Available online at www.sciencedirect.com
ScienceDirect
Journal of Science and Medicine in Sport 14 (2011) 404–410
Journal of Science and Medicine in Sport
www.elsevier.com/locate/jsams

Original research

Equating accelerometer estimates of moderate-to-vigorous physical activity: In search of the Rosetta Stone

Daniel B. Bornstein [a,*], Michael W. Beets [a], Wonwoo Byun [a], Greg Welk [b], Matteo Bottai [c], Marsha Dowda [a], Russell Pate [a]

[a] *Department of Exercise Science, University of South Carolina, USA*
[b] *Department of Kinesiology, Iowa State University, USA*
[c] *Department of Biostatistics, University of South Carolina, USA*

Received 9 December 2010; received in revised form 24 March 2011; accepted 27 March 2011

Abstract

No universally accepted ActiGraph accelerometer cutpoints for quantifying moderate-to-vigorous physical activity (MVPA) exist. Estimates of MVPA from one set of cutpoints cannot be directly compared to MVPA estimates using different cutpoints, even when the same outcome units are reported (MVPA min d^{-1}). The purpose of this study was to illustrate the utility of an equating system that translates reported MVPA estimates from one set of cutpoints into another, to better inform public health policy. Secondary data analysis. ActiGraph data from a large preschool project ($N = 419$, 3–6-yr-olds, CHAMPS) was used to conduct the analyses. Conversions were made among five different published MVPA cutpoints for children: Pate (PT), Sirard (SR), Puyau (PY), Van Cauwengerghe (VC), and Freedson Equation (FR). A 10-fold cross-validation procedure was used to develop prediction equations using MVPA estimated from each of the five sets of cutpoints as the dependent variable, with estimated MVPA from one of the other four sets of cutpoints (e.g., PT MVPA predicted from FR MVPA). The mean levels of MVPA for the total sample ranged from 22.5 (PY) to 269.0 (FR) min d^{-1}. Across the prediction models (5 total), the median proportion of variance explained (R^2) was 0.76 (range 0.48–0.97). The median absolute percent error was 17.2% (range 6.3–38.4%). The prediction equations developed here allow for direct comparisons between studies employing different ActiGraph cutpoints in preschool-age children. These prediction equations give public health researchers and policy makers a more concise picture of physical activity levels of preschool-aged children.

Keywords: Physical activity; Youth; Accelerometer

1. Introduction

Over the past two decades accelerometry-based activity monitors (accelerometers) have become an accepted method for measuring free-living physical activity across all populations. The use of accelerometers has helped advance knowledge on the correlates of physical activity behaviors,[1] provided a more rigorous estimate of population levels of physical activity,[2,3] and improved evaluations of behavioral interventions targeted at micro- and macro-levels.[4,5] In fact, a cursory search on PubMed (February 2011) for "accelerom*" and "physical activity" revealed 1924 articles. With such widespread use and expert opinions[6–10] regarding their reliability, validity, and objectivity, accelerometers have revolutionized the physical activity assessment field.

One of the primary features of accelerometers is their ability to process and segment data by time and intensity. This makes it possible to produce estimates of the amount of time spent in different intensities of physical activity. The public health field has emphasized the importance of tracking time spent in moderate-to-vigorous physical activity (MVPA), so considerable work has been done to develop cutpoints that define the threshold for MVPA. A variety of equations and cutpoints have been developed, but differences in design

* Corresponding author.
E-mail addresses: Bornstei@mailbox.sc.edu, danielbbornstein@gmail.com (D.B. Bornstein).

1440-2440/$ – see front matter © 2011 Sports Medicine Australia. Published by Elsevier Ltd. All rights reserved.
doi:10.1016/j.jsams.2011.03.013

Table 1
Demographic characteristics and MVPA estimates of preschool children ($N = 419$).

Variable	Mean	SD
Sex (boys)	47.7%	
Age (yrs)	4.2	0.6
Height (cm)	104.5	6.3
Weight (kg)	18.1	3.9
BMI percentile	63.4	28.3
Accelerometer estimates of MVPA (min/day)		
Pate et al.	102.2	40.6
Puyau et al.	39.5	22.5
Sirard et al.	46.8	27.6
Freedson et al.	269.0	70.8
Van Cauwenberghe et al.	64.3	31.4

and protocol of validation studies to develop cutpoints have tended to produce largely disparate MVPA estimates.[11]

It is well documented that estimates of MVPA derived from one set of accelerometer cutpoints may vary considerably from estimates derived from other cutpoints.[12,13] This phenomenon, previously referred to as the "cutpoint conundrum",[14] has led to considerable confusion in the physical activity literature. Perhaps a more precise description of this conundrum is what we refer to as "cutpoint non-equivalence." The most significant problem associated with cutpoint non-equivalence (CNE) is that it prevents direct comparisons among studies employing different cutpoints, although such comparisons are frequently made. A cornerstone of public health research is the practice of aggregating data across studies such that important trends in health and disease may be observed. CNE does not allow for such practice. The issue of standardizing cutpoints and accelerometer processing techniques was a theme of a 2009 (NIH-sponsored) consensus conference on objective activity monitoring (see http://conference.novaresearch.com/OMPA), however no consensus was reached.

The ability to standardize outcome measures on a single set of cutpoints would make it possible to compare outcome measures from different studies. Moreover, such a technique could unify a large body of empirical studies and provide a better picture of population levels of MVPA. In essence, such a procedure would allow for a common language to be used to evaluate between study estimates of MVPA. This is similar to the idea of the Rosetta Stone, which is simply something that is used to translate information from numerous sources into a single metric. Past attempts have been made to develop a conversion system to translate estimates of MVPA using different cutpoint criteria.[15] Unfortunately, this attempt did not use commonly employed cutpoints, but rather used 10 different cutoffs in 100 counts/min increments from 3000 to 3900 counts/min. Because such cutpoints were not empirically developed, validated, or in reference to specific cutpoints applied in the literature, this substantially limits the utility of this initial attempt[15] given cutpoints range well below and above this counts/min range. Nevertheless, it should be noted that another solution to CNE would be a set of universally accepted cutpoints developed through a multi-site calibration/validation study using identical, rigorous protocols on sufficiently large and representative samples of youth. This solution would in fact solve the problem, but would come at the cost of several years of labor and many millions of dollars. Until this happens, the pursuit of an equating system, like the one proposed herein, is necessary. Therefore, the purpose of this study was to illustrate the utility of an equating system by developing prediction equations and assessing their accuracy using a cross-validation procedure[16] in a large sample of preschool-age children.

2. Methods

This is a secondary data analysis of an existing data set (The Children's Activity and Movement in Preschool Study, CHAMPS) of 419 preschool children, age 3–5 years, from Columbia, SC. Recruitment and data collection procedures have been described in detail elsewhere.[17,18] This information is briefly reviewed here. The sample consisted of preschoolers (51% African American) attending twenty-two Commercial, Religious or Head Start preschools from the greater Columbia, South Carolina, area and served children from a variety of different types of backgrounds, including urban, rural, low and high socioeconomic status. None of the participants had any physical limitations that restricted their participation in physical activity. Physical activity data were collected during two waves at each of the 22 preschools across a 28-month period (August 2003–January 2006). The protocols of CHAMPS were approved by the University of South Carolina Institutional Review Board and written informed consent was obtained from each child's primary guardian before collection of any data.

Physical activity in this study was measured by the ActiGraph accelerometer (ActiGraph model 7146; Pensacola, FL). All data were collected using 15 s intervals (epoch). Participants wore the accelerometers on an elastic belt on the right hip (anterior to the iliac crest). Children wore monitors during the two-week monitoring period (weekdays and weekend days). Parents were instructed to remove the accelerometer only during water activities (bathing, swimming) and when the child went to bed at night. For inclusion in the current study, children were required to have at least 10 h/day of wear time and at least one complete day's worth of activity.

The four most common sets of ActiGraph accelerometer cutpoints used in the preschool age population were identified from an extensive literature search. The cutpoints were Pate et al.[19] (PT), Sirard et al.[20] (SR), Puyau et al.[21] (PY), and the Freedson et al. equation[9,22] (FR). Additionally, newly introduced cutpoints from Van Cauwengerghe et al. (VC), specifically developed for preschool-aged youth, were also used. Given that the 2009 consensus conference on objective activity monitoring did not provide definitive conclusions

about which cutpoints are most appropriate, we developed prediction equations that allow for any one set of cutpoints to predict another. Because the original cutpoints from PY and FR were developed for epochs different (60 s) from the epoch used in the CHAMPS study (15 s), we reintegrated them into cutpoints for 15 s epochs. The reintegration procedure may over or underestimate MVPA, however the procedure has been used extensively to accommodate differing cutpoint epoch length vs. the epoch of measurement.[23–25] The specific 15 s cutoffs (counts/15 s) for MVPA for each set of cutpoints are as follows: PT (≥420), SR (≥615 for 3 years; ≥812 for 4 years; ≥891 for 5 years), PY (800–1299), FR (92–632 for 3 years; 111–666 for 4 years; 131–703 for 5 years), and VC (≥585).

To develop prediction equations to convert estimates of MVPA across the five sets of cutpoints, a 10-fold cross-validation procedure was employed.[16,26] This process randomly divides the sample into 10 equal subgroups, with 9 subgroups serving as the equation development sample and the remaining subgroup serving as the cross-validation sample. This procedure is repeated 10 times with each of the 10 subgroups serving as the cross-validation sample. The model estimates (see below) were averaged across the 10 replications. For the prediction equation development, random effects models, accounting for the nesting of multiple days of measure within each child, were used to predict MVPA from one set of cutpoints from MVPA estimated from the remaining sets of cutpoints (e.g., PT MVPA predicted from FR MVPA). In total, 10 comparisons among five different sets of cutpoints were made.

The models were empirically derived with both linear and non-linear terms evaluated for potential inclusion in the model. Moreover, common demographic characteristics reported in studies were examined for inclusion in the models. These included age (years), gender (1 = boys, 0 = girls), BMI, height (cm) and weight (kg). Criteria for inclusion were a significant change in the proportion of variance explained (R^2) based on overall R^2 change from nested models and the results of a log likelihood ratio test between nested models (e.g., the addition of a single predictor), and a reduction in the average error and absolute percent error. The average error was calculated as

$$\sqrt{\left[\sum \frac{(Y - Yprime)^2}{(N-1)}\right]}.$$

where "*Y*" is the actual value and "*Yprime*" is the predicted value.[16] The absolute percent error was calculated as $[(Y - Yprime)/Y] \times 100$.

Consideration was given to balancing the relative value of increased precision with the need for simple conversions. In instances where demographic characteristics added significantly to the model, two models were reported – one with only MVPA as the predictor (both linear and non-linear terms) and the second with the inclusion of the demographic variable(s). This was done in order to account for instances where demographic characteristics are not uniformly reported across studies. Bland Altman plots[27] were constructed on the validation sample to evaluate agreement between methods across the range of activity levels. All analyses were conducted using Stata (v.10.0, College Station, TX).

3. Results

The sample consisted of 419 preschoolers, of which 47.7% were boys, 51.1% African American, with an average age of 4.2 yrs (SD = 0.6), and the average BMI percentile was 63.4% (SD = 28.3). The average MVPA in minutes per day across the four sets of cutpoints ranged from 102.2 min d^{-1} PT (±40.6), 46.8 min d^{-1} PY (±27.6), 39.5 min d^{-1} SR (±22.5), 64.3 d^{-1} VC (±31.5), and 269 min d^{-1} FR (±70.8). The estimates from the cross-validation random effects models predicting PT MVPA values across the different cutpoints are presented in Table 1. Overall, a total of 10 models were estimated. For most conversions, equations are provided for the simple model (using only linear and non-linear terms), with three models including demographic characteristics. The only demographic variable that added significantly to the models based on the criteria outlined above was age (years). Across the models, the median absolute percent error was 17.4%, with a minimum error of 6.3% (VC to PT) and a maximum error of 38.4% (FR to SR). The proportion of variance explained ranged from R^2 0.48 for estimating FR from PY, to R^2 0.97 for estimating VC from PT. Two Bland Altman plots are presented that illustrate the comparison for the best prediction equation (PT and VC) and the worst prediction equation (PY and FR) (Fig. 1, all other plots are available upon request). The mean difference for PT from VC was 0.056 min, with −14.844 to 14.956 min as the lower and upper bounds of the limits of agreement (LOA). For PY from FR the mean difference was −0.386 min (LOA −32.814 to 32.043).

4. Discussion

Accelerometers represent a significant advancement in measurement for the physical activity field. The systematic use of accelerometers has provided a way to obtain objective estimates of physical activity in. However, the confusion surrounding CNE remains highly problematic. The problem is analogous to having body weight scales made by the same manufacturer, but calibrated differently within different laboratories, such that measures of body weight vary widely across laboratories. To then aggregate published BMI data from those laboratories in order to estimate population prevalence of overweight and obesity would bias such estimates, presenting an unclear picture of the problem. The ideal solution of course would be to have widely adopted, identical procedures for calibrating scales. Short of that however, one could take the scale from the lab employing the most rig-

Table 2
Prediction equations to transform estimates of MVPA from one set of cutpoints into MVPA estimated from another set of cutpoints.

Accelerometer cutpoint MVPA min d^{-1}		Prediction equations[†]							10-fold cross validation[§]	
Outcome variable[a]	Predictor variable	Intercept	MVPA min d^{-1}	MVPA min d^{-1} Squared	MVPA min d^{-1} Square root	Age (years)	Wear time[‡]	R^2	Average error (min d^{-1})[b]	Absolute percent error [c]
Pate	Puyau	−27.07796	1.061643	−0.001669	10.41079		2.048583	0.88	11.1	11.8%
	Puyau	−3.189774	1.040246	−0.001703	11.16557			0.87	11.3	12.0%
	Freedson	8.180722	0.3922986	0.0002284			−2.108117	0.75	15.8	17.4%
	Freedson	−40.03466	0.5757257	0.0001202	−4.559613	12.51481		0.78	14.4	15.8%
	Freedson	−21.6284	0.5976948	0.0001054	−4.264987	12.82377	−2.174009	0.78	14.3	15.5%
	Sirard	5.152623	1.438485				2.246005	0.72	18.5	19.7%
	Sirard	−138.9017	0.5297728	−0.0001241	14.02476	23.64033	1.849608	0.86	12.5	13.4%
	Sirard	−118.9256	0.5321844	−0.0001937	14.50605	24.06562		0.84	12.7	13.7%
	van Cauwenberghe	17.07271	1.279121					0.96	5.9	6.4%
	van Cauwenberghe	3.41532	1.265061				1.085201	0.97	5.7	6.3%
Puyau	Pate	6.879354	0.3215901	0.0007953			−0.72323	0.87	6.0	17.2%
	Pate	−1.631061	0.3065897	0.0008218				0.86	6.1	17.4%
	Freedson	7.401612	0.1408477	0.0001596			−1.31163	0.48	11.9	37.8%
	Freedson	−37.00836	0.1004103	0.0001946	0.3095264	7.062028		0.52	11.5	36.5%
	Freedson	−24.83794	0.1181168	0.0001836	0.3915857	7.261133	−1.355968	0.52	11.4	36.1%
	Sirard	−0.5671588	0.8613491				0.015586	0.76	10.2	27.1%
	Sirard	−75.53115	0.4430329	0.0006495	4.847966	14.3972		0.91	5.4	17.2%
	Sirard	−75.37523	0.4304032	0.0006766	5.008838	14.40396	−0.0540935	0.91	5.4	17.2%
	van Cauwenberghe	−1.289946	0.5382766	0.0009392				0.95	3.5	10.0%
	van Cauwenberghe	3.560949	0.5481894	0.0009111			−0.3984867	0.95	3.6	10.0%
Freedson	Pate	1.921614	1.9832	−0.0021126			6.569524	0.77	26.7	12.3%
	Pate	77.29174	0.2173512	0.0002469	26.4726	−23.04593		0.79	25.2	10.3%
	Pate	1.407298	0.1061053	0.0004844	25.92285	−22.50468	6.517857	0.82	23.9	9.6%
	Puyau	19.03004	3.247166	−0.0098703			10.42879	0.55	37.3	18.2%
	Puyau	138.1948	−1.277124	0.001129	46.51387	−24.69632		0.55	37.6	16.9%
	Puyau	18.54305	−1.104061	0.0011465	42.00134	−24.00351	10.20374	0.61	33.3	15.8%
	Sirard	143.7481	3.14342	−0.0077486				0.56	37.6	18.8%
	Sirard	17.76059	2.868255	−0.0067386			10.10434	0.62	35.3	17.3%
	van Cauwenberghe	9.197958	2.546966	−0.0047027			8.482786	0.67	32.0	15.1%
	van Cauwenberghe	105.8778	−0.284422	0.0004263	35.31705	−24.18957		0.68	31.4	13.1%
	van Cauwenberghe	6.730405	−0.3484064	0.0007365	33.65001	−23.66149	8.386824	0.72	29.6	12.7%
Sirard	Pate	6.972053	0.3998896	0.0007227			−0.74987	0.72	12.0	30.7%
	Pate	53.22646	0.2395267	0.0009554	2.067009	−14.94238		0.85	8.3	22.6%
	Pate	62.96109	0.2620144	0.0009197	1.96676	−14.97197	−0.7800015	0.85	8.2	22.4%
	Puyau	0.429851	1.143558	−0.0005312			0.132389	0.76	11.8	27.7%
	Puyau	64.64648	0.872056	0.0001365	2.735017	−16.44998		0.91	6.2	17.1%
	Puyau	63.49087	0.876299	0.0001319	2.64906	−16.433	0.1080192	0.91	6.2	17.1%
	Freedson	−4.13197	0.2783899				−1.77046	0.55	13.9	38.4%
	Freedson	20.65111	−0.0412707	0.0003909	2.618793	−8.375547		0.60	13.2	35.8%
	Freedson	35.89801	−0.0153043	0.0003738	2.637629	−8.126762	−1.654241	0.61	13.0	35.2%
	van Cauwenberghe	0.2340504	0.7760613				−0.4056065	0.76	11.6	27.8%
	van Cauwenberghe	59.95077	0.4970589	0.0010028	1.835858	−15.72771		0.90	6.7	18.9%

Table 2 (*Continued*)

Accelerometer cutpoint MVPA min d^{-1}		Prediction equations†						10-fold cross validation§	
Outcome variable[a]	Predictor variable	Intercept	MVPA min d^{-1}	MVPA min d^{-1} Squared	MVPA min d^{-1} Square root	Age (years)	Wear time‡	R^2	Average error (min d^{-1})[b]	Absolute percent error[c]
van Cauwenberghe	van Cauwenberghe	64.25752	0.4981462	0.0009926	1.931716	−15.75026	−0.371556	0.91	6.7	18.6%
	Pate	−2.02805	0.7584412				−0.664218	0.97	4.4	7.5%
	Pate	−3.508009	0.6216894	0.0005406				0.97	4.3	7.1%
	Puyau	1.883229	1.336341				0.8734971	0.95	5.3	9.4%
	Puyau	13.12951	1.349016					0.95	5.3	9.6%
	Freedson	−6.451813	0.3680809				−1.88836	0.62	14.7	25.8%
	Freedson	−43.16919	0.2943966	0.000191	−1.585303	9.951828		0.66	13.6	23.9%
	Freedson	−23.49861	0.3412859	0.0001607	−1.940271	10.23911	−1.886545	0.67	13.6	24.0%
	Sirard	1.043279	1.175623				0.8132831	0.76	14.1	22.8%
	Sirard	−103.4327	0.5078929	0.0002861	9.528605	19.64146		0.90	7.9	13.6%
	Sirard	−109.6294	0.5173321	0.0002879	9.259545	19.51529	0.5994181	0.90	7.8	13.5%

[a] For example, the prediction of MVPA min d^{-1} from studies using Puyau cutpoints into Pate cutpoints.

[b] Average error calculated as $\sqrt{\left[\sum (Y - Y')^2/(N-1)\right]}$ where "*Y*" is the actual value, "*Y*'" is the predicted value.

[c] Absolute percent error calculated as $[(Y - Y')/Y] \times 100$.

† Prediction equations developed with the entire sample.

§ Estimates based on the average errors calculated across the 10 replications.

‡ Total accelerometry wear time per day.

Fig. 1. Bland Altman plots comparing the actual MVPA estimate vs. the predicted MVPA estimate from other cutpoints. These plots represent the best and worst models from Table 1.

orously developed methods for calibration and predict what BMI would be had all other estimates used that same method of calibration.

This analogy, while far-fetched, is precisely what the physical activity field has been doing from the application of different cutpoints to estimate MVPA. This study provides a potential solution to the issue of CNE by developing prediction equations that can convert MVPA estimates from one set of cutpoints (PY, SR, FR, PT, VC) into MVPA derived from another set of cutpoints (PY, SR, FR, PT, VC). Our results indicate that such a procedure provides sufficiently precise transformations of MVPA across cutpoints. To illustrate the utility and accuracy of this equating system, three studies[12,13,28] were identified that reported preschoolers' accelerometer estimates of MVPA using one or more sets of cutpoints (see Table 3). The results of these conversions (using the equations from Table 2) clearly establish the utility of such a system to transform MVPA estimates across different sets of cutpoints. For instance, in the VanCauween-

berghe et al. study, conversions between the PT, SR, and VC cutpoints were nearly identical to those reported in the study. Thus, if one of these sets of cutpoints were to be widely adopted (for example SR), published studies employing one of the other sets of cutpoints (PT and VC) could be transformed into "what if" estimates of MVPA had the authors originally reported the data using these cutpoints. From this, a less biased estimate of MVPA could be obtained and used to inform policy decisions.

We recognize that the original cutpoints used in this comparison (PT, SR, PY, VC and FR) were developed with some degree of error, and concede that the prediction equations offered here contribute additional error. However, we must ask ourselves which is the lesser of two evils; having widely disparate estimates of MVPA that suggest preschoolers accumulate anywhere from 18 min of MVPA based on PY cutpoints[29] to 280 min of MVPA based on FR cutpoints[30] or a system with acceptable error that allows for aggregation of data that leads to a clearer picture of physical activity estimates for that population-based on VC study[28]: 91.2 min (PT) vs. 55.2 (VC) vs. 20.8 min (SR) or 59.2 min vs. 55.2 min vs. 58.0 min? We argue for the latter, particularly in the absence of universally agreed upon cutpoints and the substantial differences among estimates of MVPA across the cutpoints.

When developing guidelines for physical activity, the usage of such an equating scheme can, at minimum, provide a common set of accelerometer cutpoints on which study findings are evaluated. This would help establish the "mass of high quality and consistent evidence" across studies that has been advocated for in past years. It is anticipated this procedure could be replicated for other age groups or populations to provide similar standardization. Large scale studies, such as NHANES, provide sufficient sample size and age ranges in order to develop additional conversion equations so that uniformity in MVPA estimates may be reached. Similar to the method presented here, the most rigorously developed cutpoints for a particular population or cutpoints validated in independent validation studies[31] could be used as the criterion into which predictions from other cutpoints could be made. Moreover, developing an equating system among different types of accelerometers (e.g., ActiGraph and Actical) is necessary in order to pool together MVPA estimates from studies using different measures of MVPA.

In future studies, there are several issues that need to be addressed. First, the procedure to develop the equations in this study resulted in reasonably accurate conversions between cutpoints. Additional work needs to explore alternative modeling techniques that would provide even greater precision, along with the addition of other salient characteristics of the sample. However, the sample characteristics evaluated in the models were based on commonly reported demographics. This is a critical point when attempting to develop equations in that the information used needs to be readily available (i.e., reported in empirical studies). Finally, all accelerometer data in the CHAMPS study were collected in 15 s epochs. It is unclear how converting from 15 s epoch to a 60 s epoch and vice versa would impact the precision of the estimates. Studies have demonstrated that smaller epochs result in higher estimates of MVPA in relation to accelerometer data collected in large ones. Thus, future studies developing conversion equations need to take this into account.

5. Conclusion

The inability to make comparisons of accelerometer-derived MVPA estimates from different studies has hampered the physical activity field. While accelerometers offer promise, their use has generated critical questions. Until now, no solutions to this issue of CNE have been provided. The potential solution proposed here demonstrates sufficient accuracy to allow comparisons across five sets of cutpoints used for measuring MVPA of preschool-aged youth. With these conversions, data across studies can be compared and aggregated so that the landscape of preschool-aged youth physical activity can be better understood. Future research should attempt to validate these equations in separate samples in addition to exploring the utility of this approach with other age groups where multiple sets of cutpoints are used to derive MVPA.

Practical implications

- The prediction equations developed herein allow for synthesis of data from four of the most commonly reported, and one of the most newly developed, accelerometer cutpoints for deriving MVPA estimates of preschool-aged children, which was previously not possible.
- Synthesizing the accelerometer-derived MVPA estimates of preschool-aged children can help to develop a clearer picture of the population prevalence of physical (in)activity of in this population.
- With a clearer picture of prevalence of preschoolers' physical (in)activity, researchers and policy makers interested in children's physical activity can make better-informed decisions for future research and policy.
- Validation of the method developed here in other populations, potentially allows for improved aggregation of data and clearer physical activity estimates in populations other than preschool-aged children.

Financial disclosure

This research was supported by a grant from the National Institute for Child Health and Human Development (NICHD) of the National Institutes of Health (NIH), R01 HD043125.

Acknowledgement

The authors would like acknowledge the feedback and comments provided by Brent Hutto on an earlier version of the manuscript.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jsams.2011.03.013.

References

1. Nilsson A, Andersen LB, Ommundsen Y, et al. Correlates of objectively assessed physical activity and sedentary time in children: a cross-sectional study (The European Youth Heart Study). *BMC Public Health* 2009;**9**:322.
2. Troiano RP, Berrigan D, Dodd KW, et al. Physical activity in the United States measured by accelerometer. *Med Sci Sports Exerc* 2008;**40**(1):181–8.
3. Ham SA, Ainsworth BE. Disparities in data on Healthy People 2010 physical activity objectives collected by accelerometry and self-report. *Am J Public Health* 2010;**100**:S263–8.
4. Elder JP, Lytle L, Sallis JF, et al. A description of the social-ecological framework used in the trial of activity for adolescent girls (TAAG). *Health Educ Res* 2007;**22**(2):155–65.
5. Wilson DK, Kitzman-Ulrich H, Williams JE, et al. An overview of "The Active by Choice Today" (ACT) trial for increasing physical activity. *Contemp Clin Trials* 2008;**29**(1):21–31.
6. Pate RR, O'Neill JR, Mitchell J. Measurement of physical activity in preschool children. *Med Sci Sports Exerc* 2010;**42**(3):508–12.
7. Reilly JJ. Low levels of objectively measured physical activity in preschoolers in child care. *Med Sci Sports Exerc* 2010;**42**(3):502–7.
8. Trost SG, McIver KL, Pate RR. Conducting accelerometer-based activity assessments in field-based research. *Med Sci Sports Exerc* 2005;**37**(11 Suppl.):S531–43.
9. Freedson P, Pober D, Janz KF. Calibration of accelerometer output for children. *Med Sci Sports Exerc* 2005;**37**(11 Suppl.):S523–30.
10. Welk GJ. Principles of design and analyses for the calibration of accelerometry-based activity monitors. *Med Sci Sports Exerc* 2005;**37**(11 Suppl.):S501–11.
11. Beets MW, Bornstein D, Dowda M, et al. Compliance with national guidelines for physical activity in U.S. preschoolers: measurement and interpretation. Pediatrics 2011;127(4):658–64. Epub 2011 Mar 21.
12. Cliff DP, Okely AD. Comparison of two sets of accelerometer cut-off points for calculating moderate-to-vigorous physical activity in young children. *J Phys Act Health* 2007;**4**(4):509–13.
13. Reilly JJ, Penpraze V, Hislop J, et al. Objective measurement of physical activity and sedentary behaviour: review with new data. *Arch Dis Child* 2008;**93**(7):614–9.
14. Trost SG. State of the art reviews: measurement of physical activity in children and adolescents. *Am J Lifestyle Med* 2007;**1**(4):299–314.
15. Guinhouya CB, Lemdani M, Vilhelm C, et al. Actigraph-defined moderate-to-vigorous physical activity cut-off points among children: statistical and biobehavioural relevance. *Acta Paediatr* 2009;**98**(4):708–14.
16. Mahar MT, Rowe DA. Construct validity in physical activity research. In: Welk GJ, editor. *Physical activity assessments for health-related research*. Champaign, IL: Human Kinetics; 2004. p. 51–72.
17. Williams HG, Pfeiffer KA, O'Neill JR, et al. Motor skill performance and physical activity in preschool children. *Obesity (Silver Spring)* 2008;**16**(6):1421–6.
18. Pfeiffer KA, Dowda M, McIver KL, et al. Factors related to objectively measured physical activity in preschool children. *Pediatr Exerc Sci* 2009;**21**(2):196–208.
19. Pate RR, Almeida MJ, McIver KL, et al. Validation and calibration of an accelerometer in preschool children. *Obesity (Silver Spring)* 2006;**14**(11):2000–6.
20. Sirard JR, Trost SG, Pfeiffer KA, et al. Calibration and evaluation of an objective measure of physical activity in preschool children. *J Phys Act Health* 2005;**2**(3):345–57.
21. Puyau MR, Adolph AL, Vohra FA, et al. Validation and calibration of physical activity monitors in children. *Obesity Res* 2002;**10**(3):150–7.
22. Freedson PS, Sirard JR, Debold E, et al. Calibration of the Computer Science and Applications, Inc. (CSA) accelerometer. *Med Sci Sports Exerc* 1997;**29**(Suppl.):S45.
23. Trost SG, Rosenkranz RR, Dzewaltowski D. Physical activity levels among children attending after-school programs. *Med Sci Sports Exerc* 2008;**40**(4):622–9.
24. Baquet G, Stratton G, Van Praagh E, et al. Improving physical activity assessment in prepubertal children with high-frequency accelerometry monitoring: a methodological issue. *Prev Med* 2007;**44**(2):143–7.
25. Nilsson A, Ekelund U, Yngve A, et al. Assessing physical activity among children with accelerometers using different time sampling intervals and placements. *Pediatr Exerc Sci* 2002;**14**:87–96.
26. Stone M. Cross-validatory choice and assessment of statistical predictions. *J R Stat Soc B* 1974;**36**(2):111–47.
27. Bland JM, Altman DG. Measuring agreement in method comparison studies. *Stat Methods Med Res* 1999;**8**(2):135–60.
28. van Cauwenberghe E, Labarque V, Trost SG, et al. Calibration and comparison of accelerometer cut points in preschool children. *Int J Pediatr Obes* 2010.
29. Kelly LA, Reilly JJ, Jackson DM, et al. Tracking physical activity and sedentary behavior in young children. *Pediatr Exerc Sci* 2007;**19**(1):51–60.
30. Heelan KA, Eisenmann JC. Physical activity, media time, and body composition in young children. *J Phys Act Health* 2006;**3**(2):200–9.
31. Trost SG, Way R, Okely AD. Predictive validity of three ActiGraph energy expenditure equations for children. *Med Sci Sports Exerc* 2006;**38**(2):380–7.