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Validation of Cut-Points for Evaluating the Intensity of Physical Activity with Accelerometry-Based Mean Amplitude Deviation (MAD)

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Abstract

Purpose

Our recent study of three accelerometer brands in various ambulatory activities showed that the mean amplitude deviation (MAD) of the resultant acceleration signal performed best in separating different intensity levels and provided excellent agreement between the three devices. The objective of this study was to derive a regression model that estimates oxygen consumption (VO2) from MAD values and validate the MAD-based cut-points for light, moderate and vigorous locomotion against VO_2 within a wide range of speeds.

Methods

29 participants performed a pace-conducted non-stop test on a 200 m long indoor track. The initial speed was 0.6 m/s and it was increased by 0.4 m/s every 2.5 minutes until volitional exhaustion. The participants could freely decide whether they preferred to walk or run. During the test they carried a hip-mounted tri-axial accelerometer and mobile metabolic analyzer. The MAD was calculated from the raw acceleration data and compared to directly measured incident VO_2. Cut-point between light and moderate activity was set to 3.0 metabolic equivalent (MET, 1 MET = 3.5 ml $\cdot$ kg^{-1} $\cdot$ min^{-1}) and between moderate and vigorous activity to 6.0 MET as per standard use.

Results

The MAD and VO_2 showed a very strong association. Within individuals, the range of r values was from 0.927 to 0.991 providing the mean r = 0.969. The optimal MAD cut-point for 3.0 MET was 91 mg (milligravity) and 414 mg for 6.0 MET.

Competing Interests: The authors have declared that no competing interests exist.

Conclusion

The present study showed that the MAD is a valid method in terms of the VO_2 within a wide range of ambulatory activities from slow walking to fast running. Being a device-independent trait, the MAD facilitates directly comparable, accurate results on the intensity of physical activity with all accelerometers providing tri-axial raw data.

Introduction

According to physical activity recommendations healthy adults need moderate intensity aerobic physical activity (PA) for a minimum of 150 or vigorous intensity PA for a minimum of 75 min on three days each week accumulating from PA bouts of at least 10 minutes [1]. Moderate intensity activities have energy expenditure between 3.0 to 5.9 metabolic equivalents (MET) and vigorous intensity activities higher than 6.0 METs. One MET is defined as the resting metabolic rate for quietly sitting and is about 3.5 ml · kg^{-1} · min^{-1}, when expressed as oxygen consumption (VO_2) rate [2]. Then 3.0 MET and 6.0 MET physical activities correspond 10.5 ml · kg^{-1} · min^{-1} and 21.0 ml · kg^{-1} · min^{-1} VO_2, respectively.

Accelerometry provides a useful and feasible method to characterize PA during free living conditions. It permits objective measurements of the intensity, duration and frequency of daily PA and exercise [3] including assessment of short activity bouts that cannot be captured with questionnaires, interviews or diaries [4, 5]. However, the main challenges in accelerometry pertain to the use of proprietary algorithms [6, 7], and lack of valid physiologically determined cut-points for intensity of PA [8, 9], which both compromise the cross-study comparisons. Storing and processing the raw acceleration data have been proposed as the means to improve the comparability between different devices and studies [10].

We recently developed a novel method for universal analysis of PA from raw tri-axial accelerometer data [11]. In that study, raw acceleration data were collected during various sedentary and ambulatory activities and analysed with several classifiers in both time and frequency domain. Of these the mean amplitude deviation (MAD) of the resultant acceleration signal consistently provided the best performance in separating different PA intensity levels from each other. Most importantly the MAD enabled a direct comparison between the results of different accelerometer brands despite clearly different technical specifications of these devices.

The MAD value describes the mean value of the dynamic acceleration component. It is calculated from the resultant value of the measured tri-axial acceleration, which comprises both tri-axial dynamic components due to velocity changes and static component due to gravity. The static component is removed from the analysed time period (epoch) and the remaining dynamic component is rectified. The MAD value is the mean of the rectified signal within the epoch and independent of static component.

There is a strong correlation between incident MAD values and heart rate both among adults [11] and adolescents [12]. We therefore hypothesized that the incident MAD value also correlates strongly with actual VO_2 at individual level. Previously similar acceleration signal-derived traits have been evaluated during treadmill walking and running and found to have strong correlation with VO_2 [13–15] and be better predictor of VO_2 than heart rate [16]. However treadmill derived relationship may overestimate the intensity of PA [17, 18], thus, accurate comparison is best achieved during actual locomotion.

The present study was carried out to develop a MAD-based model for predicting VO_2 during locomotion within a wide range of speeds and to determine its accuracy. The main objective was to determine the MAD-based universal cut-points for light, moderate and vigorous PA corresponding to commonly accepted MET values for these intensity levels [1].

Methods

Participants

The study group consisted of 29 healthy volunteers, 15 males and 14 females. Prior to testing body height, weight and waist circumference were measured with standard methods (Table 1). Participants were informed of the experimental test protocol and they gave their written informed consent. This study conformed to the code of Ethics of the World Medical Association (Declaration of Helsinki) and it was approved by the Ethics Committee of Pirkanmaa Hospital District (R13040).

Test procedure

Participants performed a pace-conducted non-stop test on a 200 m long oval indoor track with slightly banked bends. Pace was verified by a so called "light rabbit" system, which comprises light sources alongside of the track. The light sources were installed at every 2 meters and they automatically lited-up one at a time according to the required pace. Every light source was also visible to tester. So participant's location on the track could be determined with the accuracy of 2 meters. Initial speed was 0.6 m/s and it was increased by 0.4 m/s at every 2.5 minutes. The direction of travel was counter-clockwise. The participants had to keep up with the light sources and they could freely decide whether they preferred walking or running. The selected gait type was recorded for each stage. The test was continued until volitional exhaustion when the participant could not keep up with the lights anymore. End point was visually inspected by the tester and time at the end point was recorded.

Measurements

A tri-axial accelerometer (Hookie AM20, Traxmeet Ltd, Espoo, Finland) was attached to the hip-mounted elastic belt at the level of the iliac crest. The accelerometer had ± 16 *g* measurement range and acceleration was measured at 100 Hz sampling frequency. Because the indoor track has banked turns only to left, it might have effect on the accelerometer output. Thus the accelerometer was placed either at the right (r-hip) or left side (l-hip) of the hip and the side was randomly selected. The left side (i.e. inner side of curve) was assigned to 13 participants and the right side (i.e. outer side of curve) to 16 participants. In addition, all participants carried one accelerometer in the middle of the back (mid) to emulate a situation where misplacement was the longest in terms of the preferred lateral location.

During the test procedure, VO_2 was continuously measured with a portable breath-by-breath mobile metabolic analyser (Oxycon, Carefusion, Yorba Linda, CA, USA) and the data were recorded with a telemetry system. The metabolic cart was calibrated before each test according the manufacturer's instructions.

Table 1. Characteristics of the study group (mean ± SD).

Age (years)	35 ± 11
Height (cm)	172.1 ± 9.9
Weight (kg)	69.7 ± 12.4
Waist circumference (cm)	80 ± 9

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Data analysis

The analysis of the acceleration signal was based on the MAD value described recently [11].

Tri-axial acceleration was measured in raw mode from all three orthogonal measurement axes in actual g-units and stored for further analysis. In short, each measurement point (i) consisted of samples x_i, y_i and z_i. The resultant acceleration (r_i), which defines the magnitude of the acceleration vector and contains both dynamic and static component of acceleration, was calculated for each (i) time point as

$$\mathrm{r_i} = \sqrt{\mathrm{x_i^2} + \mathrm{y_i^2} + \mathrm{z_i^2}} \tag{1}$$

The epoch length used in the analysis was 6 s, and for each analysed epoch the mean resultant value (R_{ave}) describing the static component of acceleration was calculated as

$$R_{ave} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=j}}^{\mathrm{j+N-1}} \mathrm{r_i} \tag{2}$$

The MAD value of the given epoch was calculated as

$$\mathrm{MAD} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=j}}^{\mathrm{j+N-1}} |\mathrm{r_i} - \mathrm{R_{ave}}| \tag{3}$$

where N is the number of samples in the epoch (ie, 600) and j is the start point of the epoch. The unit of the MAD is milligravity (m*g*); ie, the Earth's gravity 1*g* is equal to 1000 m*g*.

To allow the participants to find the steady rhythm the acceleration was analysed for the final 2 minutes of each stage. As a measure of steady-stage VO_2 for given speed mean VO_2 of the final minute of the corresponding stage was used. VO_{2peak} value was the highest measured VO_2 for one minute period during the test. Measured end time made it possible to calculate the mean speed during the final two and half minutes of the test (v_{max}). The v_{max} value depends on the maximum speed achieved during the test and time it has been maintained. The oxygen cost of movement ($ml \cdot kg^{-1} \cdot km^{-1}$) was calculated for each stage as the ratio of measured VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$) to known speed (km/min).

Statistical methods

Data were analysed with SPSS 21.0 (SPSS Science, Chicago, USA) software. First, independent two-sample t-test was performed to investigate whether the MAD values were different between right and left side for each speed. In addition, Pearson correlation between VO_2 and the MAD was determined for each participant. Mean correlation coefficient was calculated by first z-transforming the individual correlation coefficients, taking the arithmetic mean of transformed coefficients, and then by back-transforming the mean. The generalized linear model was used to estimate VO_2. Since the data were not normally distributed, gamma regression model was used. Incident VO_2 was the dependent variable and the incident MAD value, physical characteristics (age, weight, height, and waist circumference) and performance values (VO_{2peak} and v_{max}) served as the independent predictor variables. Furthermore, because the data during walking were normally distributed, the estimation of the VO_2 during walking from the MAD value was based on linear regression model. Stages with respiratory exchange ratio over 1.0 or not fully completed were excluded from the analysis.

To find optimal intensity based cut-points for the MAD values the receiver operator characteristics (ROC) analysis was used. The measured VO_2 values were used as a golden standard. VO_2 values were converted to MET values by using the standard conversion factor (1 MET = 3.5 $ml \cdot kg^{-1} \cdot min^{-1}$) and performances were classified to light (< 3.0 MET), moderate (3.0–5.9 MET) and vigorous (> 6.0 MET) activity. For both 3 MET and 6 MET limits a new dichotomous variable was created to define the outcome of the test. If a measured MET value was less than limit, the outcome was negative and the variable value was set to 0. Otherwise the outcome was positive and the variable was set to 1. After that ROC curve analysis were conducted to determine sensitivity and specificity values. Sensitivity and specificity defines correctly identified positive and negative values. The MAD value which maximized the sum of the specificity and sensitivity was selected as the optimal cut-point. Also the area under curve (AUC) value was determined. AUC value of 1 indicates a perfect classifier whereas AUC value of 0.5 denotes no discriminatory value [19].

Results

The Fig 1 illustrates one test performance, where the participant walked the first four stages and changed to running at stage five (2.2 m/s). In the beginning of the test there was some trouble in achieving steady pace, which can be seen from MAD and VO_2 curves. The required pace was maintained almost 27 minutes.

The Fig 2 shows the number of fully completed stages and the preferred gait. Typically the participants changed the gait type (from walking to running) at the beginning of the stage. At speed 2.2 m/s (7.9 km/h) four participants changed the gait type in the middle of the stage. The mean VO_{2peak} was 56.0 ± 7.1 ml · kg^{-1} · min^{-1} (range 45–69 ml · kg^{-1} · min^{-1}). The range of the v_{max} was 3.1–5.1 m/s (11.1 km/h– 18.4 km/h). At the group level the oxygen cost of locomotion reached the minimum at the speed 1.4 m/s (Fig 2). During running, after initial increase the energy cost remained quite steady despite increasing speed. At the individual level the curve of the oxygen cost was u-shaped both for walking and running. For walking, 26 participants have the lowest oxygen cost at speed 1.4 m/ (5.0 km/h), while for running the minimum value varied between speed from 2.2 m/s (7.9 km/h) to 3.8 m/s (13.7 km/h). VO_2 showed a curvilinear increase during walking and linear during running with increasing speed (Fig 3). The highest MAD and VO_2 value for the stage containing barely walking was 651 mg and 30.2 ml · kg^{-1} · min^{-1}, whereas the lowest value for stage containing barely running was 581 mg and 26.1 ml · kg^{-1} · min^{-1}, respectively.

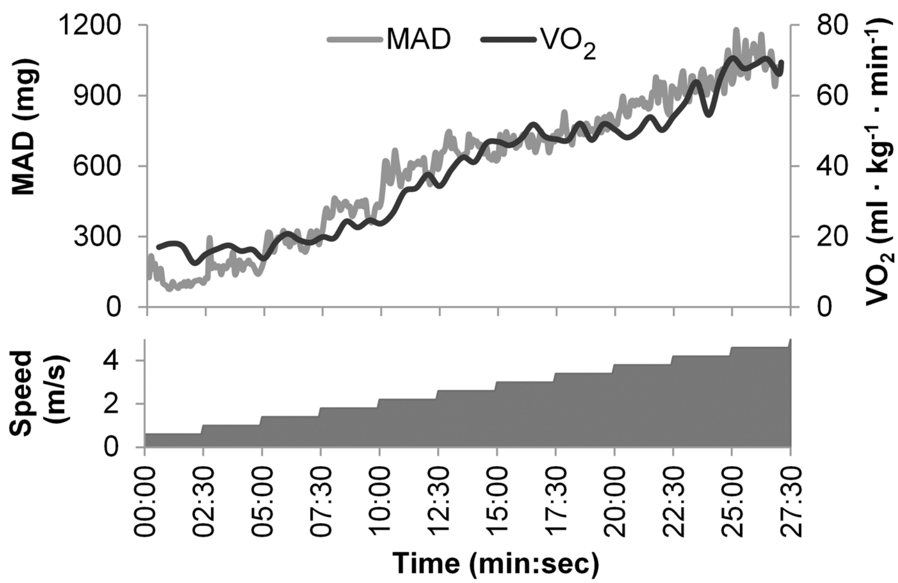

Fig 1. Illustration of pace conducted test performance. The lower graph describes the required speed and the upper curves the measured VO_2 and MAD values during the whole test. The unit mg denotes milligravity.

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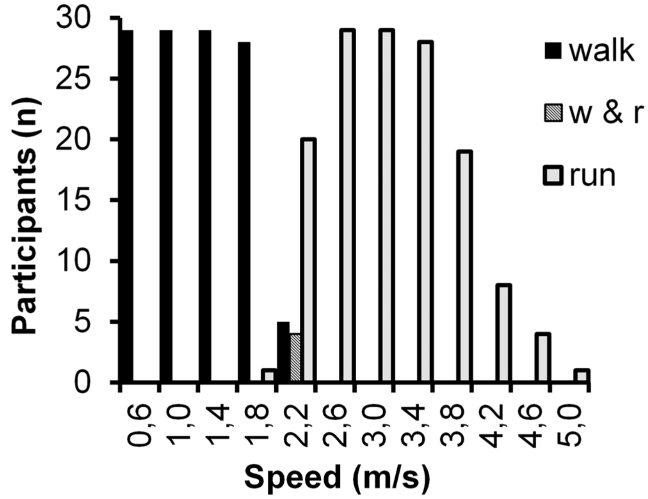

Fig 2. Preferred gait types in different speeds. The preferred gait of the fully completed stages is shown for each speed.

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Sensor placement and MAD

Sensor placement conferred a slight effect on measured MAD values, the effect being largest during running (Fig 4). With slow speed walking the mid position values and with running the right-side position values were slightly lower. The MAD values increased with increasing gait speed.

Individual correlations

Within individuals, the correlations between both MAD and VO_2, and MAD and speed were very high (Table 2). In all participants, the MAD value increased with increasing VO_2 or speed for both walking and running. Mean correlation values were highest for walking, and somewhat lower for data containing both walking and running, or running alone. This is due to

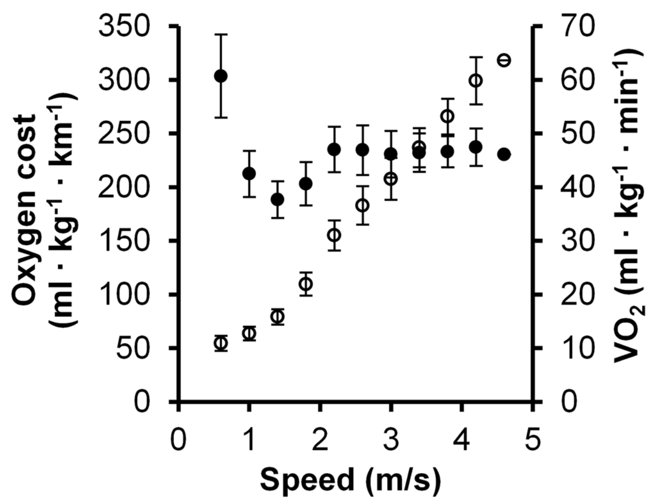

Fig 3. Oxygen cost and consumption in different speeds. The oxygen cost of the locomotion (black circles) describes the economy and the oxygen consumption (open circles) the intensity of the movement.

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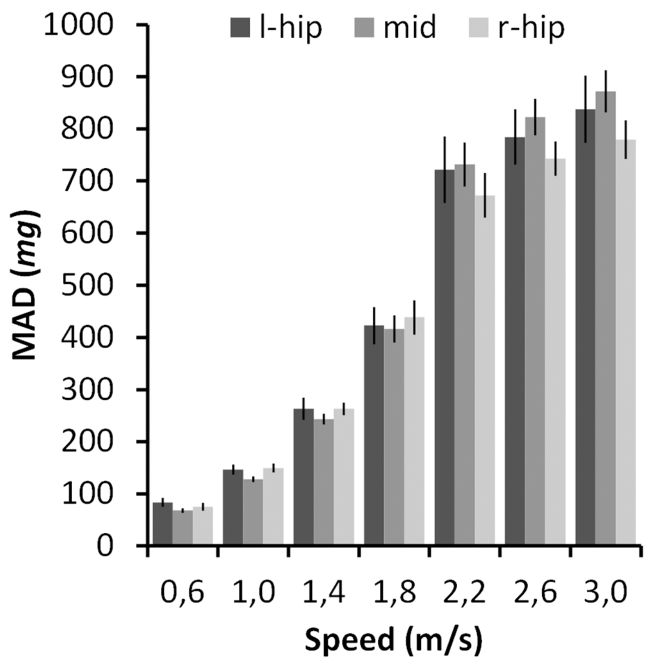

Fig 4. Sensor placement and MAD in different speeds. The measured mean MAD value with the three sensor positions is shown only for speeds performed by all 29 participants. The whiskers denote the 95% confidence intervals of the mean value. The unit m*g* denotes milligravity.

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different regression slopes between MAD and VO_2, and MAD and speed during walking and running, and larger variation in data during running (Fig 5).

Prediction models between MAD and VO_2

The direct relationship between the incident MAD and VO_2 values were estimated with following equation: VO_2 (ml/kg/min) = $10.015 \cdot e^{0.0017 \cdot \text{MAD (mg)}}$ (r = 0.958, standard error of the estimate (SEE) = 6.05 ml/kg/min), where *mg* denotes milligravity (Fig 5). For walking only, the prediction model based on linear regression was: $VO_2 = 7.920 + 0.0331 \cdot$ MAD (*mg*) (r = 0.943, SEE = 1.66 ml/kg/min) (Fig 5). By using all measured values the estimation equation was following: VO_2 (ml/kg/min) = $2.351 \cdot e^{(0.00177 \cdot \text{MAD (mg)} - 0.282 \cdot \text{vmax (m/s)} + 0.0183 \cdot \text{VO2peak (ml} \cdot \text{kg-1} \cdot \text{min-1)} + 0.0117 \cdot \text{height (cm)} - 0.0142 \cdot \text{weight (kg)} + 0.00693 \cdot \text{waist circumference (cm)} - 0.00211 \cdot \text{age (years)})}$

(r = 0.975, SEE = 4.46 ml/kg/min). Parameters in the equation are in the order of significance and for each parameter p-value was less than 0.05.

Table 2. Mean and range of within-individual correlations between MAD and VO_2, and MAD and speed.

	MAD and VO_2	MAD and speed
Both walk and run	0.975 (0.927–0.991)	0.969 (0.933–0.986)
Walking only	0.995 (0.976–1.000)	0.990 (0.962–1.000)
Running only	0.976 (0.850–0.999)	0.988 (0.886–0.999)

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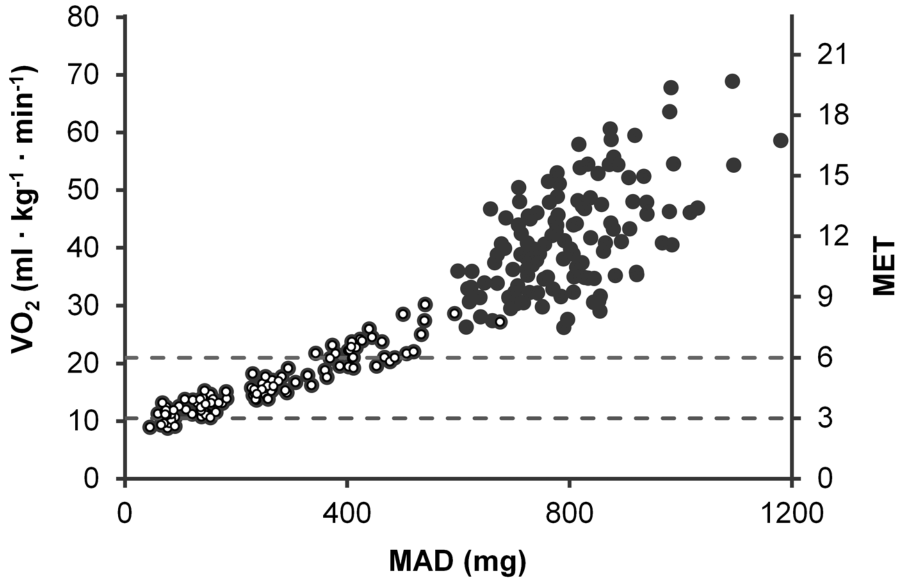

Fig 5. Relationship between VO_2 and MAD. Stages containing only walking have open circle and other stages black circle. The dotted lines denote 3 MET and 6 MET thresholds and the unit m*g* denotes milligravity.

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Optimal cut-points

According to the ROC curve analysis the optimal MAD cut-point for intensity of 3.0 MET was 91 *mg* and for 6.0 MET 414 *mg* (Fig 6). Sensitivity and specificity values were 100% and 96% for the 3.0 MET cut-point, and 96% and 95% for 6.0 the MET cut-point. The AUC and 95% confidence interval for both limits is shown in the Fig 7.

Discussion

The present study demonstrated that the MAD is a highly valid method to estimate the intensity of PA within a wide range of locomotion from slow walking to fast running. The study also

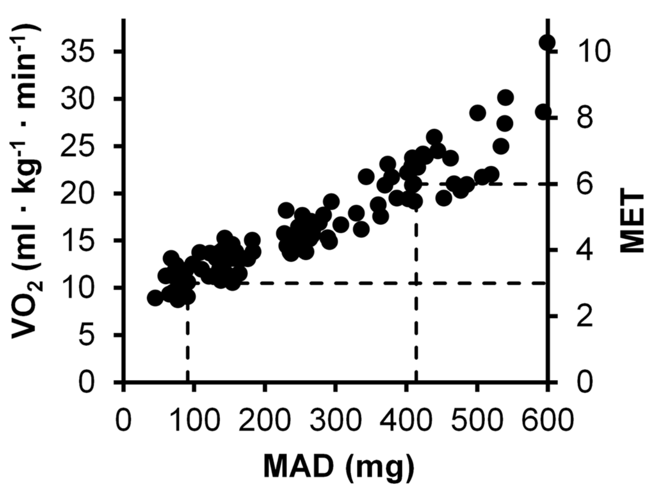

Fig 6. Optimal cut-points. The dotted lines represent the optimal MAD cut-points for 3 and 6 MET limits. The MAD values are shown up to 600 m*g*. The unit m*g* denotes milligravity.

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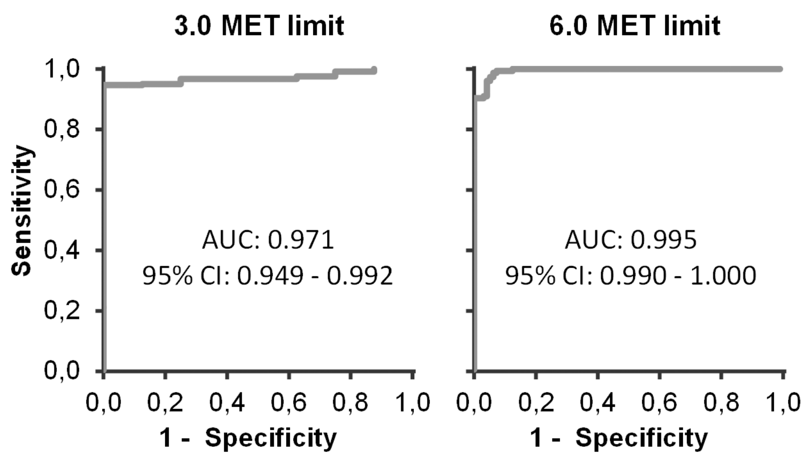

Fig 7. ROC curves and AUC for cut-points. ROC curve and AUC (mean and 95% confidence interval (95% CI)) for 3.0 MET limit (left) and for 6.0 MET limit (right).

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produced valid cut-points for accurate determination of light, moderate and vigorous intensity levels of PA that are much needed in epidemiological population studies. Because the calculation of the MAD is based on the raw acceleration data and has been shown to be device-independent, the MAD approach offers a possibility to obtain directly comparable and accurate results on the intensity of PA with all accelerometers which provide tri-axial raw data within a sufficient dynamic range [11].

The accuracy of the MAD method to predict VO_2 during walking and running compares well with other commonly used methods [20–22]. As is the case with other methods, the accuracy was better for walking than running. However the MAD value is not compromised by the common ceiling effect, where the accelerometer output values reach a peak at a certain speed and do not increase in response to further speed increments [22–24]. In the present study increasing speed produced increasing MAD values in a dose-response manner for each participant.

The oxygen cost of the locomotion was at typical level for all except the first stage of the test (i.e. slow walking), when the cost was higher than expected. Apparently the emotional excitement at the beginning of the test contributed to relatively high measured VO_2 values. Also some participants had difficulties in achieving a steady pace at the beginning of the first stage. The measured oxygen cost was 303 ± 39 ml/kg/km at the 0.6 m/s speed, while in the previous study the oxygen cost was below 250 ml/kg/km at the 0.67 m/s speed [25]. The most economical movement speed in the present study was 1.4 m/s with the oxygen cost of 188 ± 17 ml/kg/km which is line with other studies [25, 26]. Preferred gait transition speed from walking to running is slightly lower than energetically optimal transition speed [27, 28] and it seems to depend on various metabolic and biomechanical factors related to transition. In the present study preferred speed for gait transition was in line with literature [27, 28]. With running the oxygen cost was slightly lower for the higher speeds. This is probably consequence of the fact that only participants with good running economy reached the higher speeds and could maintain the speed for several minutes.

The association between the MAD and VO_2 was very strong both at individual level and at group level. By adding individual anthropometric and performance data into the prediction model only a slight improvement in the estimation of VO_2 could be attained, especially during running. However, when the MAD value was excluded, the most significant individual predictors were VO_2peak and v_{max} values, which might be difficult to obtain in practise. The contribution of these predictors is apparently related to running economy and the bouncing characteristics of running. The mechanics and energetics of running depend on the kinetic and potential energy of the whole body and the body segments, besides storage and release of mechanical energy by the contracting muscles and tendons. The accelerometer cannot separate whether the energy for the speed change is produced actively by the muscle or passively by the tendon. The simpler mechanics and energetics characteristics of the walking seem to account for more straightforward estimation of VO_2 with accelerometer [29, 30]. Nevertheless, the prediction of the incident VO_2 was excellent whether or not the additional predictors were known, and importantly, the estimation was sufficient enough for accurate classification of PA in terms of light, moderate and vigorous intensity.

Previously it has been shown that sensor placement on either hip or waist area can have effect on accelerometer output [17]. With the MAD values the effect of sensor placement was marginal in relation to the wide range of MAD values in different speeds. However, some observations are worth discussing. First, at low walking speeds the mid position showed slightly lower MAD values than the other positions. This is explained by the sensor movement which is apparently higher on the side due to pelvis tilting. Second, during running the right side MAD values were slightly lower. This is attributable to the characteristics of the indoor track used in the present study. It had banked curves and participants moved only to anti-clockwise direction. The inner (left) and outer legs (right) apparently experienced somewhat asymmetrical loading in the curves. These observations not only show how sensitive method the accelerometry can be in detecting subtle differences in movements, but also underline the importance of keeping placement of the sensor as constant as possible.

Some analysis methods of accelerometry data can produce inaccurate results, if the sensor orientation in relation to gravity is not controlled for [31]. With the MAD method this is not a concern, as illustrated by the following examples. Assuming that the orientation of the sensor x-axis is perpendicular to ground (ie, parallel to the gravity vector) while both y- and z-axes are parallel to ground, then the measurement vector M = (x, y, z) is M = (1.000, 0.000, 0.000) in *g*-units. The resultant acceleration R is in this static situation equal to Earth's gravity 1.000 *g*. If the sensor moved downwards with 0.5 g acceleration and thereafter upwards with 0.5 *g* acceleration then the sensor readings would be M = (0.500, 0.000, 0.000) and M = (1.500, 0.000, 0.000) and corresponding R values 0.500 *g* and 1.500 *g*. Both values deviate 0.500 *g* i.e. 500 *mg* from the static value. Assuming next that the sensor is rotated 45° around the z-axis resulting in M = (0.707, 0.707, 0) and R = 1.000 g in the static situation. For the above described dynamic 0.5 g downwards and upwards accelerations the sensor readings would be M = (0.354, 0.354, 0.000) and M = (1.061, 1.061, 0). Again, the corresponding R values are 0.500 *g* and 1.500 *g* and deviation from the static value is 0.500 *g* despite the different position of the sensor.

Another problem with accelerometers is their offset, which means the difference between the measured value of the accelerometer and the true acceleration. Although the sensors are calibrated during manufacturing process, the offset cannot be avoided, because it is sensitive to external conditions, like temperature [32]. Using the conditions of the previous example and assuming that all axes have 0.05 g offset the calculations are as follows: When the x-axis is perpendicular to ground, sensor readings for static condition would be M = (1.050, 0.050, 0.050) and R value 1.052 *g*. For the 0.5 *g* dynamic upward and downward accelerations the corresponding values are M = (0.550, 0.050, 0.050) and M = (1.550, 0.050, 0.050), and the R values 0.555 *g* and 1.552 *g* resulting in 0.499 *g* mean deviation from the static value. In the 45° rotated case the sensor readings for the static condition would be M = (0.757, 0.757, 0.050) and for dynamic conditions M = (0.404, 0.404, 0.050) and M = (1.111, 1.111, 0.050). The respective R values would be 1.072 *g*, 0.573 *g* and 1.572 *g* resulting in 0.499 *g* mean deviation from the static value. Inferred from the above described examples, the offset can have minor effect on the results but there is no need to use excessive methods to calibrate the sensor when the MAD approach is used.

Participant's aerobic fitness in the present study was high as can be judged from their high VO_{2max} values. All but three participants reached the highest class in seven level fitness classifications [33] and the remaining three belonged to classes 5–6. This can be considered a strength of the study because a wide speed range of locomotion and oxygen consumption was attained from very slow walking to high speed running. Other strengths were the relatively large sample size and the direct measurement of the expiratory gases during actual bipedal movement on the track instead of a treadmill. The main weakness of the study was that no other activities than walking and running on the track were studied. On the other hand, locomotion is the most common type of physical activity among ordinary people.

Conclusion

In conclusion, the MAD is a valid method to estimate the intensity of PA within a wide range of bipedal human locomotion. The MAD values highly reflect the incident oxygen consumption within a wide range of walking and running speeds. The proposed cut-points offer a valid base for assessing the health effects of PA. Sensor positioning does not compromise the results. This study further underscores the utility of the simple and universal MAD approach as the means to overcome the challenges for comparisons between studies and different accelerometers.

Supporting Information

S1 File. Measurement data. File contains measured oxygen consumption and MAD values for each stage.
(TXT)

Author Contributions

Conceived and designed the experiments: HV-Y AM ToV TiV HS. Performed the experiments: AM TiV. Analyzed the data: HV-Y. Wrote the paper: HV-Y JS PH.

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