A universal, accurate intensity-based classification of different physical activities using raw data of accelerometer

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Summary

Objective Accelerometers are increasingly used for objective assessment of physical activity. However, because of lack of the proprietary analysis algorithms, direct comparisons between accelerometer brands are difficult. In this study, we propose and evaluate open source methods for commensurate assessment of raw accelerometer data irrespective of the brand.

Design Twenty-one participants carried simultaneously three different tri-axial accelerometers on their waist during five different sedentary activities and five different intensity levels of bipedal movement from slow walking to running. Several time and frequency domain traits were calculated from the measured raw data, and their performance in classifying the activities was compared.

Results Of the several traits, the mean amplitude deviation (MAD) provided consistently the best performance in separating the sedentary activities and different speeds of bipedal movement from each other. Most importantly, the universal cut-off limits based on MAD classified sedentary activities and different intensity levels of walking and running equally well for all three accelerometer brands and reached at least 97% sensitivity and specificity in each case.

Conclusion Irrespective of the accelerometer brand, a simply calculable MAD with universal cut-off limits provides a universal method to evaluate physical activity and sedentary behaviour using raw accelerometer data. A broader application of the present approach is expected to render different accelerometer studies directly comparable with each other.

Introduction

Tri-axial accelerometer has gained popularity in objective monitoring and assessing human movements and physical activity, and is the method-of-choice in studies where accurate measurement is of primary importance (Freedson *et al.*, 2012). The small-sized and light-weight activity monitors can be worn for even 24 h a day while they can collect data over many weeks without recharging. Tri-axial accelerometers can provide actual information on the duration, intensity and pattern (number/frequency and duration) of physical activity and inactivity periods (Straker & Campbell, 2012). They are useful in evaluating the dose–response relationships between different patterns of physical activity and various health outcomes (Oliver *et al.*, 2010). It has also been suggested that the most meaningful contribution of activity monitors pertains to recording of intermittent, light-intensity activities such as everyday walking and incidental physical activity. These activities are typically less memorable and likely inaccurate when they are based on self-report measures (Esliger & Tremblay, 2007; Healy *et al.*, 2008; Bonomi *et al.*, 2009).

At present, almost all accelerometer-based activity monitors report their outcomes in counts, which is an aggregate measure of amount and intensity of activity over a specific time period. Counts are generated by closed, proprietary algorithms with different transducers, amplifiers, sampling frequencies and signal filters (Crouter *et al.*, 2006; Rothney *et al.*, 2008; Marschollek, 2013). As a result, different types of monitors can give substantially different count values even when measuring the same input acceleration signal (Marschollek, 2013). This means that the precise physical meaning of count is obscure, and it is not possible to cross-validate the results between different devices or directly compare the results from different studies. For example, regarding the energy expenditure, there are more than 30 published count-based prediction techniques that can produce widely different estimates

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(Crouter et al., 2006; Rothney et al., 2008; Kozey et al., 2010; Staudenmayer et al., 2012). Obviously, a more physical viewpoint is needed, which would permit a commensurate way of evaluating the output data in concrete physical terms (i.e. in terms of acceleration or speed of movements) irrespective of the accelerometer brand.

The aim of this study was to devise a universal and physically meaningful analysis algorithm for accurate classification of physical activity by intensity using the raw data obtained from waist-mounted, tri-axial accelerometers.

Methods

Accelerometers

In this study, three different commercially available tri-axial accelerometers [Actigraph GTX3, (Actigraph, Pensacola, FL, USA), GulfCoast X6-1A (Gulf Coast Data Concepts LLC, Waveland, MS, USA) and Hookie AM13 (Hookie Technologies Ltd, Espoo, Finland)] were used. These devices employ clearly different sampling frequencies and measurement ranges per axis: for Actigraph 30 Hz and $\pm 3\ g_0$, for GulfCoast 20 Hz and $\pm 6\ g_0$ and for Hookie 100 and $\pm 15\ g_0$ (where g_0 denotes the Earth's gravity).

Procedures

The participant's weight was measured with a digital scale and height with a stadiometer. The accelerometers were attached to a waist-mounted elastic belt so that the devices were located on either side of the hip. Then, the participant underwent a supervised array of ten 2-min periods illustrating five typical free-living sedentary behaviours and five physical activities: lying supine on a bed, sitting on a chair, sitting while working on a computer, standing, standing while moving light (1 kg) weights on a table surface; and slow walking, normal walking, brisk walking, jogging and running. All types of walking, jogging and running were performed on an inside track at preferred pace according to verbal instructions (slow, normal, brisk, jogging and running). An examiner (PH) observed the participant during the activities and timed the 2-min periods with a stopwatch. A break of 15 s was allocated for changing from one activity to another.

Besides three accelerometers, a heart rate monitor (Polar M61 Electro Ltd, Kempele, Finland) was used. The chest strap of the monitor was fastened around the participant's chest, and the wrist unit was attached to the right wrist. The examiner (PH) recorded the heart rate from the wrist unit at the beginning, at 1 min and at the end of each 2-min period.

Participants

Twenty-one adults (four men, 17 women) volunteered to participate in the study. Their mean age was 42 ± 11 (SD) years, height 171 ± 9 cm and weight 67 ± 13 kg. All participants gave an informed consent, and the study was approved by the Ethics Committee of Pirkanmaa Hospital District (R10126).

Data analysis

The acceleration data from all three devices were collected in raw mode and were transformed into actual g-units. For each time point, the resultant acceleration (r_i) was calculated as follows:

$$r_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$$

where x_i, y_i and z_i are the ith measurement sample of the raw acceleration signal in x-, y- and z-directions. The resultant acceleration signal was then processed and analysed both in time and frequency domains. Approximately, 5-s epoch duration was considered sufficient for appropriate description of different physical activities (Matthews et al., 2012). Thus, the number of consecutive data points was 128 for Actigraph and GulfCoast devices, and 512 for Hookie device. The corresponding epoch durations were 4·3, 6·4 and 5·1 s. For each type of activity, three different time points were analysed at about 30 s, at about 60 s and at about 90 s after the start of given activity. When necessary, the position of the epoch was adjusted so that the epoch represented typical acceleration signal of the given activity without evident discontinuity in movement.

For the three epochs, several traits in time and frequency domain were derived (Tables 1 and 2), and the mean value of each trait was calculated. For the time domain analysis, linear analysis was applied to the resultant acceleration signal. Similarly, frequency spectrum of the resultant acceleration signal was determined either with 128-point (Actigraph and GulfCoast devices) or 512-point (Hookie device) fast Fourier transform (FFT) analysis. Before applying FFT, the data in the epoch of interest were detrended by subtracting the mean resultant acceleration of the given epoch from each data point.

Linear and spectral analyses were also applied to the detrended, integrated resultant acceleration signal. The integral (v_j) reflecting the velocity signal of the movement was calculated as follows:

$$v_j = \sum_{1}^{j} a_n \Delta t$$

where v_j is the jth integrated data point, a_n is the nth detrended data point of the resultant acceleration signal, and Δt is 1/20 s for GulfCoast, 1/30 s for Actigraph and 1/100 s for Hookie devices. For the velocity signal, all time and frequency domain traits listed in Tables 1 and 2, except percentiles, were calculated.

Statistical analysis

The mean values of time and frequency domain traits derived from the acceleration and velocity signals served as classifiers used for separating different physical activities from each

Table 1 Time domain analysis of acceleration signal.

Trait	Equation[a]
Mean power deviation (MPD) describes the dispersion of data points about the mean	$\mathrm{MPD} = \sqrt{\frac{(r_i-\bar{r})^2}{n}}$
Mean amplitude deviation (MAD) describes the typical distance of data points about the mean	$\mathrm{MAD} = \frac{1}{n}\lvert r_i - \bar{r}\rvert$
Skewness (skewR) describes the asymmetry of dispersion of data points about the mean	$\mathrm{skewR} = \frac{n}{(n-1)(n-2)}\sum\left(\frac{r_i-\bar{r}}{\mathrm{sdR}}\right)^3$
Kurtosis (kurtR) describes the peakedness of the distribution of data points	$\mathrm{kurtR} = \frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{r_i-\bar{r}}{\mathrm{sdR}}\right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)}$
Mean of the 95th percentile (perc95) describes the highest resultant accelerations within the epoch of interest	Interpolation of the 7th and 8th (128 data points) or 26th and 27th (512 data points) value of the ascending sorted data
Mean of the 5th percentile (perc5) describes the lowest resultant accelerations within the epoch of interest	Interpolation of the 7th and 8th or 26th and 27th value of the descending sorted data
Difference between the high and low percentile means (dPerc) describes the dynamic range of resultant accelerations within the epoch of interest	dPerc = perc95 − perc5

[a]r_i is the ith resultant sample within the epoch of interest, $\bar{r}$ the mean resultant value of the epoch of interest, n the number of samples in the epoch, and sdR is the standard deviation value of the resultant values of the epoch of interest.

Table 2 Frequency domain analysis of the acceleration signal.

Trait	Equation[a]
Dominant frequency (f_d)	The frequency bin with the highest signal power
Peak power (Pf_d)	The signal power present at the dominant frequency
Product of peak power and dominant frequency (PPf_d)	$PPf_d = f_d \times Pf_d$
Entropy (H) of frequency spectrum describes its disorder	$H = -\sum p(f_i) \log p(f_i)$
Sum of products of frequencies and respective signal power values over the whole frequency (Pf_{sum})	$Pf_{sum} = \sum P_i f_i$
Sum of signal power values over the whole frequency range (P_{sum})	$P_{sum} = \sum P_i$

[a]f_i is the ith frequency value of the FFT, P_i the power at f_i and $p(f_i)$ is the probability calculated as P_i/P_{sum}. The maximum frequency bin of the spectrum is the half of the sampling frequency (i.e. 15 Hz for Actigraph, 10 Hz for GulfCoast and 50 Hz for Hookie), whereas the frequency resolution is the sampling frequency divided by the number of points used in the FFT (i.e. 0·23 Hz for Actigraph, 0·16 Hz for Gulfcoast and 0·20 Hz for Hookie).

other. Activities were divided into five distinct intensity classes; the class 0 denoted the five sedentary behaviours together, the class 1 slow walking, the class 2 normal walking, the class 3 brisk walking and the class 4 jogging and running together.

The performance of different classifiers was ranked using receiver operating characteristic (ROC) analysis. First, the accelerometer-specific area under curve (AUC) was calculated for each classifier. Then, for the best-performing classifier showing the greatest AUC, the cut-off limits were determined. The optimal cut-off limit was yielded from the minimum distance between the ROC curve and the left upper corner of the ROC space. Limit 1 separates the intensity class 0 from class 1, limit 2 the class 1 from class 2, limit 3 the class 3 from class 2 and limit 4 the class 4 from class 3.

The best-ranked classifier was analysed further. First, to investigate whether the activity-specific classifier values were different between the three accelerometers, one-way ANOVA was performed and a Tukey *post hoc* test was used if main effect was indicated. In addition, correlation between heart rate and best-performing trait was determined to assess its relationship to the apparent energy expenditure of physical activity. Here, the sedentary activities were excluded from the correlation analysis because in some participants – most likely due to the excitement – heart rate was clearly higher during inactivity than during light activity. Mean correlation coefficient for the whole data was calculated by *z*-transforming the individual correlation coefficients, taking the arithmetic mean of transformed coefficients and by back-transforming the mean.

Results

Table 3 shows the ranking of different classifiers for all three accelerometers. Quite consistently, the mean amplitude deviation (MAD) appeared to be the best-performing classifier to separate activity levels from each other. Almost equally, well-performing classifiers were mean power deviation, difference between the high and low percentile means, peak power and product of peak power and dominant frequency. The following results are based on MAD only.

Figure 1 illustrates the variation in MAD during different activities. For activity class 0 (sedentary behaviour), Actigraph and especially Hookie showed significantly higher MAD values than GulfCoast values ($P<0{\cdot}01$). For activity classes 1 and 2,

Table 3 The rank of the area under curve (AUC) of the ROC in separating adjacent intensity classes[a] for each trait and the mean value of the ranks.

	ActiGraph				GulfCoast				Hookie				
Trait	**Limit 1**	**Limit 2**	**Limit 3**	**Limit 4**	**Limit 1**	**Limit 2**	**Limit 3**	**Limit 4**	**Limit 1**	**Limit 2**	**Limit 3**	**Limit 4**	**Mean rank**
MPD	4	1	5	3	6	5	7	1	3	1	5	1	3·5
MAD	1	1	3	1	6	1	6	3	3	1	4	1	2·6
kurtR	22	19	18	18	18	18	18	20	20	19	20	20	19·2
skewR	20	22	23	20	19	20	20	19	15	20	18	18	19·5
perc95	11	1	7	16	12	10	2	13	18	1	8	16	9·6
perc5	1	1	11	5	3	11	11	5	7	12	12	8	7·3
dPerc	1	1	6	2	5	9	8	1	6	1	6	6	4·3
f_d	18	20	21	22	21	21	22	23	19	21	22	22	21·0
Pf_d	4	1	2	7	6	1	5	10	2	1	2	7	4·0
PPf_d	15	11	1	4	15	6	1	4	17	13	1	1	7·4
H	16	17	17	19	17	15	17	17	14	15	17	17	16·5
Pf_{sum}	4	15	15	9	1	17	15	11	8	16	15	11	11·4
P_{sum}	4	13	13	6	11	14	14	6	9	14	14	9	10·6
∫MPD	12	1	9	11	13	6	13	14	11	1	9	4	8·7
∫MAD	10	1	4	14	10	1	10	15	12	1	7	12	8·1
∫kurtR	19	18	19	21	20	19	19	21	21	18	19	21	19·6
∫skewR	23	23	20	17	22	22	21	18	22	22	21	19	20·8
$\int f_d$	17	16	16	12	16	16	3	7	16	11	11	15	13·0
$\int Pf_d$	14	1	10	15	14	1	9	16	13	1	10	14	9·8
$\int PPf_d$	12	1	8	13	6	6	4	9	10	1	2	10	6·8
∫H	21	21	22	23	23	23	23	22	23	23	23	23	22·5
$\int Pf_{sum}$	9	14	14	8	1	12	12	8	1	17	16	5	9·8
$\int P_{sum}$	8	12	12	10	4	13	16	12	5	1	13	13	9·9

MPD, Mean power deviation; MAD, Mean amplitude deviation; kurtR, Kurtosis; skewR, Skewness; perc95, Mean of the 95th percentile; perc5, Mean of the 5th percentile; dPerc, Difference between the high and low percentile means; f_d, Dominant frequency; Pf_d, Peak power; PPf_d, Product of peak power and dominant frequency; H, Entropy; Pf_{sum}, Sum of products of frequencies; P_{sum}, Sum of signal power values over.
[a]Intensity classes are described in Table 2. Limit 1 separates class 0 from 1, limit 2 class 1 from 2, limit 3 class 2 from 3 and limit 4 class 3 from 4.

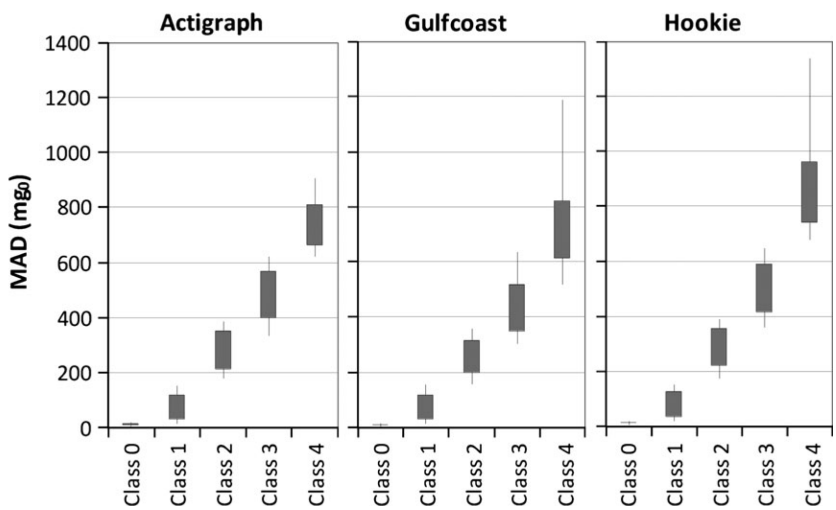

Figure 1 Mean amplitude deviation (MAD) at different activity levels measured with different accelerometers. The box and whisker plot shows the one standard deviation above and below the mean and the minimum and maximum of the data.

there were no significant differences in MAD values between the accelerometers. For activity class 3, GulfCoast values were significantly lower than Hookie values ($P<0·05$), and for class 4 both GulfCoast and Actigraph gave significantly lower values than Hookie ($P<0·01$). Table 4 shows the best-performing universal cut-off limits for classification of different activity levels.

Figure 2 shows the individual MAD values as a function of heart rate. During bipedal locomotion, the correlation between the incident MAD and heart rate was very strong over a wide intensity range. For Actigraph, the mean correlation coefficient was 0·950, for GulfCoast 0·962 and for Hookie 0·972. However, because of large individual variation, the heart rate itself cannot accurately separate different activities

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Table 4 Universal cut-off limits for activity classification by mean amplitude deviation (MAD) and corresponding sensitivity and specificity and the area under curve (AUC).

	Limit (mg_o)	Sensitivity (%)	Specificity (%)	AUC
Limit 1	16·7	98·7	99·7	0·9995
Limit 2	157·4	100·0	100·0	1·0000
Limit 3	331·2	98·9	96·9	0·9984
Limit 4	599·3	98·3	98·8	0·9990

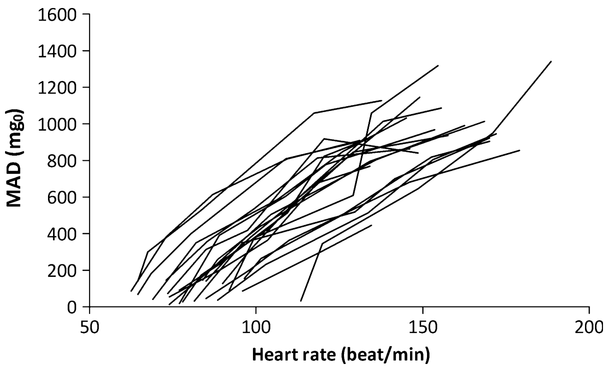

Figure 2 Individual mean amplitude deviation (MAD) values measured with Hookie accelerometer plotted against incident heart rate during slow walking, normal walking, brisk walking, jogging and running at preferred speed.

from each other in contrast to clear discriminatory power of MAD (data not shown).

Discussion

This study is the first to compare the performance of three technically different, commercial tri-axial accelerometers (GulfCoast X6-1A, Actigraph GTX3 and Hookie AM 13) in classifying different physical activities in terms of their intensity. The pivotal result of this methodological study is the introduction of universal cut-off limits that provide a highly accurate classification of intensity of bipedal movement with a simple calculable classifier (MAD), irrespective of the accelerometer brand. Despite clearly different technical specifications between the brands, all the three tested accelerometers gave similar MAD values for slow and normal walking., The universal cut-off limits separated different intensity levels from each other equally well, or even better, compared with what has recently been obtained with more sophisticated methods (Pärkkä *et al.*, 2006; Ermes *et al.*, 2008; De Vries *et al.*, 2011). Accordingly, any hip-mounted device equipped with a tri-axial accelerometer can be used as a reliable physical activity monitor and provide physically meaningful and comparable results, provided that the raw data were analysed with the MAD classifier and universal cut-off limits were applied. In so doing, results would be directly comparable, and there would be no need for cross-calibration between obscure count values of different studies. The use of cross-calibration equations for transforming data always

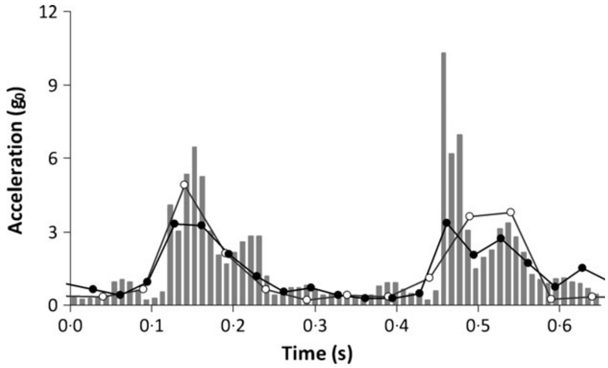

Figure 3 Resultant acceleration signal of the two running steps as measured with Hookie (grey bars), Actigraph (black circles) and GulfCoast (open circles) accelerometer. The MAD for the Hookie is 1399 mg_0, for the Actigraph 900 mg_0, and for the GulfCoast 1281 mg_0.

induces uncertainty in individual results. The present MAD approach provides a novel means of data analysis for all types of accelerometers producing raw data without the need for cross-calibration between studies and devices.

Ground contacts during weight-bearing activities can generate a wide range of impact forces to the human body that are measured with accelerometry. The impact at the measurement level is attenuated within external and internal structures of the body such as ground surface, footwear, muscles, cartilage, tendons and bones (Zhang *et al.*, 2008; Abt *et al.*, 2011). As one could expect, running generated the highest peak accelerations in the present study. With the Hookie, the highest measured resultant value was over 10 g during the foot contact, while with the Actigraph, at least one measurement axis was always saturated during the foot contact of running (Fig. 3). Obviously, the $\pm 3\ g_0$ measurement range, which in theory can measure resultant acceleration up to $5{\cdot}2\ g_0$ ($\sqrt{3 \times 3^2}$), is too narrow for running. The $\pm 6\ g_0$ measurement range of the GulfCoast was not saturated, but the acceleration signal was distorted because of the low-sampling rate (Fig. 3).

The effect of the sampling rate on the measured acceleration signal is distinct from the accelerometer's capability to distinguish between the braking and propulsive phase of the foot contact. Figure 3 shows two running steps measured by the three studied accelerometers. The 100-Hz sampling rate of Hookie faithfully revealed the details of the acceleration signal of running. At 100 Hz, there are four to six data points per braking or propulsive phase. With the 20-Hz sampling rate of GulfCoast, every fifth and with 30 Hz of Actigraph about every third point is measured. This means that the whole braking or propulsive phase can be missed with GulfCoast, while Actigraph cannot always reveal the braking and propulsive phases of running.

In the long-term measurements, the epoch length can modulate the results. Short bursts of high-intensity activities within a long epoch become attenuated but by shortening the epoch length, these events can be detected. According to the sampling theorem, the 4–6 s epoch used in this study can capture

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about 8–12 s burst of the activity and classify its intensity accurately. Even a shorter epoch length may be required to properly measure the intensity in rapid vigorous activities such as spurts in football. With steady activities used in the present study, the epoch length had basically no effect on the MAD results. The average level of MAD remained at same level even with 1-s epoch length (data not shown).

Accelerometers are typically used for estimating energy expenditure in different physical activities (Crouter *et al.*, 2006). In the present study, the participants used self-selected speed for walking and running and neither speed nor metabolic cost was measured, which can be considered a limitation. On the other hand, incident heart rate correlated very strongly with the MAD values in each individual case. It is thus likely that MAD, besides having an excellent discriminatory power, is also closely related to the individual energy expenditure during walking or running at different speeds. Further research is needed for validation. However, in support for this argument, heart rate has been shown to predict the energy expenditure well, especially at high-intensity levels (Hiilloskorpi *et al.*, 2003).

Further regarding the estimation of energy expenditure, it is recalled that accelerometer can detect movement only if the produced force is smaller or higher than the resisting force. For weight-bearing activities such as level walking and running, this is straightforward because the main resisting force is gravity, which is intrinsically measured by accelerometer. In contrast to level movement, if the movement is performed on inclined or declined terrain or an additional static load (e.g. a heavy backpack) is carried, the intensity may not be accurately determined. Further, if the main resistive force is air or fluid resistance as in high-speed cycling or rowing, or friction as in skiing, it is difficult to estimate muscle force production and energy consumption with accelerometer. Also, in static isometric activities, the produced force and resisting force are equal in magnitude but opposite in direction producing no measurable acceleration despite even high forces involved. Similarly in many gym exercises, the extremities may perform vigorous movements while the hip region remains rather steady and shows no substantial acceleration. In sum, the present accelerometer-based method applies well to estimation of intensity during bipedal locomotion at different speeds, whereas other types of physical activity, such as cycling, skiing, swimming and gym training, require more sophisticated analyses for accurate estimation of intensity.

Conclusion

In conclusion, this study introduced a novel accelerometer-based analysis method, which can accurately classify different physical activities by its intensity employing a simply calculable trait from the resultant acceleration signal, the mean amplitude deviation (MAD). Particularly, noteworthy is that the proposed classification scheme is virtually device-independent and the proposed cut-off limits can be universally applied to different tri-axial accelerometer brands despite substantial differences in their measurement ranges and sampling rates. A broader application of the present approach is expected to render the results from different studies directly comparable with each other.

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Conflict of interest

The authors have no conflict of interest.

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