Journal of Science and Medicine in Sport 20 (2017) 1003–1007

Contents lists available at ScienceDirect

Journal of Science and Medicine in Sport

journal homepage: www.elsevier.com/locate/jsams

Original research

Evaluation of the activPAL accelerometer for physical activity and energy expenditure estimation in a semi-structured setting

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ARTICLE INFO

Article history:
Received 20 September 2016
Received in revised form 13 February 2017
Accepted 16 April 2017
Available online 21 April 2017

Keywords:
Accelerometry
Ambulatory
Indirect calorimetry
Health behavior
Activity monitor
Sedentary behavior

ABSTRACT

Objectives: Evaluate accuracy of the activPAL and its proprietary software for prediction of time spent in physical activity (PA) intensities (sedentary, light, and moderate-to-vigorous) and energy expenditure (EE) and compare its accuracy to that of a machine learning model (ANN) developed from raw activPAL data.
Design: Semi-structured accelerometer validation in a laboratory setting.
Methods: Participants ($n = 41$ [20 male]; $age = 22.0 \pm 4.2$) completed a 90-min protocol performing 13 activities for 3–10 min each and choosing activity order, duration, and intensity. Participants wore an activPAL accelerometer (right thigh) and a portable metabolic analyzer. Criterion measures of time spent in sedentary, light, and moderate-to-vigorous PA were determined using measured MET values of ≤ 1.5, 1.6–2.9, and ≥ 3.0, respectively. Estimated times in each PA intensity from the activPAL software and ANN were compared with the criterion using repeated measures ANOVA. Window-by-window EE prediction was assessed using correlations and root mean square error.
Results: activPAL software-estimated sedentary time was not different from the criterion, but light PA was overestimated (6.2 min) and moderate- to vigorous PA was underestimated (4.3 min). ANN-estimated sedentary time and light PA were not different from the criterion, but moderate- to vigorous PA was overestimated (1.8 min). For EE estimation, the activPAL software had lower correlations ($r = 0.76$ vs. $r = 0.89$) and higher error (1.74 vs. 1.07 METs) than the ANN.
Conclusions: The ANN had higher accuracy for estimation of EE and PA than the activPAL software in this semi-structured laboratory setting, indicating potential for the ANN to be used in PA assessment.

1. Introduction

Accelerometer-based physical activity (PA) monitors have been used with increasing regularity in surveillance and intervention studies due to their ability to provide objective, non-invasive measurement of PA and sedentary behavior (SB).[1] For the promotion of general health and prevention of disease, the United States Department of Health and Human Services recommends that adults achieve at least 150 min week^{-1} of moderate-intensity PA, 75 min week^{-1} of vigorous-intensity PA, or a combination of moderate-to-vigorous intensity PA (MVPA), defined as activities eliciting an energy expenditure (EE) of ≥ 3.0 METs.[2] There is also an increasing body of evidence that SB, defined as time spent in a seated or lying posture with an $EE \leq 1.5$ METs, and light-intensity PA (LPA; activities requiring EE of >1.5 and <3.0 METs) both affect health independent of time spent in MVPA.[3] Because both daily EE and time spent in different PA intensities affect health, an effective PA measurement tool should be able to assess both constructs.

The activPAL3 accelerometer (PAL Technologies Ltd., Glasgow, UK), an accelerometer designed for wear on the thigh, uses a proprietary software package which combines acceleration data and accelerometer orientation to define postures into one of three categories: sitting/lying, standing, and stepping, which are then converted to estimates of METs. The activPAL software also provides an EE estimate based on both posture and cadence. Stated

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[1] Data collection was completed in the Department of Kinesiology at Michigan State University.

http://dx.doi.org/10.1016/j.jsams.2017.04.011
1440-2440/

another way, sitting/lying will elicit an EE of 1.25 METs, standing an EE of 1.40 METs, and stepping an EE of ~4.00 METs but directly related to cadence.[4] Therefore, the activPAL has been designed to assess both EE and time spent in each PA intensity. When used with the activPAL's proprietary software, the activPAL has shown high accuracy for assessment of SB[5–7] but underestimation of predicted EE, especially during higher-intensity activities.[4,8,9] However, it is not yet known if underestimation of EE translates to misclassification of activity intensity, i.e., how accurately the activPAL assesses time spent in MVPA.

An added advantage of using the activPAL accelerometer is that the manufacturer makes the raw acceleration data available upon download, allowing researchers to develop their own data interpretation methods. Members of our research group previously achieved high accuracy for estimation of EE and activity intensity by developing machine learning models for analyzing raw accelerometer data collected from a thigh-worn ActiGraph accelerometer.[10] Therefore, we hypothesized that it would be possible to improve predictive accuracy of the activPAL through development and validation of a machine learning algorithm for analyzing raw activPAL data.

This study had two purposes. The first purpose was to assess the ability of the activPAL accelerometer to estimate EE on a temporal basis (i.e., every 30 s) and to estimate time spent in SB, LPA, and MVPA compared to criterion-measured EE. The second purpose was to develop a machine learning model for estimating EE using the raw activPAL data and evaluate its accuracy (again compared to criterion-measured EE) for estimating EE and time spent in SB, LPA, and MVPA compared to the accuracy of the activPAL's proprietary software.

2. Methods

Forty four healthy adults (22 male, 22 female) aged 18–35 years were recruited for participation in this study through email, fliers, and word of mouth. Inclusion criteria included absence of major chronic disease and ability to perform activities such as jogging and stair climbing for at least 3 min. This study was approved by the university's Institutional Review Board.

Participants were fitted with an activPAL3, which was attached to the right thigh using hypoallergenic sticky tape, one third of the distance between the patella and inguinal crease at the midline of the anterior surface of the thigh. The activPAL records raw, triaxial acceleration data at a frequency of 20 Hz, with a dynamic range of ± 2 gravitational (g) units. The activPAL Research Edition 6.4.1 software was used for activPAL initialization, download, and data interpretation. Participants were also fitted with an Oxycon Mobile (Cardinal Health, Yorba Linda, CA) portable metabolic analyzer, which is a lightweight unit (~950 g) secured to participants via a shoulder harness. Expired gases were collected through a mask secured to participants' heads using an adjustable mesh cap. Prior to use, the Oxycon was calibrated according to manufacturer specifications. The Oxycon has been validated previously for measurement of oxygen consumption across a range of intensities and served as the criterion measure of EE (in METs) and time spent in SB, LPA, and MVPA in this study.[11]

The activity protocol has been described in detail previously.[10] Briefly, participants reported to the laboratory for a single visit lasting ~2.5 h. After being fitted with the activPAL and Oxycon, participants performed 13 activities during a 90-min, semi-structured activity protocol within the laboratory. Activities performed fell into 4 general categories comprising a range of types and intensities: (1) sedentary behaviors (lying down, reading a magazine, using a computer), (2) household activities/chores (standing, laundry, sweeping), (3) ambulatory activities (walking slowly, walking quickly, jogging, walking up and down a flight of stairs), and (4) exercise/recreation activities (stationary cycling, biceps curls, squats). Each activity was performed for 3–10 min, but participants chose the order and exact duration of activities performed and could repeat the performance of any activity. General instructions for how to perform an activity were given to participants prior to beginning the protocol, but the exact method of performing each activity was left up to participants. For example, participants could choose their walking speed and jogging speeds, how they folded laundry, etc. Trained research assistants recorded the timing, order, and duration of activities and updated participants periodically on what activities they needed to perform during the protocol.

The activPAL data were processed in two ways. First, the manufacturer's proprietary software provides a MET estimate for EE in 15-s windows. In order to determine the window-by-window accuracy of EE estimates by the activPAL, the MET values were reintegrated to 30-s windows for comparison with measured METs from the Oxycon. Second, raw activPAL data were extracted into .csv files and used to develop an artificial neural network (ANN) model, a commonly used machine learning technique for modeling accelerometer data, for estimating EE as a continuous variable in 30-s windows. Further description of the theoretical structure of ANN models can be found in previous work.[10,12] A customized macro in Microsoft Excel (Microsoft Corp., Redmond, WA) extracted 39 features in 30-s windows. However, to simplify the ANN and reduce risk of overfitting, only two features, mean and variance of the raw acceleration signal for each measurement axis (2 $\text{axis}^{-1} \times 3$ axes, 6 total features), were used. The ANN was created using the *nnet* package in R and was tested using a leave-one-out cross-validation.[13] ANNs created using the *nnet* package are feed-forward and contain only one hidden layer; we chose 15 hidden units for the hidden layer for consistency with past work.[10] Additionally, as is the default in the *nnet* package, skip-layer connections were not allowed, and a Broyden–Fletcher–Goldfarb–Shanno (BGFS) optimization algorithm was used. For both the proprietary software and ANN, total time spent in SB, LPA, and MVPA was determined by summing time spent in estimated MET ranges of ≤ 1.5, >1.5 and <3.0, and ≥ 3.0, respectively. Additionally, window-by-window MET estimates from the proprietary software and ANN were compared to METs measured by the Oxycon. The ANN created for this study can be accessed at the following link: https://drive.google.com/open?id=0B-BgdTzyd2OxQllsS19wLXBNVjQ.

Breath-by-breath Oxycon data were reintegrated to 30-s windows for analysis. Relative oxygen consumption ($\text{ml O}_2\,\text{kg}^{-1}\,\text{min}^{-1}$) in each 30-s window was converted to METs by dividing by 3.5. While $3.5\,\text{ml O}_2\,\text{kg}^{-1}\,\text{min}^{-1}$ is an imperfect estimate of resting EE, we chose this approach for consistency with past accelerometer validation research.[12,14,15] Criterion measures of time spent in SB, LPA, and MVPA were determined from time spent with a measured EE ≤ 1.5, >1.5 and <3.0, and ≥ 3.0 METs, respectively.

EE estimation accuracy was assessed on a window-by-window basis. Correlations, bias, and root mean square error (RMSE) were calculated for estimated EE compared to Oxycon-measured EE. Since correlations were negatively skewed, a Fisher-Z transformation was used to normalize data prior to statistical testing. Paired t-tests were used to compare transformed correlations, RMSE, and bias between the activPAL software and ANN. Additionally, Bland–Altman plots were constructed to better assess bias in EE estimation.[16] For comparing time spent in SB, LPA, and MVPA estimated by the activPAL software and ANN and measured by the Oxycon, repeated measures ANOVA analyses were conducted, with a Bonferroni post hoc correction. An adjusted p-value of $p < 0.05$ was used to determine statistical significance. Analyses were conducted using SPSS version 23.0 (SPSS Inc., Chicago, IL).

Table 1
Accuracy of the activPAL software and artificial neural network for estimating energy expenditure.

Statistic	activPAL software	ANN
Correlation	0.76 (0.12)[a]	0.89 (0.05)
RMSE	1.74 (0.40)[a]	1.07 (0.27)
Bias	−0.87 (0.33)[a,b]	0.00 (0.37)

Data shown as mean (standard deviation).
ANN: artificial neural network.
RMSE: root mean square error.
[a] Indicates significant difference from ANN ($p < 0.05$).
[b] Indicates significant bias from 0 ($p < 0.05$).

3. Results

Of the 44 participants in the study, the Oxycon battery malfunctioned during 3 participants' protocols, resulting in their data being excluded from analysis. Demographics for the 41 participants included in the analysis (20 male, 21 female) were as follows. Average age (standard deviation) was 22.0 (4.2) years, weight was 71.8 (16.1) kg, and height was 171.1 (10.2) cm. Approximately 32% of participants (13 out of 41) had a BMI of $\geq 25.0\,\mathrm{kg\,m^{-2}}$. Correlations, RMSE, and overall bias are shown in Table 1. With a significantly lower correlation with measured EE, higher RMSE, and greater overall mean bias, the activPAL software was consistently outperformed by the ANN for temporal EE prediction. Fig. 1 shows Bland–Altman plots comparing estimated and measured EE. Fig. 1a reveals underestimation of EE by the activPAL software for higher-intensity activities, resulting in overall underestimation of EE (mean difference [MD]: −0.87 METs) and wide 95% limits of agreement (−3.94, 2.19 METs). The ANN (Fig. 1b) had no overall mean bias (MD: 0.00 METs) and narrower 95% limits of agreement (−2.17, 2.17 METs) than the activPAL software, although there appeared overestimation of the lowest-intensity activities. Regression analyses (see Supplementary figure) showed similar trends, with lower correlations with measured EE and overall underestimation at higher intensity activities by the activPAL software.

Activity-specific EE estimates (see Supplementary table) revealed large underestimates of several higher intensity activities by the activPAL software compared to the Oxycon, notably squats (MD: −2.41 METs), walking up and down a flight of stairs (MD: −3.43 METs), and jogging (MD: −3.91 METs). The software also significantly overestimated the EE for standing (MD: +0.13 METs) and slow walking (MD: +0.57 METs) but significantly underestimated EE for laundry (MD: −0.48 METs), sweeping (MD: −0.98 METs), stationary cycling (MD: −0.44 METs), and biceps curls (MD: −0.51 METs). Conversely, the ANN had small but significant overestimation of EE compared to the Oxycon for using a computer (MD: +0.10 METs) and standing (MD: +0.29 METs). The ANN also significantly overestimated EE of walking slowly (MD: +0.67 METs), walking quickly (MD: +0.57 METs) but underestimated the EE of walking up and down a flight of stairs (MD: −0.95 METs), biceps curls (MD: −0.19 METs), and squats (MD: −0.54 METs).

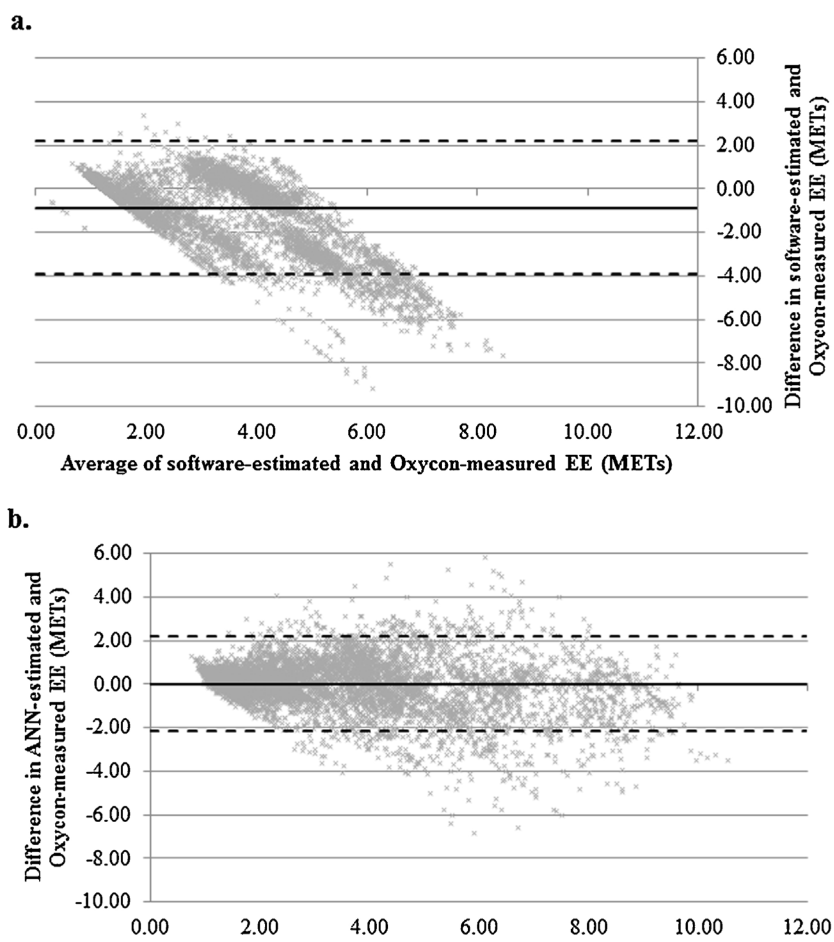

Fig. 1. Bland–Altman plots for measured and estimated energy expenditure. (a) Plot for activPAL software energy expenditure estimates. (b) Plot for artificial neural network energy expenditure estimates. ANN: artificial neural network. EE: energy expenditure.

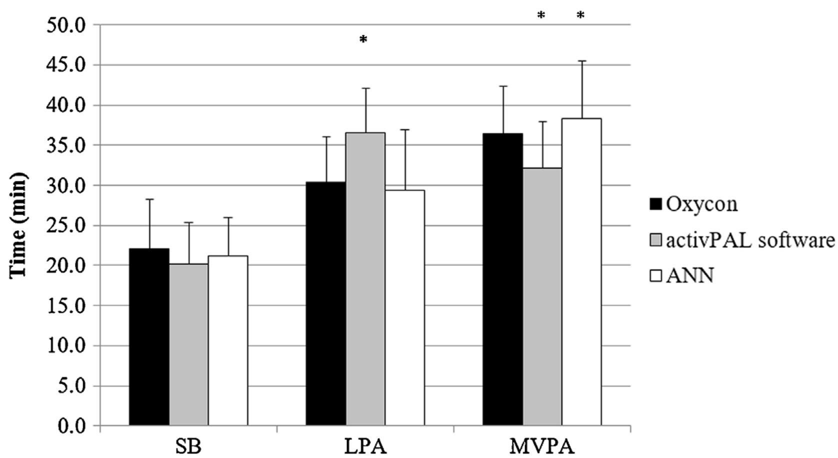

Fig. 2. Time spent in each physical activity intensity measured by the Oxycon and estimated by the activPAL software and artificial neural network. *Indicates significant difference from Oxycon. ANN: artificial neural network. LPA: light-intensity physical activity. MVPA: moderate-to-vigorous physical activity. SB: sedentary behavior.

Fig. 2 shows time spent in each PA intensity as estimated by the activPAL software and ANN and measured by the Oxycon. Estimates of SB from the activPAL software and ANN were not significantly different from the Oxycon. The activPAL software overestimated time spent in LPA by 6.2 min and underestimated time spent in MVPA by 4.3 min compared to the Oxycon. Conversely, ANN-estimated time in LPA was not significantly different from the ANN, but ANN-estimated MVPA was significantly overestimated by 1.8 min compared to the Oxycon.

4. Discussion

The purpose of this study was to evaluate the activPAL accelerometer for estimating EE and time spent in different intensities of PA. Our results indicated that an ANN developed for analyzing raw activPAL data outperformed the activPAL's proprietary software for estimation of EE, with higher correlations, lower error, and no overall mean bias. The ANN also produced estimates of SB and LPA not significantly different from the criterion measure, while the software's only accurate measure was time spent in SB.

Unlike most other PA monitors, the activPAL monitor's primary intended use is for classification of posture by classifying time spent sedentary, upright, and stepping. Although the software underestimated MVPA, our study found that the activPAL provided accurate estimates of time spent in SB and in non-sedentary activities (i.e., upright + stepping), in agreement with previous research.[5,6,17] Given that PA recommendations specify a minimum weekly time spent in MVPA, it is also important to understand how well PA monitors estimate time spent in MVPA. Our study revealed underestimates of MVPA by the activPAL software, driven primarily by underestimation of EE for higher intensity activities. The magnitude of underestimation by the activPAL software in this study was small (4.3 min); however, it is important to note that this level of error could be unacceptably high for PA interventions, which often result in only small (i.e., <5 min/day) changes in MVPA.[18–20] The cadence-based equation for prediction of EE by the activPAL was originally developed for the older, uniaxial version of the activPAL and has not been updated with the current, triaxial activPAL monitors.[21] Our finding of EE underestimation by the activPAL software at higher intensities and activities such as jogging and stair use is in agreement with past studies encompassing both the uniaxial and triaxial versions of the activPAL,[4,8,21] suggesting that EE prediction based purely on step cadence is not an adequate method for determining energy cost of activities, especially those which are non-ambulatory or of higher intensity. Given this accumulating evidence, the EE prediction from the activPAL software should be used cautiously, especially if MVPA or MET-min are outcomes of interest.

Unlike the activPAL software, the ANN developed to analyze raw data collected by the activPAL monitor showed performed well in this semi-structured validation for estimation of time spent in SB and LPA and good window-by-window EE estimation, as indicated by a high correlation ($r = 0.89$) and low RMSE (1.07 METs) when comparing estimated to measured EE. The accuracy of the ANN in this study is similar to the accuracy achieved by an ANN created for a thigh-worn ActiGraph accelerometer that our research group has developed and published previously ($r = 0.89$, RMSE = 1.08 METs),[10] indicating that the activPAL appears to function equally well to the ActiGraph when both are placed on the thigh and collecting raw data for EE estimation. This finding is also in agreement with the work of Steeves et al.,[17] who found high agreement between thigh-worn activPAL and ActiGraph monitors for measures of sitting time. Together, these studies indicate that thigh-worn accelerometers have strong utility for assessment of EE and SB, independent of the accelerometer brand used. Additionally, machine learning models have consistently shown improved EE measurement accuracy over traditional data analysis techniques (i.e., cut-points) and have also allowed for high measurement accuracy using accelerometers placed on alternative body locations such as the wrist and thigh.[10,14]

Despite superior accuracy of the ANN compared to the activPAL software seen in this study, it is problematic that MVPA estimates from the ANN were significantly different than the criterion, especially considering that MVPA is a primary outcome variable in many intervention and surveillance studies and even small changes have health consequences.[19,22] A well-known limitation of using a continuous variable (METs) and rigid thresholds to define activity intensity categories is that activities of a similar intensity may fall into different intensity categories. For example, an activity eliciting 2.9 METs is considered LPA and an activity eliciting 3.0 METs is MVPA, even though their energy cost is similar. A different approach involves avoiding EE prediction but rather differentiating activity intensity categorically by determining activity type. Such methods have been successfully conducted by our research group and others and should be considered as potential alternative methods for improving the ability to characterize MVPA using accelerometers.[7,23,24]

This study had several limitations that must be noted. The study sample was a fairly homogenous group of individuals who were younger and leaner than the average US adult; thus, the ANN model created may not generalize well for EE prediction in other, more diverse groups or in children. Additionally, the 90-min visit had a high percentage of time spent in MVPA and low percentage of time spent in SB compared to what would be experienced in an individual's typical day, which is predominantly spent in SB.[25,26] Therefore, findings of this study do not necessarily indicate how the activPAL software and ANN would perform in a true free-living setting. Instead, our findings give an indication of accuracy of the software and ANN during a relatively active period of time and also indicate their strengths and weaknesses for estimation of EE and activity intensity for a variety of different types and intensities of activity. This study also had numerous strengths, including the variety of activities performed and potentially higher generalizability of study findings due to use of a semi-structured setting (compared to strict laboratory-based protocol). Additionally, the semi-structured setting allowed for use of a metabolic analyzer, which is considered a gold standard method for EE measurement.

5. Conclusion

Our study provides evidence that the activPAL manufacturer software can provide accurate estimates of SB and non-sedentary activity, but estimates of time spent in MVPA and EE estimates (especially for higher intensity PA) should be interpreted with caution. Conversely, a machine learning model created to analyze raw activPAL data had high accuracy for assessing time spent in SB and LPA and comparable accuracy to other accelerometer-based machine learning methods for EE estimation during a semi-structured activity protocol. These laboratory-based findings provide preliminary support for use of a thigh-worn accelerometer and associated machine learning model for SB and EE assessment of SB and EE but should be confirmed in a free-living environment.

Practical implications

- The activPAL proprietary software underestimated physical activity, especially at higher intensities.
- A machine learning model developed for analyzing raw activPAL data had high accuracy for measuring energy expenditure but underestimated time spent in moderate- to vigorous-intensity physical activity.
- Thigh-worn accelerometers, when matched with appropriate data analysis methods, offer a viable approach for measurement of physical activity.

Acknowledgments

Todd Buckingham, Ryan Hulteen, Brandon Krinock, Elizabeth Lenz, and Stefan Rowland assisted with data collection and participant recruitment. This research was supported by the Michigan State University College of Education and by a Student Award Program grant (1997.SAP) from the Blue Cross Blue Shield of Michigan Foundation. This article was prepared while Dr. Mudd was employed at Michigan State University. The opinions expressed in this article are the author's own and do not reflect the view of the National Institutes of Health, the Department of Health and Human Services, or the United States government.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jsams.2017.04.011.

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