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Original research

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

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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 ± 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 ≤ 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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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 axis^{-1} × 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 (ml O_2 kg^{-1} min^{-1}) in each 30-s window was converted to METs by dividing by 3.5. While 3.5 ml O_2 kg^{-1} 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).