A new 2-regression model for the Actical accelerometer

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ABSTRACT

Objective: The objective of this study was to develop a new 2-regression model relating Actical activity counts to METs.

Methods: Forty-eight participants (mean (SD) age 35 (11.4) years) performed 10 min bouts of various activities ranging from sedentary behaviours to vigorous physical activities. Eighteen activities were split into three routines with each routine being performed by 20 individuals. Forty-five routines were randomly selected for the development of a new 2-regression model and 15 tests were used to cross-validate the new 2-regression model and compare it against existing equations. During each routine, the participant wore an Actical accelerometer on the hip and oxygen consumption was simultaneously measured by a portable metabolic system. The coefficient of variation (CV) of four consecutive 15 s epochs was calculated for each minute. For each activity, the average CV and the counts min^{-1} were calculated for minutes 4–9. If the CV was $\leqslant 13\%$ a walk/run regression equation was used and if the CV was $>13\%$ a lifestyle/leisure time physical activity regression was used.

Results: An exponential regression line ($R^2 = 0.912$; standard error of the estimate (SEE) $= 0.149$) was used for activities with a $CV \leqslant 13\%$, and a cubic regression line ($R^2 = 0.884$, SEE $= 0.804$) was used for activities with a $CV > 13\%$. In the cross-validation group the mean estimates, using the new 2-regression model with an inactivity threshold, were within 0.56 METs of measured METs for each of the activities performed ($p \geqslant 0.05$), except cycling ($p < 0.05$).

Conclusion: For most activities examined the new 2-regression model predicted METs more accurately than currently available equations for the Actical accelerometer.

Accelerometers are objective measurement tools that allow researchers to track the amount of physical activity (PA) individuals are performing. During the past several years, the use of accelerometers in research has become more widespread; however, the conversion of accelerometer data into an accurate and reliable measurement of PA has been a difficult task.[1] In December 2004 a conference on "Objective Measurement of Physical Activity: Closing the Gaps in the Science of Accelerometry," was held at the University of North Carolina, which highlighted the use of accelerometry in research and the pitfalls associated with it.[1] This conference urged researchers to improve upon the current techniques used to analyse accelerometer data to achieve more accurate estimates of energy expenditure (EE) as well as time spent in light (<3 metabolic equivalents (METs)), moderate (3–5.99 METs) and vigorous ($\geqslant 6$ METs) PA.

Crouter *et al.*[2] developed a new 2-regression model for the ActiGraph accelerometer, which distinguishes between walking/running and lifestyle activities based on the variability in accelerometer counts. This method is based on the fact that walking and running are rhythmic locomotor activities, whereas other lifestyle activities are more intermittent in nature. This new model provides a substantial improvement in the estimate of both METs and time spent in light, moderate and vigorous PA versus other ActiGraph prediction equations.

The Actical accelerometer (Mini Mitter, Bend, OR, USA) is becoming more widely used by researchers, as evidenced by its use in the upcoming Canadian Health Measures Survey.[3] The Actical has the ability to collect accelerometer data in epochs as short as 15 s, which would make it suitable for using a 2-regression model similar to what has been developed for the ActiGraph.[2] In addition, there are limited calibration studies relating the Actical counts min^{-1} to EE; there are three for children[4–6] and one for adults.[7] There are distinct differences between the Actical and ActiGraph limiting the ability to interchange the count values between devices. For example, the ActiGraph is a uni-axial accelerometer, which measures acceleration in the vertical plane, whereas the Actical is an omni-directional accelerometer, which has the ability to measure acceleration in multiple planes. There are also differences in the count values provided by these devices at different activity intensities. The ActiGraph provides higher count values for most light and moderate activities,[8] while at higher intensities the ActiGraph counts level off or even decrease slightly, while the Actical continues to have an increase in count values.[8 9] Therefore, the purpose of this study was to develop a new prediction equation for the Actical accelerometer that would consist of two regression lines: one for walking/running and one for lifestyle activities. The determination of which line to use would be based on the coefficient of variation (CV) of four consecutive 15 s epochs within a 1 min period.

METHODS

Subjects

Forty-eight participants from the University of Tennessee, Knoxville and surrounding community volunteered to participate in the study. The procedures were reviewed and approved by the University of Tennessee Institutional Review Board before the start of the study. Prior to beginning the study each participant signed a written informed consent and completed a Physical Activity Readiness Questionnaire.

Table 1 Physical characteristics of the participants (mean (SD) (range))

Variable	Male (n = 24)	Female (n = 24)	All participants (n = 48)
Age (years)	36 (12.8) (21–69)	35 (10.3) (22–55)	35 (11.4) (21–69)
Height (cm)*	180.1 (7.1) (159.5–188.5)	165.4 (5.8) (152.9–174.0)	172.7 (9.7) (152.9–188.5)
Body mass (kg)*	83.9 (20.2) (59.4–141.0)	62.3 (12.3) (45.4–109.0)	73.1 (19.6) (45.4–141.0)
BMI ($kg \cdot m^{-2}$)*	25.8 (5.2) (19.1–40.6)	22.7 (4.0) (17.9–36.4)	24.2 (4.8) (17.9–40.6)
Resting VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$)	3.6 (0.8) (2.1–5.0)	3.4 (0.8) (2.0–4.9)	3.5 (0.9) (2.0–5.0)

*Significantly different from females, $p<0.05$.
BMI, body mass index.

Participants were excluded from the study if they had any contraindications to exercise. The physical characteristics of the participants are shown in table 1.

Procedures

This study was part of a larger study using the same participants and the methods are published in more detail elsewhere.[2 10 11] Prior to testing, participants had their height and weight measured (in light clothing, without shoes) using a stadiometer and a physician's scale, respectively. Participants performed various lifestyle and sporting activities that were broken into three routines (table 2). Each routine was performed by 20 participants (two participants performed all three routines, eight performed two routines and 38 performed only one routine). Each activity was performed for 10 min with a 1–2 min break between each activity. An Actical accelerometer was worn on the left hip and oxygen consumption (VO_2) was simultaneously measured throughout the routine by indirect calorimetry (Cosmed K4b^2, Rome, Italy). In addition, during the course of this study participants also wore an Actiheart, ActiGraph, AMP-331 and three tri-axial accelerometers. The total weight of all the devices and the Cosmed K4b^2 was 2.0 kg. Thus, 2.0 kg was added to the participant's body mass to account for the added weight of the devices. Routine 1 and 2 were performed at University facilities, and routine 3 was performed in the home environment. The participants who did not perform routine 1 were asked to sit quietly for 5 min before the start of the routine so that a resting VO_2 could be measured.

Indirect calorimetry

The Cosmed K4b^2 is a lightweight device that has been shown to be valid for measuring VO_2 and VCO_2, compared to the Douglas Bag method during cycle ergometry.[12] Prior to each test the oxygen and carbon dioxide analysers and the flow turbine were calibrated according to the manufacturer's instructions. For more detail see Crouter *et al*.[2] During each test a gel-seal was used to help prevent air leaks from the face mask.

Actical accelerometer

The Actical accelerometer is a small (28×27×10 mm) device that uses an omni-directional accelerometer and weighs 17 g.

Table 2 Activities performed in each routine

Routine 1	Routine 2	Routine 3
Lying	Slow track walk (~3 mph)	Vacuuming
Standing	Fast track walk (~4 mph)	Sweeping/mopping
Computer work	Basketball	Washing windows
Filing papers	Racquetball	Washing dishes
Ascending/decending stairs	Slow track run (~5 mph)	Lawn mowing
Stationary cycling (~100 W)	Fast track run (~7 mph)	Raking grass/leaves

The Actical can measure accelerations in the range of 0.05–2.0 G and is sensitive to movements in the range of 0.35–3.5 Hz. The Actical was worn at waist level attached to a belt in the left anterior axillary line. The device was initialised using 15 s epochs and the time was synchronized with a digital clock so the start time could be synchronized with the Cosmed K4b^2. At the conclusion of each routine the Actical data were downloaded to a laptop computer for subsequent analysis. The Actical was calibrated at the factory, where calibration offset factors are entered into the memory. At the end of the study the Actical was returned for recalibration and it was found to be within 1% of the initial calibration.

Data analysis

Breath-by-breath data were collected using the Cosmed K4b^2, which were averaged over a 1 min period. For each activity, the VO_2 ($ml \cdot min^{-1}$) was converted to METs (1 MET = 3.5 $ml \cdot kg^{-1} \cdot min^{-1}$) and the MET value for minutes 4–9 were averaged and used for the subsequent analysis.

For the Actical the CV was calculated for each minute by using four consecutive 15 s epochs. The average CV and the average counts min^{-1} were calculated for minutes 4–9 of each activity, which were used for the development of the new model. The Actical software has two equations to predict METs from the activity counts min^{-1}. These equations were developed by Klippel and Heil[13]; one uses a single regression line (Klippel and Heil single regression equation) (table 3) and one uses a 2-regression equation (Klippel and Heil 2-regression equation) (table 3). Thus, the average MET values for minutes 4–9 of each activity were calculated using the Klippel and Heil equations so they could be compared against the new 2-regression model developed for the Actical. The Klippel and Heil regression equations were developed on 24 adults, who performed 10 activities ranging from supine rest to treadmill running. These equations are unpublished, but preliminary results from them are presented in an abstract.[13] The methodology and subjects used to develop the equations are presented in an article by Heil[7] that published the activity energy expenditure (AEE) equations used by the Actical.

Statistical treatment

Statistical analyses were carried out using SPSS version 14.0 for windows (SPSS Inc., Chicago, IL, USA). For all analyses, an alpha level of 0.05 was used to indicate statistical significance. All values are reported as mean (SD). Independent t tests were used to examine the difference between genders for anthropometric variables. To enhance comparison with the Crouter 2-regression model for the ActiGraph[2] the same 45 tests were chosen for the development of the new Actical 2-regression model and the same 15 tests were used to cross-validate the new Actical 2-regression model. Due to waist-mounted accelerometers not being able to detect cycling activity, cycling was not included in the development of the new Actical 2-regression model.

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Table 3 Klippel and Heil single regression equation for the Actical accelerometer

MET constant: when AC ⩽ 50*	MET constant when: 50<AC<CP1	CP1	Predicted METs when: AC⩾CP1		
1.0	1.83	350	2.826 + (0.0006526* counts min^{-1}) (R^2 = 0.71; SEE = 1.2)		
MET constant: when AC ⩽ 50*	**MET constant when: 50<AC<CP1**	**CP1**	**CP2**	**Predicted METs when: CP1 ⩽ AC<CP2**	**Predicted METs when: AC⩾CP2**
1.0	1.83	350	1200	1.935 + (0.003002* counts min^{-1}) (R^2 = 0.74; SEE = 0.8)	2.768 + (0.0006397 * counts min^{-1}) (R^2 = 0.84; SEE = 0.9)

*When the counts min^{-1} are less than 50 for 10 min or longer MET constant equals 0.9.
AC, accelerometer counts min^{-1}; CP1, accelerometer counts min^{-1} cut-point 1; SEE, standard error of the estimate.

For the development of the new Actical 2-regression model, each minute was first classified as a walk/run or lifestyle activity based on the CV ((standard deviation of four consecutive 15 s epochs within 1 min divided by the mean)×100). Regression analysis was then used to predict METs from the counts min^{-1} for the walk/run activities and lifestyle activities separately.

Pairwise comparisons with Bonferroni adjustments were used to compare actual (Cosmed K4b^2) and predicted METs (new Actical 2-regression model and current Actical prediction equations) for each activity and all 17 activities combined using the cross-validation group.

Modified Bland-Altman Plots were used to graphically show the variability in individual error scores (actual METs minus predicted METs).[14] This allowed for the mean error score and 95% prediction interval (95% PI) to be shown. Prediction equations that display a tight prediction interval around zero are deemed more accurate. Data points below zero signify an overestimation, while points above zero signify an underestimation.

To examine time spent in light, moderate and vigorous PA, the minute-by-minute values for the Cosmed K4b^2 and each Actical prediction equation were compared using the entire routine (including structured activities and transition between activities) for each participant in the cross-validation group. Pairwise comparisons with Bonferroni adjustments were used to locate significant differences between the Cosmed K4b^2 and each prediction equation. In addition, the absolute value of the per cent difference |{[(measured METs-prediction equation)/measured METs]×100}| was calculated and Kappa statistics were used to assess the level of agreement between the Cosmed K4b^2 and the prediction equations for estimating time spent in light, moderate and vigorous PA.

RESULTS

Mean (SD) counts min^{-1} and the CV of the counts per 15 s, for each activity, from the Actical accelerometer are shown in table 4 (developmental group only). During the walk/run trials the CV was always ⩽13%, while for the other activities the CV was almost always >13% (fig 1). Specifically, 0.2% of the activity bouts (ie, 1 lawn mowing (CV = 9.0%) and 2 stair-climbing bouts (CV = 8.4% and 8.8%)) had a CV⩽13%. In addition, 56 (21.5%) of the activity bouts (eg, lying and sitting) had mean count·min^{-1} values of zero, thus the CV could not be calculated. For activities where a CV could not be calculated they were placed in the CV>13% group for the purpose of developing the new Actical 2-regression model.

Thus, for the group used to develop the new 2-regression model, each activity performed by an individual was classified based on the CV value of four successive 15 s epochs; CV from 0.1% to 13% (CV⩽13%) and CV>13% or not able to calculate (CV>13%).

Figure 2 shows the linear and exponential regression lines to predict METs from the counts min^{-1} for activities where the CV was ⩽13% (ie, walk/run activities). The linear regression line provided a strong fit (R^2 = 0.895; SEE = 1.051), however the exponential regression line provided a better fit (R^2 = 0.912, SEE = 0.149) as evidenced by the improvement in the SEE. For activities where the CV was >13% (ie, intermittent lifestyle activities), the natural log (Ln) of the counts min^{-1} was used for the development of the regression equation. The use of a linear regression line relating the Ln of the Actical counts min^{-1} and METs provided a good fit (R^2 = 0.731; SEE = 1.215), but this relationship was improved by using a cubic curve (R^2 = 0.884, SEE = 0.804) (fig 3).

To avoid overestimating sedentary activities such as lying and sitting, we propose an inactivity threshold of 10 counts min^{-1}. Thus, when the activity counts min^{-1} are ⩽10, an individual will be credited with 1.0 MET.

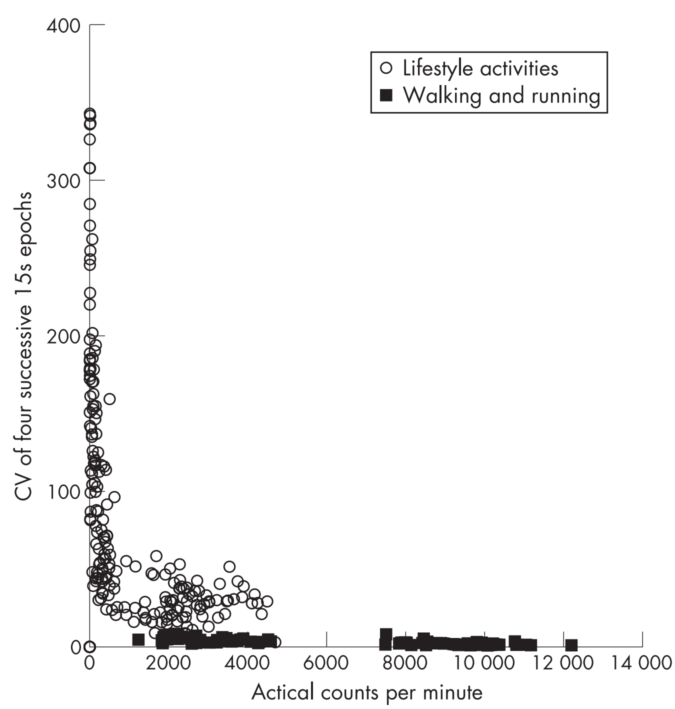

Figure 1 Relationship between counts per minute from an Actical accelerometer and the coefficient of variation (CV, %) of the 15 s counts for various activities. 11 CVs between 400 and 600 were excluded from the graph, all of which were lifestyle activities.

Table 4 Mean (SD), median and range for the Actical counts min^{-1} and coefficient of variation (CV, %) for 4 consecutive 15 s epochs for 18 activities using the developmental group

		Actical counts min^{-1}		CV (%) for 4 consecutive 15 s epochs	
Activity	**n**	**Mean (SD)**	**Median (range)**	**Mean (SD)**	**Median (range)**
Lying	15	0.1 (0.1)	0.0 (0.0–0.4)	29.8 (115.5)	0.0 (0.0–447.2)
Standing	15	2.2 (4.7)	0.4 (0.0–18.2)	250.5 (176.4)	307.8 (0.0–447.2)
Computer work	15	1.6 (4.2)	0.0 (0.0–15.6)	17.0 (65.8)	0.0 (0.0–254.7)
Filing	15	20.1 (28.8)	5.2 (0.0–89.0)	146.0 (147.2)	111.5 (0.0–447.2)
Ascending/descending stairs	15	2349.2 (358.7)	2430.6 (1823.4–3010.4)	22.2 (7.5)	23.5 (8.4–33.9)
Cycling (avg. 105 W)*	15	298.2 (413.6)	156.6 (2.4–1500.6)	60.4 (70.6)	34.4 (7.5–219.0)
Slow walk (avg. 81 m min^{-1})	15	2351.1 (555.5)	2313.4 (1235.0–3227.2)	4.6 (1.7)	4.6 (2.2–8.5)
Brisk walk (avg. 104 m min^{-1})	15	3672.7 (627.6)	3595.0 (2559.6–4698.8)	3.9 (1.0)	3.6 (2.5–5.7)
Basketball	15	3616.0 (626.8)	3746.0 (2384.0–4495.4)	32.8 (8.4)	32.0 (18.8–51.6)
Racquetball	15	2302.3 (536.3)	2268.6 (1566.8–3471.2)	39.7 (9.7)	41.2 (26.9–58.4)
Slow run (avg. 159 m min^{-1})	15	9217.1 (979.7)	9277.6 (7488.4–10766.8)	2.1 (0.8)	2.2 (0.9–3.6)
Fast run (avg. 192 m min^{-1})	15	10014.5 (1066.4)	10174.0 (8451.0–12198.6)	1.9 (1.1)	1.4 (1.0–5.4)
Vacuum	15	273.5 (92.0)	282.8 (143.0–419.2)	60.3 (29.1)	54.1 (24.1–119.9)
Sweep/mop	15	267.2 (131.8)	212.0 (108.2–505.2)	83.2 (34.2)	73.7 (39.6–136.9)
Washing windows	15	174.2 (142.4)	104.2 (10.8–504.4)	157.3 (73.4)	154.8 (47.9–341.5)
Washing dishes	15	19.6 (25.8)	7.0 (0.0–80.0)	196.8 (100.0)	174.2 (0.0–447.2)
Lawn mowing	15	1722.0 (533.6)	1652.0 (884.4–2602.4)	20.5 (7.2)	52.4 (9.0–38.8)
Raking grass/leaves	15	520.9 (240.7)	495.8 (156.8–1160.2)	56.9 (29.5)	51.7 (20.6–113.8)

*Cycling was not used for the development of the new 2-regression model.

The newly developed model to predict METs from the Actical counts min^{-1} consists of a three-part algorithm (2-regression model with an inactivity threshold), which will be referred to as the new Actical 2-regression model:

1. if the counts min^{-1} are $\leqslant 10$, METs = 1.0,
2. if the counts min^{-1} are >10

a. and the CV of 4 consecutive 15 s epochs are $\leqslant 13\%$, then $METs = 2.55095 \times (\exp(0.00013746 \times \text{Actical counts min}^{-1}))$; ($R^2 = 0.912$; SEE = 0.149),

b. or the CV of 4 consecutive 15 s epochs are $>13\%$, then $METs = 1.466072 + 0.210755 \times (\ln(\text{Actical counts min}^{-1})) - 0.0595362 \times (\ln(\text{Actical counts min}^{-1}))^2 + 0.0157002 \times (\ln(\text{Actical counts min}^{-1}))^3$; ($R^2 = 0.835$; SEE = 0.878).

Table 5 shows the measured METs and estimated METs for the cross-validation group using the new Actical 2-regression model and the regression equations by Klippel and Heil.[13] Figures 4 and 5 show the measured and predicted MET values for each of the activities, using the cross-validation group, for the Klippel and Heil regression equations and the new Actical 2-regression model, respectively. The new Actical 2-regression model was within 0.56 METs of mean measured METs for all activities ($p>0.05$), except cycling ($p<0.05$). In addition, the correlation between the predicted METs from the new Actical 2-regression model and measured METs was $r = 0.89$ ($p<0.05$). The Klippel and Heil equations gave accurate predictions for sedentary behaviours, fast walking and running, but these equations overestimated slow walking and underestimated most intermittent activities.

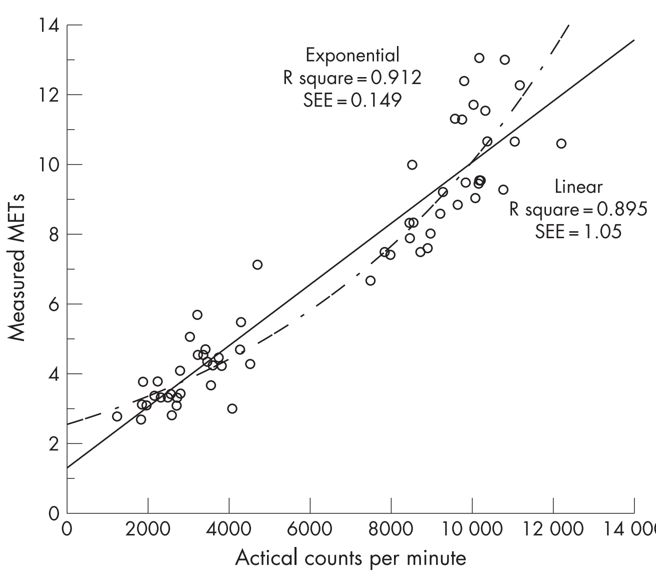

Figure 2 Regression lines for the Actical counts·per minute versus measured METs (Cosmed K4b²), for activities where the CV $\leqslant$ 13% (developmental group only).

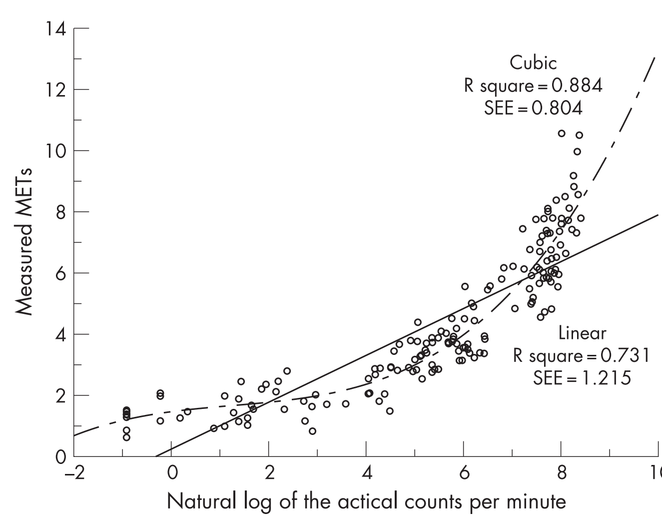

Figure 3 Regression lines for the Actical counts per minute versus measured METs (Cosmed K4b²), for activities where the CV>13% (developmental group only).

Table 5 Energy expenditure (METs) of the cross-validation group for the Cosmed K4b², the new Actical 2-regression model and the Klippel and Heil single regression equation and the Klippel and Heil 2-regression equation, during various activities

	Cosmed K4b² measured values	New Actical 2-regression model		Klippel and Heil single regression equation		Klippel and Heil 2-regression equation	
	Mean (SD)	Mean (SD)	RMSE	Mean (SD)	RMSE	Mean (SD)	RMSE
Lying	**0.91 (0.20)**	**1.00 (0.00)**	**0.13**	**0.97 (0.01)**	**0.12**	**0.97 (0.01)**	**0.12**
Standing	1.19 (0.18)	1.00 (0.00)	0.25	0.90 (0.00)	0.34	0.90 (0.00)	0.34
Computer work	**1.03 (0.13)**	**1.00 (0.00)**	**0.09**	**0.90 (0.00)**	**0.17**	**0.90 (0.00)**	**0.17**
Filing papers	1.56 (0.16)	1.28 (0.63)	0.66	0.90 (0.00)*	0.61	0.90 (0.00)*	0.61
Ascending/descending stairs	6.83 (0.65)	6.02 (1.39)	1.25	4.30 (0.23)*	2.16	4.21 (0.22)*	2.25
Cycling (avg. 79 W)†	5.88 (1.19)	1.38 (0.86)*	4.68	1.13 (0.39)*	4.89	1.13 (0.39)*	4.89
Slow walk (avg. 85 m·min^{-1})	**3.33 (0.32)**	**3.49 (0.18)**	**0.26**	**4.30 (0.25)***	**0.99**	**4.22 (0.25)***	**0.91**
Fast walk (avg. 100 m·min^{-1})	**4.41 (0.82)**	**4.19 (0.40)**	**0.53**	**5.17 (0.44)**	**0.89**	**5.06 (0.43)**	**0.80**
Basketball	7.33 (0.52)	7.45 (0.33)	0.34	4.99 (0.22)*	2.36	4.89 (0.22)*	2.46
Racquetball	6.63 (0.46)	6.71 (0.13)	0.37	4.37 (0.15)*	2.28	4.36 (0.10)*	2.30
Slow run (avg. 159 m·min^{-1})	**8.06 (0.63)**	**8.14 (0.78)**	0.63	**8.32 (0.46)**	**0.56**	**8.15 (0.45)**	**0.51**
Fast run (avg. 179 m·min^{-1})	9.41 (1.63)	9.10 (1.33)	1.45	8.82 (0.71)	1.44	8.65 (0.70)	1.52
Vacuum	**3.37 (0.51)**	**3.25 (0.31)**	**1.29**	**2.36 (0.52)**	**3.08**	**2.31 (0.47)**	**2.70**
Sweep/mop	**3.32 (0.56)**	**3.18 (0.58)**	**0.19**	**2.21 (0.52)***	**1.13**	**2.28 (0.62)***	**1.06**
Washing windows	2.86 (0.93)	3.01 (0.43)	0.56	2.12 (0.62)	0.89	2.10 (0.62)	0.91
Washing dishes	1.98 (0.33)	1.57 (0.79)	0.90	0.99 (0.10)*	1.03	0.99 (0.10)*	1.03
Lawn mowing	6.06 (0.59)	5.88 (0.57)	0.59	3.77 (0.36)*	2.34	4.25 (0.28)*	1.95
Raking grass/leaves	3.69 (0.89)	3.88 (0.74)	0.38	2.90 (0.60)	0.86	3.17 (0.80)	0.61
Average for all activities without cycling	4.23 (2.68)	4.13 (2.65)	0.58	3.43 (2.42)*	1.25	3.43 (2.38)*	1.19
Average for all activities with cycling	4.60 (2.62)	3.97 (2.66)	0.81	3.30 (2.42)*	1.45	3.30 (2.37)*	1.40

RMSE, root mean square error.
Bold type indicates activities similar to some of those used by Klippel and Heil to develop their equations.[13]
*Significantly different from Cosmed K4b² ($p<0.05$).
†Cycling was not included for the development of the new 2-regression model.

The rows shown in bold type in table 5 represent activities that were similar to some of those used by Klippel and Heil to develop their equations.[13]

The Bland-Altman plots show improved accuracy on an individual basis with the new Actical 2-regression model (fig 6). Specifically, the new Actical 2-regression model had a mean bias for the prediction of METs of 0.1 METs (95% PI; −1.2,1.4 METs); whereas the Klippel and Heil single regression equation had a mean bias of 0.8 METs (95% PI; −1.4,2.9 METs) and the Klippel and Heil 2-regression equation had a mean bias of 0.8 METs (95% PI; −1.4,2.9 METs). The improved accuracy of the new Actical 2-regression model was also confirmed by the differences in the root mean square error (RMSE) values. The RMSE for the new Actical 2-regression model was significantly better than both Klippel and Heil regression equations regardless of whether cycling was included (all, $p<0.02$).

The mean (SD) minutes spent in light, moderate and vigorous PA, using the Cosmed K4b², were 28.7 (16.0), 22.3 (14.7) and 17.1 (14.8), respectively. The new Actical 2-regression model was within 2.9 min of actual time spent in light, moderate and vigorous PA ($p>0.05$) (fig 7). The Klippel and Heil single regression equation and Klippel and Heil 2-regression equation were within 8 min of actual time spent in light and moderate PA ($p>0.05$); however, they significantly underestimated time spent in vigorous PA by 11.4 min ($p<0.05$). Because overestimations and underestimations can be averaged out, some researchers prefer to examine the absolute value of the per cent error as shown in fig 8. The new Actical 2-regression model provided a closer estimate of time spent in light, moderate and vigorous PA than the Klippel and Heil equations. In addition, all three prediction equations had significant measurement agreement (Kappa Statistic) with the Cosmed K4b² for estimating time spent in light, moderate and vigorous PA ($p<0.001$). The new Actical 2-regression model had moderate agreement with the Cosmed K4b² (Kappa (SE) = 0.531 (0.022)), while the Klippel and Heil 2-regression equation (Kappa (SE) = 0.367 (0.023)) and Klippel and Heil single regression equation (Kappa (SE) = 0.319 (0.023)) had fair agreement with the Cosmed K4b².

Regression analysis relating speed (m·min^{-1}) to Actical counts min^{-1} during the walking and running trials showed a strong relationship between counts and speed ($R^2 = 0.94$, $p<0.001$). Based on this analysis we propose a threshold of 5700 counts min^{-1} to discriminate between walking and running.

DISCUSSION

This study describes the development of a new 2-regression model to predict METs using the Actical accelerometer. The resulting equation improved the estimate of METs and time spent in light, moderate and vigorous PA compared with previously developed equations for the Actical.

Due to the new Actical 2-regression model being cross-validated on the same activities it was developed with, one would expect it to work better than other equations that were developed on different activities. Thus, the bolded rows in table 5 represent activities that were similar in both our study and the study of Klippel and Heil.[13] Among the seven activities highlighted, the Klippel and Heil equations had a lower RMSE for lying and slow running, while the new Actical 2-regression

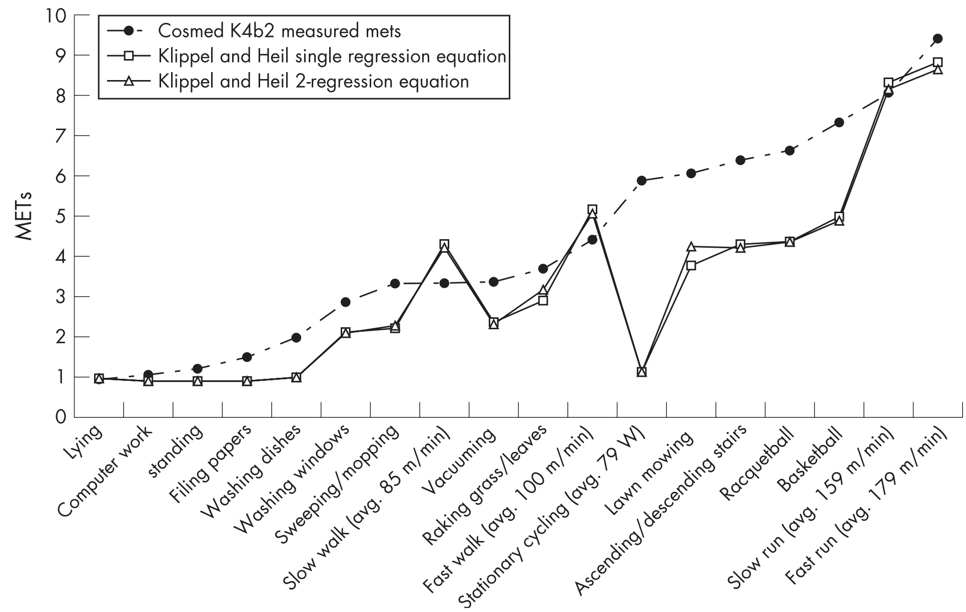

Figure 4 Measured (Cosmed K4b^2) and predicted METs (Klippel and Heil single regression equation and Klippel and Heil 2-regression equation) for the cross-validation group, across 18 different activities.

model had a lower RMSE for the other five activities. A lower RMSE indicates that a prediction equation is more precise for estimating METs. Across the seven highlighted activities, there was no statistical difference in the RMSE values for any of the equations, indicating that they worked in a similar manner across these activities. However, when all 18 activities included in the study are examined the new Actical 2-regression model had a significantly lower RMSE than the other Actical equations.

The Klippel and Heil 2-regression equation[13] and the new Actical 2-regression model shown in this paper both use two regression lines to predict METs; however, there are distinct differences between them. First, they use different inactivity thresholds (current study, 10 counts min^{-1} vs Klippel and Heil 50 counts min^{-1}). Specifically, in the current study only one individual exceeded 10 counts min^{-1} during standing and one individual exceeded 10 counts min^{-1} during computer work. However, during the light intermittent activities performed in this study (ie, filing, washing dishes and washing windows) 26 (43%) of the 60 bouts had less than 10 counts min^{-1}. Thus, even with an inactivity threshold of 10 counts min^{-1} several individuals performing light activities would be misclassified as inactive. In contrast, if an inactivity threshold of less than 50 counts min^{-1} is used as suggested by Klippel and Heil, then 35 (58%) of the light intermittent activities would be misclassified as inactive.

Another difference between the new Actical 2-regression model and the Klippel and Heil 2-regression equation is that Klippel and Heil determine which line to use based on the mean counts min^{-1}, while the new Actical 2-regression model determines which line to use based on the CV of four successive 15 s epochs.

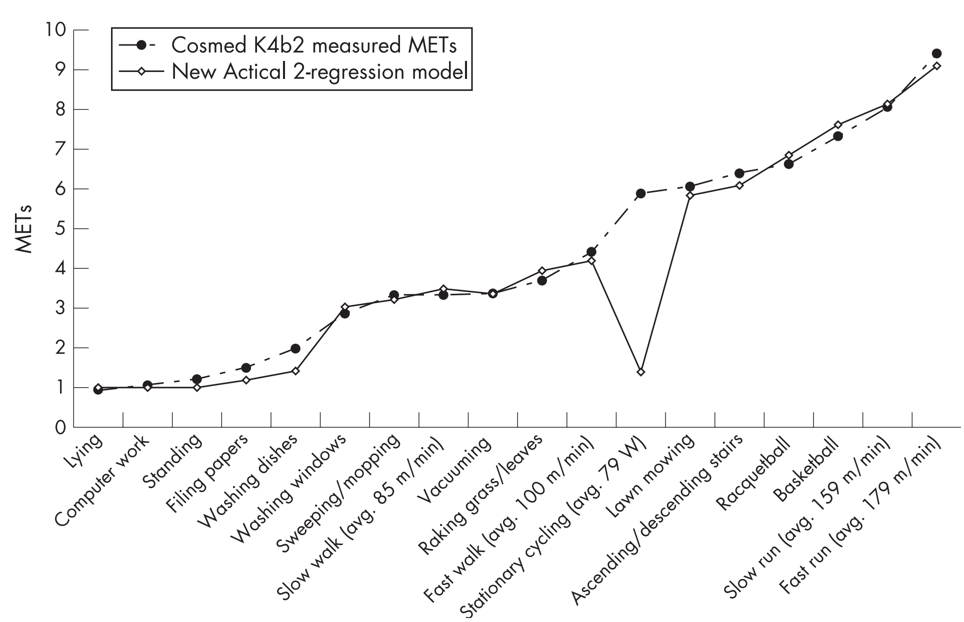

Figure 5 Measured (Cosmed K4b^2) and predicted METs (new Actical 2-regression model) for the cross-validation group, across 18 different activities.

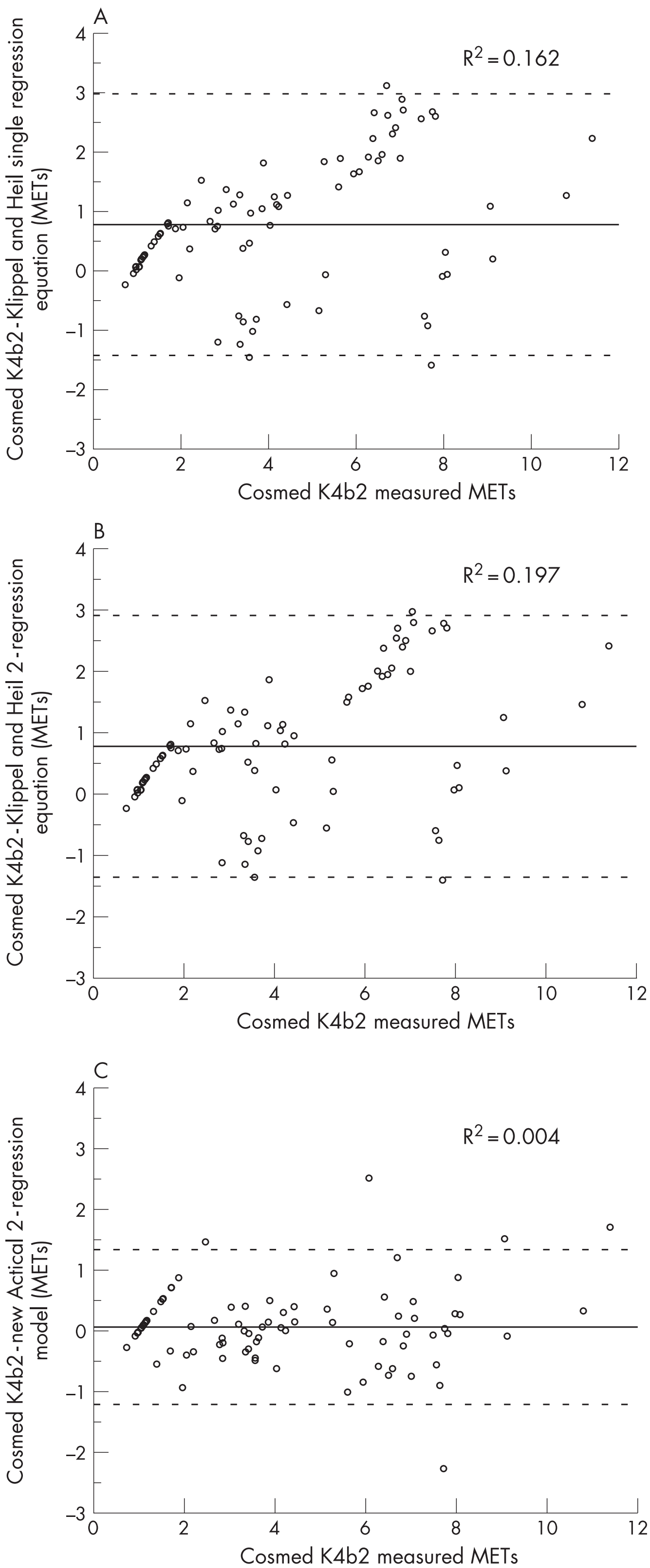

Figure 6 Modified Bland-Altman plots depicting error scores (actual minus prediction) for (A) the Klippel and Heil single regression equation, (B) the Klippel and Heil 2-regression equation and (C) the new Actical 2-regression model. The solid line represents the mean and dashed lines represent the 95% confidence interval of the observations. Cycling is not included in these graphs.

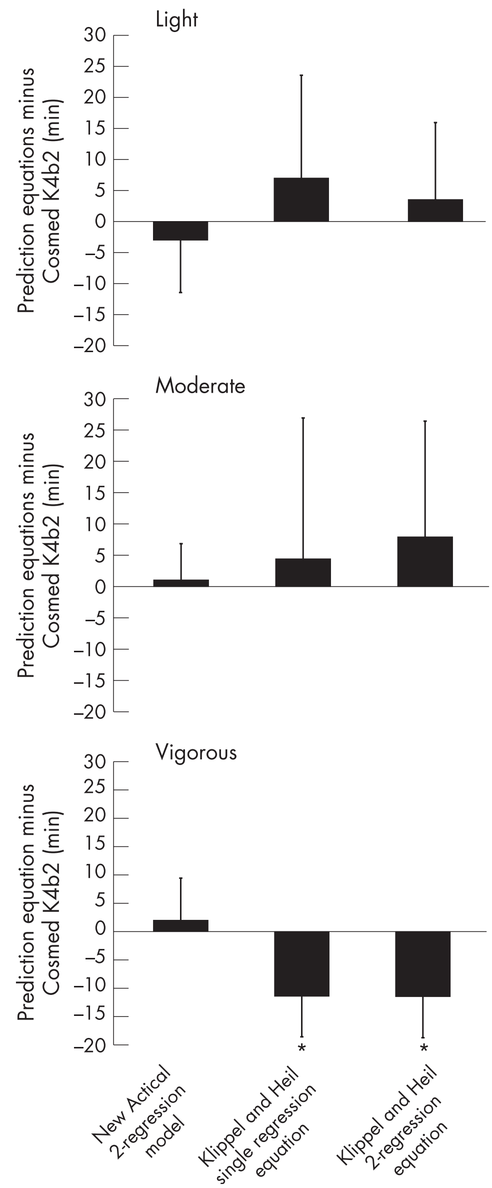

Figure 7 Mean error scores (prediction minus actual) for minutes spent in light (<3 METs), moderate (3–5.99 METs) and vigorous (⩾6 METs) physical activity, in the cross-validation group. Values are mean (SE); *Significantly different from criterion ($p<0.05$).

The new Actical 2-regression model compares favourably with the Crouter 2-regression model developed for the ActiGraph accelerometer using the same activities and participants.[2] The Crouter 2-regression model was within 0.75 METs of actual METs for each of the 17 activities and had a mean bias of 0.1 METs (95% PI; −1.4,1.5 METs) and provided mean values within 2.5 min of actual time spent in light, moderate and vigorous PA, which is similar to the new Actical 2-regression model. In addition, the Crouter 2-regression model for the ActiGraph had a RMSE of 0.69 (cycling excluded), which was not statistically significant from the new Actical 2-regression model ($p = 0.32$). Considering the importance placed on standardizing methods used to monitor free-living activity this becomes an important issue. Now researchers have the ability to use either the ActiGraph or Actical to obtain similar results using a 2-regression model that was developed using the same activities and participants.

The new Actical 2-regression model has several limitations that should be discussed. First this new method was developed using 10 min bouts of specific activities and cross-validated on the same activities, thus it is not known how it will work on

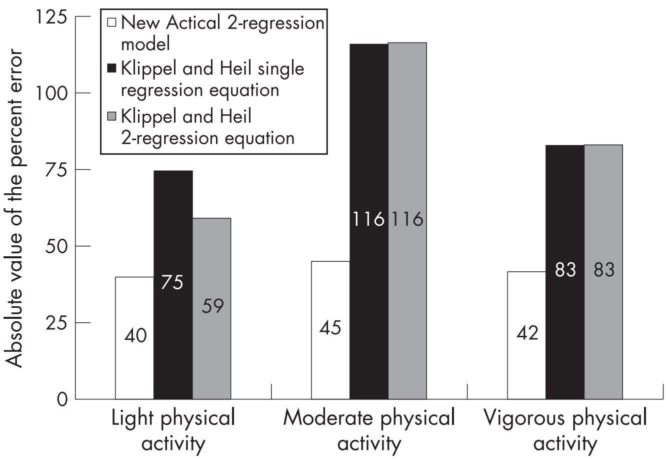

Figure 8 Absolute per cent difference between the Cosmed K4b[2] and each prediction equation for time spent in light (<3 METs), moderate (3–5.99 METs) and vigorous (⩾6 METs) physical activity, in the cross-validation group.

other activities performed throughout the day. Second, this new model will misclassify walking bouts lasting less than 1 min since it relies on examining four successive 15 s epochs. Lastly, this new model was developed on structured activities with activity patterns that may not represent how activities are performed in real life. It is possible that in free-living situations the CV of walking/running could be >13% resulting in misclassification of the activity, which has implications for the prediction of METs. For example, if the CV of a walk/run bout was 14% instead of ⩽13% there could be a twofold difference in the prediction of METs. Further studies are needed to address the validity of this approach using data obtained on free-living adults.

In conclusion, the new Actical 2-regression model, which is based on the counts min^{-1} and variability in counts between 15 s epochs, improves upon currently available methods for the prediction of METs and time spent in light, moderate and vigorous PA, when using the Actical. In addition, this new method has the ability to distinguish between walking, running and all other activities. Since the new Actical 2-regression model was developed and cross validated on the same activities, further testing is needed to examine its accuracy for use during free-living conditions.

What is already known on this topic

Current equations that predict energy expenditure from accelerometer counts generally work well for walking but they overestimate the energy cost of most sedentary activities and underestimate the energy cost of most moderate and vigorous physical activities.

What this study adds

- By examining the variability in accelerometer counts it is possible to distinguish between walking/running and other activities performed throughout the day.
- This allows for a better prediction of energy expenditure and time spent in light, moderate and vigorous physical activity.

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