conversion algorithm would largely overestimate ActiGraph counts from Actical counts for higher intensities. For any of the two methods of comparability presented above to be valid, the assumption of a linear relationship between the two different PA outputs has to be maintained. However, a leveling off of the counts from the ActiGraph at the hip has been demonstrated with increasing PA intensity (5, 8, 12). Therefore, the leveling off of the ActiGraph needs to be taken into account for a comparability of either the daily PA or intensity classification to be valid.

Some of the limitations in the studies presented above was targeted in a study by van Hees et al (31) where raw acceleration data from the GENEA accelerometer was converted to ActiGraph counts by following the technical specifications by ActiGraph of processing acceleration data. Their method explained 94.2% of the variation in ActiGraph counts, although poor intensity classification was achieved. Not all technical specifications of the processing of ActiGraph data have been released, which interferes with the generation of ActiGraph counts from acceleration data collected with other brands. For example, error in the estimation of the band-pass filter algorithm by van Hees et al (31) could have contributed to the poor results with the intensity classification. Instead of approximations based on available technical specifications, a better solution would be a direct determination of ActiGraph processing characteristics by generating pre-specified raw acceleration data and run them through the ActiGraph processings to detect the response on the counts output.

Estimating a PA measure from accelerometry typically follow the same processing principles and involves frequency filtering, thresholding, rectification and integration. Frequency filtering is a fundamental step and is used to extract human movement and to attenuate noise and artifacts. Attenuating noise and artifacts from raw acceleration data is typically done using a band-pass filter defined by two cut-off frequencies (low and high) and an order. The cut-off frequencies define the signal frequency boundaries and the order defines at what rate data is suppressed below the low-pass and above the high-pass frequencies (18). A first order band-pass filter reduces data with -20 dB/decade (log scale) whereas a second order reduces data with -40 dB/decade and third order with -60dB/decade. The official ActiGraph band-pass filter is specified at 0.25 Hz and 2.5 Hz but with no information about the filter order (9). The filter and data reduction of the original model AM7164 is described by Tryon and Williams (28). In this work, the frequency filter was estimated as a first order and with cut-off frequencies at 0.29 Hz and 1.66 Hz, respectively. In the study by van Hees et al a third order frequency filter using the 0.25 Hz and 2.5 Hz cut-off frequencies was found to be the most accurate for model GT1M (31).

Multiple days recording of raw accelerometry data was made available with the introduction of the Actigraph GT3X+ model. Data processing and thus frequency filtering was moved into the analysis software ActiLife to provide flexible and off-line handling. Data processing off-line provides the potential to determine the processing characteristics by entering fictitious acceleration data into ActiLife. This approach was also used in the study by Peach et al. (21) to explore the filtration algorithm of ActiLife but no attempt was made to replicate the actual output. Therefore, the aim of the present study was to examine a method to generate ActiGraph counts from raw acceleration data collected with an alternative accelerometer brand.

Methods

Study design

This study is divided into two experiments to target the aim: 1) mechanical and 2) free-living validation of the ActiGraph counts generated from raw data recorded by the Axivity AX3 accelerometer. The mechanical testing was used to evaluate the independent movement frequency related validity of the method and the free-living testing for the combined amplitude and frequency related validity of the method. The free-living test provides an option to evaluate the validity of the method for a large range of amplitudes and frequencies, but only if the results are evaluated on an individual level and ensuring that the subjects engage in many different activity types using a large range of intensities.

Subjects

A nine-subject convenient sample (4 men, 5 women) was recruited among physical education students and staff. The subjects were careful selected to ensure a large variation in PA intensity with different activities like competitive sports, commuter biking, occasional running and strength training, household activities and sedentary behavior. The mean (SD) age, body weight and height of the subjects were 24.8 (8.7) years, 70.1 (11.0) kg and 173.9 (8.6) cm, respectively. All subjects received a letter with information and signed a participation agreement. The National Danish Ethics committee was notified about the study and concluded that it did not require ethical approval.

Activity monitors

The Computer Science and Application (CSA) model AM7164 was one of the first commercially available activity monitors and was introduced in 1996. It used a uniaxial piezo-electrical accelerometer with a dynamic range of ±2.13 g. The analog acceleration signal was digitized using an eight-bit conversion providing a 1.664 mg resolution. A full description of the AM7164 can be found in the study by Tryon and Williams (28). ActiGraph Inc. (former CSA) has over the past decade introduced eight different models and new ones are still emerging as technology evolves. The Actigraph GT3X+ model (Actigraph LLC, Pensacola, FL) was introduced in 2009 and is a triaxial micro-electro-mechanical system (MEMS) accelerometer that offers the storage of raw triaxial acceleration data and selectable sampling frequency. The dynamic ranges of the new Actigraph instruments are fixed at either ±6g or ±8g. The Axivity AX3 (Axivity, Newcastle UK) is a relatively new activity monitor and share similar electronic specifications as the Actigraph GT3X+. The Axivity AX3 is also a tri-axial MEMS based accelerometer that stores raw acceleration data with selectable sampling frequency but with the addition of an adjustable dynamic range (±2g, ±4g, ±8g, ±16g). As with the ActiGraph devices the AX3 also provides light (lux) measurements and have similar battery and recording durations. The AX3 also includes temperature measurements. Some of the more interesting differences between the two devices are size, weight and documentation. The AX3 physical size is almost four times smaller and with only half the weight of the GT3X+. The Axivity AX3 is based on an open source strategy and has full documentation transparency with respect to hardware blue prints, firmware and other software components (10). The detailed hardware and software information for the GT3X+ monitor is not disclosed to the end-user.

Activity monitor initialization and data preparation

Fourteen GT3X+ and 14 AX3 monitors were run in the mechanical validation and 9 GT3X+ and 9 AX3 monitors were used in the free-living validation. In a study by Brønd and Arvidsson it was shown that the ActiGraph counts output from the GT3X+ sampled at 40, 50, 70, 80 and 100 Hz is biased as compared to the output sampled at frequencies 30, 60 and 90

Hz (6). The default 30 Hz sampling frequency was therefore selected for the GT3X+ and the default 100Hz sampling frequency selected for the AX3. The dynamic range of the AX3 was set to ±8 g. The ActiLife version 6.11.7 was used for the GT3X+ monitors and the OMGui version 1.0.0.20 for the AX3 monitors (10). The AX3 100 Hz raw acceleration data was calibrated and resampled into 30Hz raw acceleration data using the OMGui after download. The 30 Hz raw acceleration data for both activity monitors was manually time synchronized. The processing of the three different axes of the GT3X+ in ActiLife is the same and thus only the vertical axis was considered in the experiments of this study. All data handling and processing was performed in Matlab (Build 8.6.0.267246 (R2015b) 64 Bit).

Actigraph counts aggregation from raw Axivity AX3 acceleration

The generation of ActiGraph counts from Axivity AX3 raw acceleration data was implemented in Matlab using the same processing steps as included in the original study by Tryon and Williams (28) with some additions. All processing steps of the proposed method is presented in figure 1 and implemented for raw acceleration data sampled at 30 Hz. If the proposed ActiGraph counts aggregation method is to be used with raw acceleration sampled at a different sampling frequency it will require resampling into 30 Hz. The first step in the ActiGraph counts aggregation method is an aliasing filter to ensure compatibility with the Nyquist-Shannon sampling theorem (18). The second step is the frequency band-pass filter, which is implemented as a standard filter transfer function. A standard filter transfer function consists of multiple filter coefficients, which can be approximated from the frequency response of the original ActiGraph counts aggregation using the invfreqz function available in the Signal processing toolbox of Matlab (19, 25). The filter coefficients are thus assessed in two steps, 1) measuring the frequency response of the original ActiGraph counts aggregation from ActiLife and 2) determining the filter coefficients using the invfreqz function (25). The frequency response of the original ActiGraph counts aggregation is measured by entering standardized sinusoidal acceleration into ActiLife, which is similar to the method used by Peach et al. (21). The frequency range of 0.01-10 Hz was divided into 100 individual log spaced signal frequencies and each signal frequency was used to generate 100 periods of sinusoidal acceleration data blocks with constant ±2.13 g amplitude. The duration of each period was 300 seconds and chosen to account for the long cycle time at low signal frequencies. All acceleration data was generated in Matlab using a 30 Hz sampling frequency. The total duration of the data was 500 minutes and contained 900000 (100*300*30) raw acceleration data points. The acceleration data was stored into an ActiGraph binary file (.gt3x) and processed in ActiLife to ActiGraph counts using 1 sec epoch. The ActiGraph binary file was converted using the file format information available from Actigraph (14). The measured frequency response of the ActiGraph counts aggregation was transformed into an amplitude gain (A_{Gain}) by accumulating the output into 10-second epoch and estimating an averaged individual counts frequency response (AC) using the mean of the individual frequency periods (considering 29 epochs omitting the first epoch to account for the frequency transition). The final amplitude gain was then calculated from:

$$A_{Gain} = 20 * \log_{10}(\frac{AC}{AC_{0.75Hz}})$$

The frequency response below 0.2 Hz and above 1.8 Hz is greatly influenced by the dead-band threshold and does not reflect a first order filter as in the original study (28). The range below 0.2 Hz and above 1.8 Hz was thus substituted with first order (-20 dB/decade) linear approximated values. The sampling frequency was set to 30 Hz and the transfer function order, fast Fourier frequency (FFT) size and gain factor was approached successively by evaluating the error cost function:

$$err = \sum_{f=0.01Hz}^{f<10Hz} \left(\sum_{t=5}^{t<300} AC_{Actilife} - \sum_{t=5}^{t<300} AC_{Prediction} \right)^2$$

A transfer function order of 20, FFT size of 4096 and a gain factor of 0.965 was found to be most optimal. The coefficients for the final filter transfer function resulted in a root mean squared error (RMSE) of 25.7 counts and mean absolute error (MAE) of 15.0 counts. The amplitude response of the final filter transfer function is presented in Figure 2 and the filter coefficients are available in the supplementary material. The -3.01dB low pass filter cut-off frequency was found at 0.29 Hz and the high pass cut-off frequency was found at 1.63 Hz. Step three resample the 30 Hz raw acceleration into 10 Hz. The dead band threshold used in step 6 of the processing was specified in the original study at ±1 Analog/Digital (A/D) value at midscale (28). A ±1 A/D value for the original 8 bit analog to digital conversion (ADC) is equal to 0.033 g in acceleration units (28). The dead band threshold for newer ActiGraph models (GT3X+ and newer models) is specified at 0.05 g (11). The dead-band threshold of ActiLife was measured by mathematically generating a sinusoidal acceleration in Matlab. The acceleration data covered the full amplitude range of the GT3X+ (±6 g) and the frequency of the sinusoidal acceleration was fixed at 0.75 Hz as this frequency is passed through the filter with no attenuation (28). The full amplitude range was divided in 2048 intervals giving a resolution of 2.93 mg, which equals the sensitivity of the analog to digital conversion of the GT3X+ activity monitor. Each amplitude level was kept constant for 300 seconds to account for the cycle time of the sinusoidal data. No ActiGraph counts were measured for signal amplitudes below 0.068 g and a dead-band threshold of 0.068 g was therefore implemented instead of the 0.050 g as originally specified. An amplitude-dependent leveling-off of the counts was observed with the amplitude data, starting from 2.13 g. The leveling off at 2.13g was implemented as step 4 in the processing. Step seven converts the acceleration data into the original 8-bit ADC resolution (128 levels across the 0-2.13g range) and the final processing step (eight) accumulates 10 consecutive samples into the 1-second epoch counts data.

Experiment 1: Mechanical validation

The benefit of a mechanical validation is a standardized and controlled exposure using a signal frequency and amplitude range covering more than the full movement potential of humans. Mechanical validation reduces the trial-by-trial error and variation of the exposure. Different mechanical setups have been proposed and some studies generated the exposure by mimicking the sinusoidal movement apparent with human locomotion (23, 24). This setup will cause the activity monitor acceleration amplitude to depend on rotational frequency with small acceleration amplitude values with low rotation frequencies and large acceleration amplitude values with high rotation frequencies. Thus, the signal frequency, and amplitude change with the rotational frequency, imposes some challenges when estimating monitor characteristics over the total range of signal frequencies. Bouten et al. presented a different mechanical setup in which the gravity component was used to generate sinusoidal acceleration amplitude (3). In this setup the acceleration amplitude is only biased by the centrifugal force. This bias can be reduced to a constant by keeping the rotational frequency constant for a longer period of time. This mechanical setup was used in the present study, with the activity monitors mounted in pairs of two on the rotating aluminum arm using double adhesive tape and close to the rotational center to reduce the inertia of the total system.

Two DC-brushless motors were used to create a rotational frequency range of 0.12-5.95 Hz. A Pololu 131.25:1 37D mm gear motor with an 64 counts/revolution encoder was used for a low frequency protocol (0.12-1.5 Hz) and a Pololu 30:1 37D mm gear motor with an 1920 counts/revolution for the high frequency protocol (1.76-5.9 Hz). A Pololu JRK 21v3 motor controller with encoder feedback was used to ensure stable rotational speed. The motor controller was connected through USB to a host computer in order to enable a software controlled exposure protocol. The software were developed using the available Jrk Configuration Utility and the official C# library (22). The protocol was set to run each possible rotational speed (limited by the digital nature of the controller) for 2 minutes giving a total of 30 steps for the low frequency protocol and 10 steps for the high frequency protocol for each monitor. The proportional, integral and derivative (PID) regulation of the rotational speed was adjusted to minimize jerks and movement artifacts during rotation. The rotational frequency was measured using a frequency analysis (16384 point fast fourier transform (FFT)) of the GT3X+ raw acceleration data generated. The highest peak in the frequency domain was regarded as the rotational frequency. The raw acceleration data was manually aligned and merged for each activity monitor before processed into 10-second epoch ActiGraph counts. The first 5 seconds of data were omitted for each frequency to account for the increase in acceleration when switching rotational speed.

Experiment 2: Free-living validation

The activity monitors were worn for 24 hours free-living and only to be removed during water activities and sleep time. The ActiGraph GT3X+ and the Axivity AX3 were mounted back-to-back using double adhesive tape and worn on the right hip in an elastic belt. The subjects were carefully instructed to ensure the monitors were at the right position and not tilted. The times when the monitors were not worn were removed and thus excluded from the analysis.

The raw acceleration data was processed into 1-second epoch ActiGraph counts, although accumulated into 10-second and 60-second epochs for the presentation herein. The Freedson et al. intensity cut points for adults were used in the analysis of time spent at different intensities (7).

Statistics

A paired t-test (difference from zero) and the Lilliefors test of normal distribution using the absolute differences at each individual rotational frequency was used to determine the performance of the proposed filter function in the mechanical validation. A Bland-Altman plot of each subject was used to investigate validity under free-living (2). A log spaced x-axis (mean of methods) was used to facilitate visual inspection of low PA intensities and thus the complete range of intensities covered. Linear regression was used to investigate any association between error and intensity. Cohen’s Kappa with quadratic weighting and corrected for chance was used for statistical assessment of agreement in the classification of five intensity categories (15). The strength of agreement was determined based on the work by Landis and Kock (16). A paired t-test was used to evaluate the difference in estimated daily averaged PA between methods. All statistical analysis and data processing was done with Matlab (Build 8.6.0.267246 (R2015b) 64 Bit).

Results

Experiment 1: Mechanical validation

The frequency analysis of the GT3X+ raw acceleration data showed that the mechanical validation generated a rotational frequency range of 0.12-5.95 Hz. The rotational frequency was identical and stable across all runs. A visual inspection of the frequency analysis showed minimal noise for other frequencies than the rotational frequency.

Axivity AX3 demonstrated lower inter-monitor reliability than the Actigraph GT3X+ monitor across all 14 repeated runs (Figure 3). Still, the inter-monitor variation was small. The means of the ActiGraph counts generated from the proposed method applied on AX3 data (AX3-PM) were almost identical to the means of the ActiGraph counts generated from ActiLife using GT3X+ data (GT3X-AL) across all signal frequencies (Figure 3). The absolute differences across all frequencies were normally distributed (Lillefors test p=0.34) with mean (sd) -0.11 (0.97) counts per 10 sec that was not significantly different from zero (t-test p=0.41).

Experiment 2: Free-living validation

Figure 4 presents a Bland-Altman plot of the 10-second epoch-by-epoch comparison of the AX3-PM with GT3X-AL data for the nine subjects during the 24 hours free-living period. The bias between methods ranged from -16.2 to 0.9 counts with a group mean (sd) difference of 5.6 (5.1) counts. The difference was larger for subject 3 than for the other subjects. The largest limits of agreement (LOA) were found for subject 5 (-155.5 to 140.3 counts) and the smallest for subject 9 (-49.4 to 41.0 counts). Regression analysis with activity level (x-axis) and difference between methods (y-axis) demonstrated small slopes with a group mean (sd) of -0.015 (0.015) and small intercepts with a group mean (sd) of -1.76 (3.04), indicating no relationships between the PA intensity and the size of the error.

Figure 4 also demonstrated a systematic grouping of some epochs at the vigorous intensity level for subject 1-3 and a visual inspection of the counts data revealed a continuous activity of very vigorous intensity of 30-70 minutes duration. In subject 3, the visual inspection showed a substantial higher intensity using the proposed method. Processing the GT3X raw acceleration data from subject 3 with the proposed method (GT3X-PM) generated identical intensity values as the GT3X-AL output indicating that the difference is attributed to the raw acceleration data. Figure 5 presents a sub-section of the raw acceleration vector magnitude data from the continuous activity of subject 3. The raw acceleration amplitude from the GT3X+ is clearly attenuated compared to the AX3, explaining the difference between AX3-PM and the other methods (GT3X-PM, GT3X-AL).

The summarized results for the 24 hours averaged PA and intensity classification of each subject is presented in Table 1. The averaged PA ranged from 361.9 to 1746.3 counts per minute for the AX3-PM and from 345.7 to 1689.7 counts per minute for the GT3X-AL. The absolute difference between methods ranged from -3.8 (Subject 6) to 56.6 (subject 3) counts per minute group mean (sd) of 16.7 (18.0) counts per minute. The paired t-test indicated that the absolute differences were significantly different from zero (p=0.023). The relative difference ranged from -0.5% (Subject 6) to 4.7% (Subject 5) with a group mean (sd) of 2.2% (1.7%). The time spent at different intensity levels from the two methods showed almost identical values. The largest group mean (sd) absolute difference was 1.7 (miss sd value) minutes for time spent sedentary, but there were exact matches for the vigorous intensities. The 5-category quadratic weighted Cohen's kappa for the 10-second epoch-by-epoch classification of intensities was above 0.945 for all subjects indicating almost perfect agreement.

Discussion

The present study provides a method to generate ActiGraph counts from raw acceleration data recorded by an alternative accelerometer brand, in this case Axivity AX3. The processing steps of the ActiLife were mimicked with the analysis of the signal amplitude and frequency response to standardized accelerations. The frequency band-pass filter function was successfully replicated with minimal errors. Both the mechanical and free-living experiments demonstrated high reliability and validity of the proposed method, with minimal errors, also at individual level, for all signal frequencies investigated and for the free-living activity, as well as almost perfect agreement for intensity classification. The difference in daily PA was only 2.2% (-0.5−4.7%) and the coefficient of agreement for intensity classification was 0.945. Although the absolute difference was statistically significant, the value could be considered too small to be relevant. Some of the differences observed especially for vigorous activities could be attributed to inaccessible processing located on the GT3X+ monitor itself. This is supported by the difference between GT3X+ and AX3 in raw acceleration data for the mechanical and free-living validation, and by the identical counts generated when the GT3X+ raw acceleration data was processed with ActiLife or the proposed method and their difference when AX3 raw acceleration data was processed with the proposed method. Internal processing of the GT3X+ has been indicated by the results in our previous study (6) and further supported by the results in the study by John et al comparing raw acceleration data from the GENEA monitor to GT3X+ (13).

The study by Van Hees et al. (31) is the only other study to approach the across-brand comparison of ActiGraph counts by mimicking the data processing of the original study by Tryon and Williams (28). The cut-off frequencies implemented in the study by Van Hees et al. (31) were the signal frequencies with an attenuation of -6dB (half magnitude), i.e. 0.21 Hz and 2.28 Hz. The -3.01 dB band-pass (half power) cut-off frequencies required to implement the digital filtering was specified at 0.29 Hz and 1.66 Hz, which were similar to the ones found and implemented in our study. The slope of the attenuation after the cut-off frequencies was estimated to -20 dB/decade and suggests a first order band-pass filter, which we implemented to derive our filter function. The wider range in cut-off frequencies implemented in the study by Van Hees et al. (31) could explain the need for a third order attenuation below and above the cut-off frequencies instead of the original first order. The differences in both cut-off frequencies and order might explain the poor performance at the individual level and intensity classification in their study.

The estimated dead-band threshold in our study (0.068 g) is clearly different from the threshold values specified in the original study (0.033 g) (28) and suggested by John et al (0.050 g) (11). This suggests that different filter characteristics are needed to generate ActiGraph counts comparable with the original AM7164 model. Difference in filter characteristics between AM7164 and GT3X+ is confirmed by the study by Ried-Larsen et al. using a mechanical setup generating a range of movement frequencies (23). An increased dead-band threshold would require more body movement before the acceleration signal is processed into Actigraph counts. This might explain the 30-60 minutes of consecutive zeros defined as cut-off for non-wear time proposed with the GT3X model compared to the typical 10 minutes accepted with the AM7164 model (27). Non-wear removal affects the assessment of sedentary time and habitual PA, but further studies are warranted to investigate the effect of the dead-band threshold on non-wear removal.

Another finding concerning the signal processing in ActiLife was the truncation of the signal amplitude starting from 2.13 g. This is performed to ensure compatibility with the 8 bit analog to digital conversion of the AM7164 (28) and needs to be implemented to generate comparable ActiGraph counts. For most movements recorded at the center of mass a dynamic range of ±2.13 g would be sufficient. It has been shown that the vertical acceleration amplitude from slow walking to fast running ranges between 0.5-2.0 g (12). Altogether, the discoveries of the band-pass filter order and cut-points, the dead-band threshold, the truncation of the signal amplitude, the pre-processed raw acceleration signal of the GT3X+

and the deviations from the technical specifications provided confirms the necessity of direct determination of processing characteristics of the specific monitor model and software based on the response to pre-specified raw acceleration data.

The processing characteristics to be implemented to generate ActiGraph counts from raw data collected with the Axivity AX3 monitor, or from any other accelerometer collecting unfiltered raw data, can be found in the supplemental material. Providing this information would support the application of previous published ActiGraph calibration and validation data to other accelerometer brands and improve comparability between studies. Still, even if access to these processing characteristics would generate valid ActiGraph counts, one needs to be aware of their limitations. For example, a leveling-off and even a decrease of the ActiGraph counts have been demonstrated for activity intensities corresponding to speeds higher than 10 $km \cdot h^{-1}$ (4,14). This is explained by the ActiGraph frequency band-pass filter function and its attenuation of unwanted signal frequencies (6, 12). As shown in figure 3 in our study, more than 50% of the activity counts are eliminated for signal frequencies higher than 2.5 Hz. These are frequencies generated by most vigorous physical activities (12). Access to the filter function and processing characteristics provides a comprehensive understanding of the proprietary aggregation of raw acceleration into the Actigraph counts per se but also the strengths and limitations of the method to provide a simple, useful and accurate objective measure of physical activity intensity also valid in the future. The open and transparent implementation of the ActiGraph counts aggregation method further facilitates the needed investigation on how different modifications might reduce the known measurement bias (5, 12) and how this compares to other aggregation methods like the mean averaged deviation (MAD) or Euclidian norm minus one (ENMO) (4, 29, 30).

Strengths and limitations

Approaching the ActiGraph counts processing by direct determination of the amplitude gain characteristics, dead-band threshold and the filter transfer function using least squares fitting is the primary strength of the study. The secondary strength of the study is the combined mechanical and free-living validation of the proposed method. A limitation of the study may be the number of subjects used in the free-living validation as well as the inclusion of only 24 hours. However, with the minimal errors observed for the proposed method, a larger sample would not add relevant information. Further, it is possible that, by including more days and consequently more activity patterns, the error of our proposed method might have looked different. However, a major part of this error would have been attributed to inaccessible processing on the GT3X+ monitor.

Conclusion

The proposed method generated ActiGraph counts with high reliability and validity at an epoch, individual and group level. Physical activity measures from the ActiGraph monitors can now be generated from raw acceleration data recorded by alternative accelerometer brands. Comparability between studies would increase tremendously and cheaper, smaller and water resistant options to the ActiGraph monitors can be considered in large-scale epidemiological projects and processing raw acceleration into ActiGraph counts can be made available on most common platforms (OSX, Linux, IOS, Android) using most programming languages and statistical software packages. The Matlab code for processing raw acceleration into counts can be provided by request to the authors.

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Conflict of interest

The authors have no financial or other conflicts of interest that might bias the work.

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Figure captions

Figure 1

Processing steps and values implemented in the proposed method to generate ActiGraph counts from raw acceleration data.

Figure 2

Graphical presentation of the band-pass filter transfer function developed from the direct determination of the ActiLife data processing characteristics and selected for mechanical and free-living validation.

Figure 3

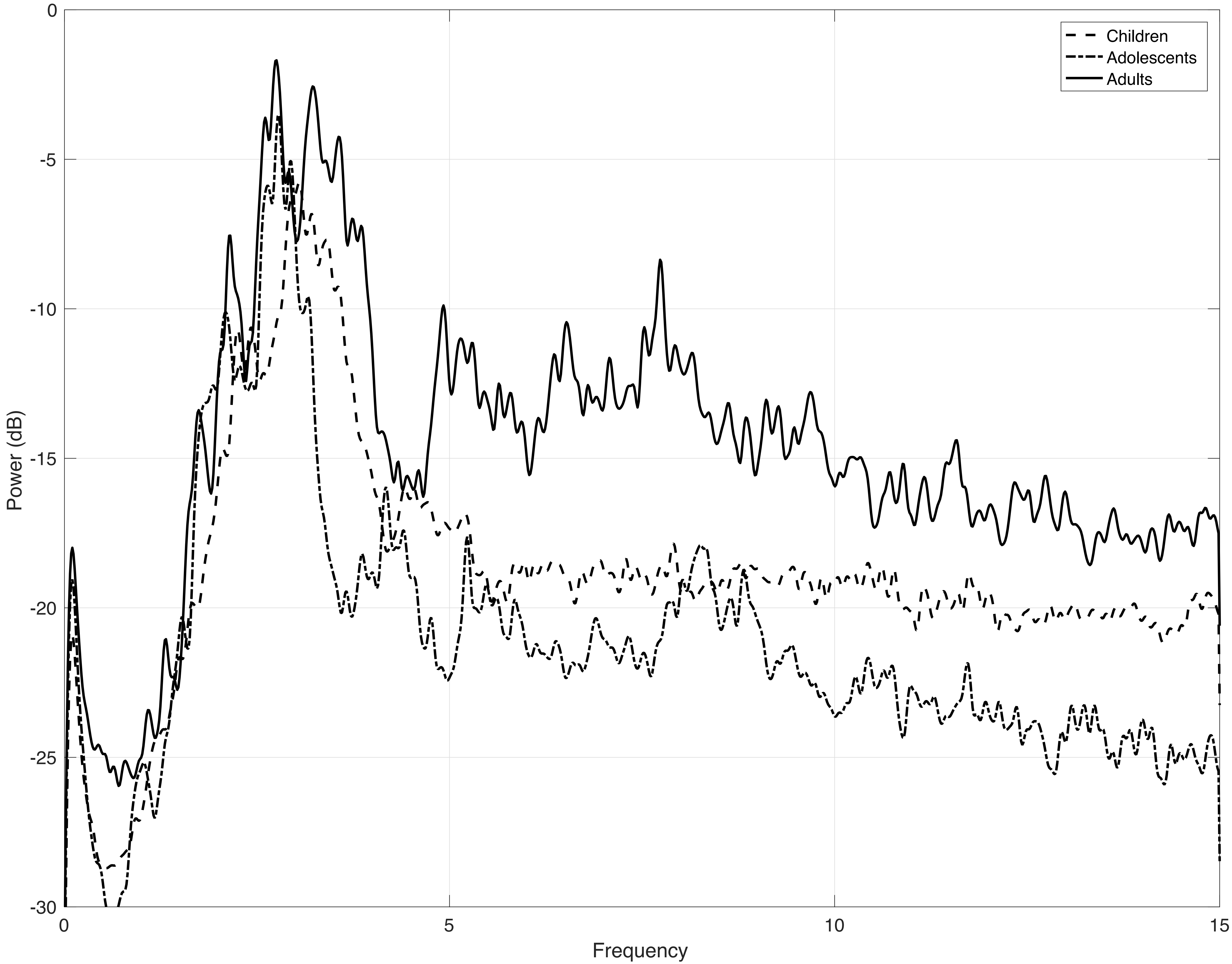
Mean (sd) counts generated from the proposed method applied on Axivity AX3 data (AX3-PM, grey line) and from ActiLife using ActiGraph GT3X+ data (GT3X-AL, black line) during repeated runs at a rotational frequency range of 0.12-5.95 Hz in the mechanical validation experiment.

Figure 4

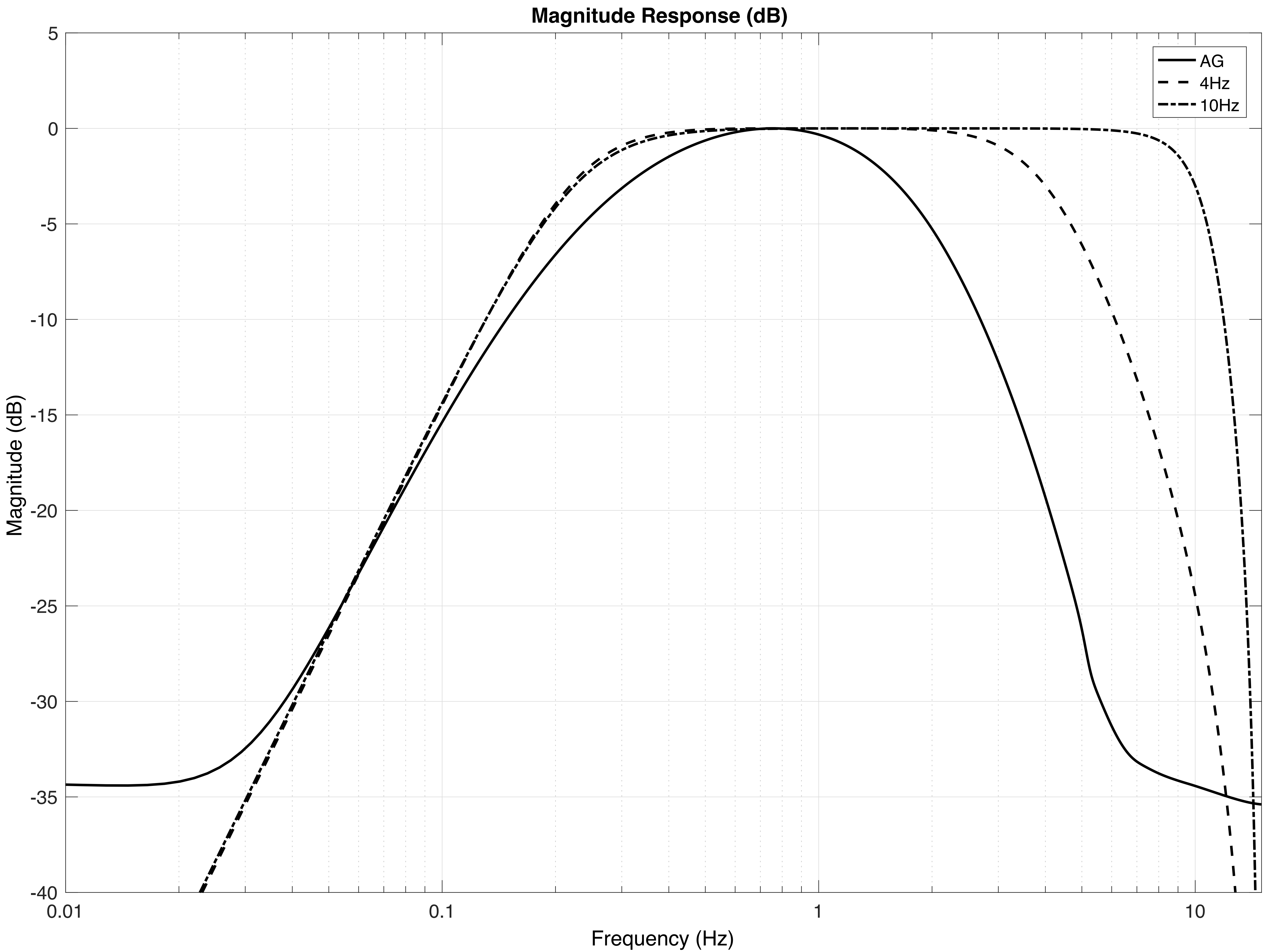
A Bland-Altman plot of the difference in 10-second epoch counts (y-axis) generated from the proposed method applied on Axivity AX3 (AX3-PM) data compared to ActiGraph GT3X+ data processed using ActiLife (GT3X-AL) across the activity intensity range (x-axis) for each subject in the free-living experiment. Note that the individual plots are not adjusted to the same scale on the y-axis to facilitate inspection of the absolute difference.

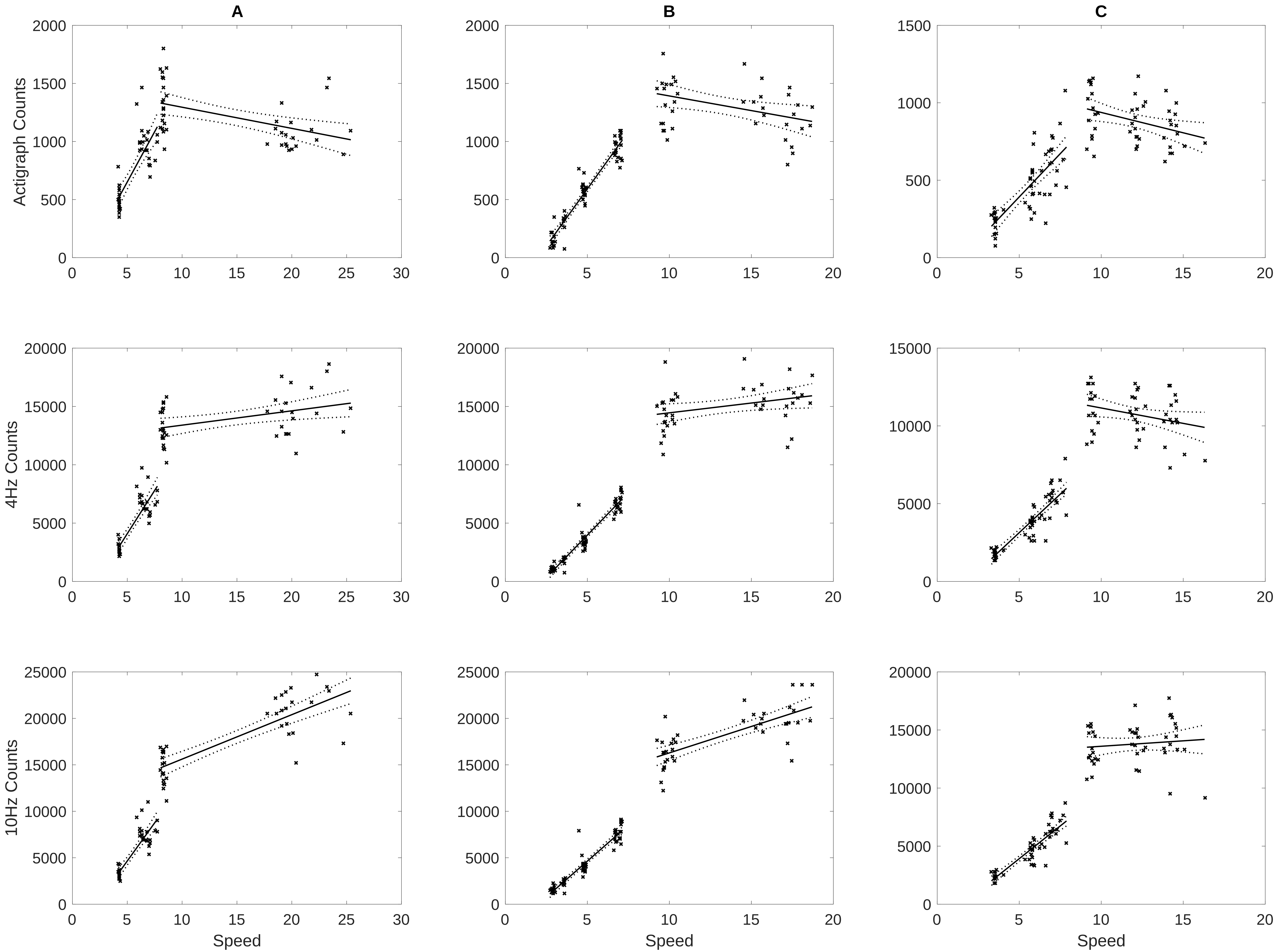
Figure 5

Section of raw acceleration data from Axivity AX3 (black line) and ActiGraph GT3X+ (grey line) during running in subject 3.



Children
Adolescents
Adults
Power (dB)
0
-5
-10
-15
-20
-25
-30
0
5
10
15
Frequency


Magnitude Response (dB)
AG
4Hz
10Hz
5
0
-5
-10
-15
-20
-25
-30
-35
-40
Magnitude (dB)
0.01
0.1
1
10
Frequency (Hz)



A
B
C
Actigraph Counts
4Hz Counts
10Hz Counts
Speed
Speed
Speed

Table 1. The root mean squared error (RMSE) and explained variance (R^2 Adjusted) for the linear and quadratic regression analysis of aggregated counts output (outcome) with locomotion speed for locomotion speeds below 12 kmh^{-1}.

	Children						**Youth**						**Adults**					
Model	**Linear**			**Quadratic**			**Linear**			**Quadratic**			**Linear**			**Quadratic**		
Outcome	AG	4HZ	10HZ	AG	4HZ	10HZ	AG	4HZ	10HZ	AG	4HZ	10HZ	AG	4HZ	10HZ	AG	4HZ	10HZ
RMSE	181	1758	2063	182	1566	1814	154	1275	1457	147	1044	1151	201	1840	1996	203	1664	1802
R^2 Adj.	0.64	0.77	0.77	0.64	0.81	0.82	0.89	0.94	0.93	0.90	0.96	0.96	0.74	0.83	0.83	0.73	0.86	0.86

The equation for the linear regression model is $outcome = b_0 + b_1 Speed$ and the quadratic model $outcome = b_0 + b_1 Speed + b_2 Speed^2$.

Table 2. Substitution analysis by aggregation method in five selected participants for 24 hours free-living.

	ActiGraph			**4Hz**			**10Hz**		
	MDCPM			MDCPM			MDCPM		
Subject	Exercise	No exercise	% diff.	Exercise	No exercise	% diff.	Exercise	No exercise	% diff.
1	454	267	70	3628	1569	131	4092	1903	115
2	751	551	36	6171	3858	60	7708	5034	53
3	1667	1002	66	13111	6082	116	15325	7636	101
4	361	279	29	2610	1738	50	3456	2480	39
5	641	235	173	4975	1237	302	5804	1786	225

Mean daily counts per minute (MDCPM) from intensive exercise is substituted by MDCPM that would have been generated from non-exercise.