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Dinesh John

John Staudenmayer

Patty S. Freedson, *University of Massachusetts - Amherst*

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Simple to complex modeling of breathing volume using a motion sensor

Dinesh John^{a,*}, John Staudenmayer^b, and Patty Freedson^c

^aDepartment of Health Sciences, Northeastern University, 360 Huntington Avenue, 316 Robinson Bldg., Boston, MA 02115, United States

^bDepartment of Mathematics and Statistics, University of Massachusetts, Amherst, United States

^cDepartment of Kinesiology, University of Massachusetts, Amherst, United States

Abstract

Purpose—To compare simple and complex modeling techniques to estimate categories of low, medium, and high ventilation (VE) from ActiGraphTM activity counts.

Methods—Vertical axis ActiGraphTM GT1M activity counts, oxygen consumption and VE were measured during treadmill walking and running, sports, household chores and labor-intensive employment activities. Categories of low (<19.3 l/min), medium (19.3 to 35.4 l/min) and high (>35.4 l/min) VEs were derived from activity intensity classifications (light <2.9 METs, moderate 3.0 to 5.9 METs and vigorous >6.0 METs). We examined the accuracy of two simple techniques (multiple regression and activity count cut-point analyses) and one complex (random forest technique) modeling technique in predicting VE from activity counts.

Results—Prediction accuracy of the complex random forest technique was marginally better than the simple multiple regression method. Both techniques accurately predicted VE categories almost 80% of the time. The multiple regression and random forest techniques were more accurate (85 to 88%) in predicting medium VE. Both techniques predicted the high VE (70 to 73%) with greater accuracy than low VE (57 to 60%). ActigraphTM cut-points for light, medium and high VEs were <1381, 1381 to 3660 and >3660 cpm.

Conclusions—There were minor differences in prediction accuracy between the multiple regression and the random forest technique. This study provides methods to objectively estimate VE categories using activity monitors that can easily be deployed in the field. Objective estimates of VE should provide a better understanding of the dose–response relationship between internal exposure to pollutants and disease.

Keywords

Breathing volume; Accelerometer; Machine learning

1. Introduction

The etiology of several diseases is attributed to interactions among the physical, chemical, and biological characteristics of the environment with the human genome (Hunter, 2005). Inhalation is a common pathway for various chemical and biological toxins to enter the human body. Environmental researchers are interested in quantifying inhalation exposure to

understand the relationship between toxin exposure and disease development (Boffetta et al., 1997; Dons et al., 2012; Mills et al., 2007). Various devices are now available to measure the concentrations and type of toxins in the environment. In addition to toxin concentration, the accurate assessment of inhalation exposure requires information on breathing rate and volume (VE). Breathing rate is measured as the total number of breaths per minute and VE is the total volume of air inspired per minute (breathing rate $\times$ tidal volume). Combining data on the type and concentration of inhaled toxins with VE is necessary to comprehensively understand the dose–response relationship between toxic exposure and disease development. Recent evidence suggests that motion sensors such as accelerometers may be useful to estimate VE (Kawahara et al., 2011; Rodes et al., 2012).

Accelerometers have been extensively used to estimate metabolic equivalents (METs) or energy expenditure (kcal) (Crouter et al., 2006; Freedson et al., 1998; Staudenmayer et al., 2009). Accelerometers vary in the number of axes that detect acceleration, data storing capacity, onboard data processing capabilities and battery life. Output from these monitors increase linearly with activity intensity during most light and moderate intensity activities (Freedson et al., 1998, 2011; Staudenmayer et al., 2009). A commonly used accelerometer is the uniaxial ActiGraph™ monitor (ActiGraph™, LLC, Pensacola, FL). Activity counts from ActiGraph™ accelerometers have been used to develop both simple and complex modeling methods to quantify physical activity (Freedson et al., 1998, 2011; John et al., 2011; Staudenmayer et al., 2009). These techniques are typically developed and validated in the lab with measured VO_2 during various ambulatory and simulated free-living activities as the criterion measure. The models are then applied in the free-living environment to estimate physical activity variables. A similar approach may be useful to estimate breathing volume intensity categories using the ActiGraph™ accelerometer. Recently, an accelerometer was used to estimate VE in children (Kawahara et al., 2011) and Rodes et al. (2012) used simple linear regression to estimate VE from various accelerometers in adults.

Machine learning techniques using advanced statistical prediction models are trained on input data to predict an outcome variable. These techniques are novel because they detect underlying patterns in the input data and are adaptable to improve prediction accuracy. The potential of using machine learning techniques to estimate VE from accelerometer data has not been examined. The objective of this study was to use simple and complex modeling techniques to estimate categories of low, medium, and high VEs from ActiGraph™ activity counts during a variety of ambulatory and simulated free-living activities.

2. Material and methods

2.1. Participants

Two hundred and seventy-seven healthy men and women (mean $\pm$ SD: age = 38.0 ± 12.4 years, BMI = $24.6 \pm 4.0 \text{ kg/m}^2$) were recruited from the University of Massachusetts, Amherst and surrounding areas. The study was approved by the University of Massachusetts, Amherst Institutional Review Board and all participants provided written informed consent. Participants were screened for chronic diseases including cardiovascular and pulmonary disorders and exercise readiness using a health history questionnaire and the Physical Activity Readiness Questionnaire (PAR-Q). Male and female participants above the age of 40 and 50 years, respectively, were screened for cardiovascular disease risk with a physician-supervised 12-lead ECG stress test in accordance with the American College of Sports Medicine Guidelines for Exercise Testing (2009). Participants reporting any contraindications to exercise on the health history and PAR-Q questionnaires, displaying symptoms of cardiovascular disease during the stress test, or were on any medication that alter metabolic rate were excluded from the study.

2.2. Resting metabolic rate

Resting metabolic rate (RMR) was measured using the MedGem Analyzer (HealtheTech, Inc., Golden, CO). The MedGem is a valid device for measuring RMR (Nieman et al., 2003). Following a 4-h restriction of food, caffeine and exercise, participants rested quietly for 15 min in the supine position. Measured RMR was used to calculate METs to indicate the intensity for each activity from the lab-based activity protocols (explained below).

2.3. ActiGraph™ accelerometer

The uniaxial ActiGraph™ GT1M ($5.1 \times 3.8 \times 1.5$ cm, 42.6 g) monitor was used in this study. The GT1M detects accelerations in the vertical plane ranging between 0.05 and 2.0 G that lie within a frequency range of 0.25 to 2.5 Hz. Accelerations are sampled at a rate of 30 Hz and then converted to activity counts for a user specified time interval (epoch). The monitors were initialized to collect data in 1-s epochs and the results were downloaded using software (ActiLife v. 3.1.0.) provided by the manufacturer. One-second activity counts were summed to obtain 1-min values (counts per minute or cpm) that were used in the data analyses. Participants wore the GT1M monitor snugly at the waist in line with the anterior axillary line using an elastic belt. ActiGraph™ monitors are commonly worn at the hip because of its proximity to the center of mass of the body and hip movement is representative of whole body movement.

2.4. Activity protocols

The activity protocol consisted of two routines of nine activities and the activities were performed in random order. Each routine consisted of treadmill activities and activities of daily living. Participants performed six treadmill activities at three speeds (1.34, 1.56, and 2.23 m.s^{-1}), each at 0 and 3% grade. Three activities of daily living were randomly selected from the following set of 15 activities: cleaning the room, dusting, gardening, laundry, mopping, moving a box, mowing, painting, raking, sweeping, trimming, vacuuming, washing dishes, basketball and tennis. These activities represent common household, leisure time and sporting activities and were performed at a self-selected pace. Each activity was performed for 7 min with 4 min of rest between activities. Participants were allowed to stop performing an activity if they were unable to maintain activity intensity (e.g. high treadmill speed).

2.5. Indirect calorimetry

Criterion VE and oxygen consumption (VO_2) were measured on a breath-by-breath basis using a portable metabolic measurement system (Oxycon Mobile™; CareFusion, Yorba Linda, California) during each activity. The Oxycon Mobile™ system consists of a facemask with a small flow-meter and sampling line (for expired air) connected to two small units mounted in a harness secured to the upper back. This system was calibrated using its automatic flow calibrator and a known gas mixture of oxygen (16%) and carbon dioxide (4%) before each use.

2.6. Data reduction and analyses

Activity data were not included in the analyses if a participant was unable to complete the activity or if either the Oxycon Mobile™ or ActiGraph™ activity monitor malfunctioned. Steady state VE, VO_2 and activity counts for each activity were obtained after discarding data for the first two minutes and averaging values for minutes 3 to 7. MET cut-offs (derived from measured VO_2 and RMR) for light (less than 3 METs), moderate (3 to 6 METs), and vigorous (greater than 6 METs) activities were used to determine low, medium and high VEs. Due to the near linear relationship between activity intensity and VE, simple linear regression between steady state METs (independent variable) and VE was used to determine

VE values corresponding to 3 and 6 METs. Medium and high VE cut-offs corresponded to 19.3 ± 1.6 and 35.4 ± 0.14 L/min, respectively. Similar MET-based methodologies have been used by the United States Environment Protection Agency (EPA) to account for differences arising from individual variability (McCurdy, 2000).

Two simple techniques and one complex modeling technique were evaluated to predict VE categories from activity counts. The simple modeling techniques were multiple regression analysis and an activity count ‘cut-point’ method. Activity count cut-points for medium and high VE categories were determined using receiving operator characteristic (ROC) curves. We calculated two variables over a wide range of cpm cut-points: true positive percentage (y-axis) and false positive percentage (x-axis). Fig. 2A and B depict the ROC curves used to determine cut-points for medium and high VEs. We considered cut-points from 60 cpm to 12240 cpm. Each data-point in 2A and B represents different cut-points equally spaced by 60 cpm. In Fig. 2A, the true positive percentage (sensitivity) on the y-axis is the fraction of minutes of medium VE correctly detected by the cut-point. The false positive percentage (1-specificity) is the fraction of minutes that are not at least medium VE but were incorrectly determined to be at least medium VE by the cut-point. Fig. 2B is similar, but detects high VE. On each graph, we identify the cut-point that is closest in Euclidean distance to an ideal of 100% true positive and 0% false positive.

The complex modeling technique was the random forest machine learning technique. This technique is a ‘supervised ensemble learning’ method consisting of multiple independently constructed decision trees (Breiman, 2001). This technique uses different subsets of training data from a larger data set to generate and train each decision tree (Breiman, 2001). The most common classification among the results from all the decision trees is predicted VE category. The random forest technique is robust against over-fitting and is often superior to commonly used classification techniques such as discriminant analysis, support vector machines and neural networks (Breiman, 2001).

We used the ‘best subset variable selection’ method to determine the prediction features for the multiple regression and random forest analyses. This selection method uses chi-square analyses to identify the best possible subset of predictor variables. The final subset of input features were (i) mean 1-min ActiGraph™ activity counts (M), (ii) standard deviation of 1-min ActiGraph™ activity counts (SD), (iii) the 10th percentile of 1-min ActiGraph™ activity count distribution (10PCT), (iv) the 25th percentile of 1-min ActiGraph™ activity count distribution (25PCT), (v) the 50th percentile of 1-min ActiGraph™ activity count distribution (50PCT), (vi) the 75th percentile of 1-min ActiGraph™ activity count distribution (75PCT), (vii) the 90th percentile of 1-min activity count distribution (90PCT), (viii) participant height in cm (HT), (ix) participant weight in kg (WT) and (x) product of M and SD. These features represent various characteristics of the distribution of acceleration signal and participant characteristics. Accuracy of the three estimation techniques was evaluated by computing the percent of correctly classified activities in each VE category. Leave-one-subject-out cross-validation was used to evaluate performance.

3. Results

Data for 2185 activities were included in the final analyses. There were a total of 212 low, 1268 medium, and 705 high VE activities. Fig. 1 illustrates the correct classification rates for multiple regression, cut-point, and random forest techniques in predicting low (<19.3 l/min), medium (19.3 to 35.4 l/min), and high (>35.4 l/min) VE categories. The complex random forest technique had the highest overall accuracy (80.7%). The simple multiple regression had a slightly lower overall accuracy rate (78.7%). The cut-point method has the lowest overall accuracy rate at 65%. Fig. 2A and B depict the ROC curves used to determine

cut-points for medium and high VEs. Activity count cut-points for low, medium and high VEs were 1381, 1381 to 3660, and 3660 cpm, respectively. Accuracy rates between the multiple regression and random forest techniques were similar for the different categories of VE. The prediction accuracy for low VE ranged from 57 to 59%. However, these two techniques returned high prediction accuracies for medium (85 to 89%) and high VEs (72 to 73%). The simple cut-point method had a high accuracy rate for low VE (80%). Accuracy rate for predicting medium VE was poor (58.6%) for the cut-point technique. High VE prediction was 72%. Confusion matrices for VE classification by the three estimation techniques are shown in Table 1A, B and C. The random forest technique misclassified 40% of the low VE activities as medium VE activities, 8% of medium VE activities as high VE and 38% of high VE activities as medium VE. The multiple regression technique misclassified 42% of low VE activities as medium VE activities, 11% of medium VE activities as high VE and 26% of high VE activities as medium VE. The cut-point method misclassified 17% of low VE activities as medium VE activities and 26% of high VE activities as medium VE. This technique misclassified 16% and 25% of medium VE activities as low and high VE activities, respectively. The correlations between estimated and measured VE was 77.5% and 82.1% for the multiple regression and random forest, respectively. The multiple regression prediction equation to estimate VE is: $VE = 2.098 + 0.003 * M + 0.002 * SD - 0.002 * 10PCT - 0.002 * 25PCT - 0.006 * 50PCT + 0.009 * 75PCT - 0.0006 * 90PCT - 0.00004 * (M * SD) + 0.002 * HT + 0.006 * WT$ (M = mean 1-min counts, SD = standard deviation of 1-min counts, 10PCT = 10th percentile of 1-min count distribution, 25PCT = 25th percentile of 1-min count distribution, 50PCT = 50th percentile of 1-min count distribution, 75PCT = 75th percentile of 1-min count distribution, 90PCT = 90th percentile of 1-min count distribution, HT = participant height in cm and WT = participant weight in kg).

4. Discussion

The EPA recognizes breathing volume as an important determinant of human exposure to air contaminants and identified energy expenditure as the ‘systemic organizing principle’ to estimate breathing volume (McCurdy, 2000). We used a MET-based approach to develop simple to complex prediction models that estimate low, medium and high VEs using an objective motion sensor. To the best of our knowledge, no study has examined the prediction accuracy of both simple and advanced pattern recognition techniques to estimate VE using an accelerometer.

4.1. Comparison to previous research

Rodes et al. (2012) conducted a pilot study (N = 22 adults) to examine the prediction accuracy of a simple linear regression model to estimate VE using a single composite acceleration measure as the independent variable. The prediction accuracy of several different activity monitors were tested in this study. The authors reported coefficients of determination greater than 0.85 for almost all the devices during activities having an intensity of less than 4 METs. High intensity activities were eliminated from the analyses because the performance of the single variable models declined with the inclusion of these activities (Rodes et al., 2012).

Rodes et al. (2012) recognized the need for advanced analyses using pattern recognition techniques that combine multiple acceleration features with variables such as participant height and weight to predict VE. The performance of these sophisticated techniques needs to be examined in large and diverse cohorts of both males and females across various age groups. Our study expands the work by Rodes et al. (2012) by comparing the prediction accuracy of simple to complex modeling techniques to predict low, medium and high VEs in a large and diverse sample. Predictor variables included various attributes of the acceleration

signal and participant characteristics that may influence VE. As surmised by Rodes et al. (2012), prediction models with multiple features yielded reasonably good overall percent classification (80%). In our study, predicting VE using only one feature (cpm) in the ROC cut-point method decreased performance to approximately 65%. However, this technique performed reasonably well for low (80% accuracy) and high (71%) VEs.

4.2. Multiple regression vs. random forest

The complex random forest technique performed the best (90% accuracy) for predicting medium VE. In comparison, accuracy of the simple multiple regression technique was marginally lower (4%). This small difference may be due to the adaptive learning capability of the random forest technique. Pattern recognition techniques tend to improve performance as training cases or data points increase in number. Almost 60% of the total number of activities belonged to the medium VE category. The random forest and multiple regression techniques yielded similar accuracy rates (72%) in predicting high VE. Accuracy rates for these methods decreased to about 57% in predicting low VE. The decrease may be due to a small sample (212) of activities in the low VE category and high variability in breathing patterns during low VE (Bendixen et al., 1964). Training the random forest and multiple regression techniques on a larger sample to recognize and account for the variability in breathing may yield improved estimates of low VE.

Interestingly, the inter-technique comparison suggests that the complexity of a prediction technique may be less important in improving estimation accuracy. The inclusion of relevant and appropriate prediction features into a model may be more decisive in improving prediction accuracy. This is highlighted by only a marginal increase in accuracy rates of predicting medium VE by the random forest technique over the multiple regression method. Complex pattern recognition techniques are also more computationally intense than simple techniques and may require additional software and hardware resources. Thus, it may be more feasible to use the simple multiple regression technique to predict free-living VE categories from an accelerometer measured over long durations.

4.3. Advancing VE estimation

Modern technology has enabled the development of multi-sensor monitors to objectively measure VE. These monitors typically detect chest or abdominal wall expansion using piezoelectric sensors (John et al., 2011), magnetometers (Gastinger et al., 2010), smart fabrics (Hailstone and Kilding, 2011), or inductive plethysmography (Witt et al., 2006). We have also validated multi-sensor monitors to predict VE and breathing frequency using various predictor variables from the different sensors (John et al., 2011). However, the feasibility and practicality of these monitors for sustained daily use for several weeks is not known. The primary factors preventing these novel monitors from long term use is battery life and user wearability. Battery life on most of these monitors limits continuous data collection to anywhere between a few hours to 30 h. Tightly worn chest straps may be uncomfortable and also capture tissue and movement artifact (e.g., arm movement) that contaminate the true signal attributable to breathing (John et al., 2011; Rodes et al., 2012). These issues may prevent the use of these devices for extended periods of time (weeks to months) that may be necessary to better understand the dose–response relationship between internal toxin exposure and disease development. Advanced modeling of triaxial raw acceleration from a single sensor to estimate VE may overcome issues limiting the wearability of multi-sensor monitors. Although some devices collect raw acceleration over long periods of time, post processing of raw data places a very high demand on resources. Currently, there is no practical method to predict VE from raw triaxial acceleration. However, technological advances in post processing of data may facilitate this in the future. Until these issues are resolved, the methods developed in our study may serve as a

reasonably accurate alternative to measuring VE over extended periods of time. The ActiGraph™ monitor can continuously record data for at least 30 days on a single battery charge. It has also been continuously used for extended periods of time to measure physical activity as it is minimally invasive (Dias et al., 2009; Mota-Pereira et al., 2011).

4.4. Dose–response paradigm

The relationship between physical activity and health is a well known dose–response paradigm (Haskell, 1994). Frequency, duration and intensity of physical activity have independent and combined effects on various health outcomes (Haskell, 1994). The dose–response relationship between inhalation exposure and disease may be similar to the physical activity and health paradigm. For example, a significant increase in mortality risk among funeral industry workers from myeloid leukemia was associated with increases in the concentration (parts per million) and the rate (parts per million/h) of inhaled formaldehyde and with the total duration of exposure (Hauptmann et al., 2009). Therefore, to improve our understanding of the relationship between inhalation exposure and disease, it may be necessary to study the independent and combined effects of the frequency, duration and intensity of internal toxin exposure. Our study serves as a first step to understanding the independent and combined effects of these three characteristics of toxin exposure. We first used empirical data to develop light, medium and high VE categories and calibrated the ActiGraph™ accelerometer to predict the different breathing volume categories. The accelerometer data may also be used to determine the duration and frequency of inhalation exposure in the free-living environment. Improved estimates of the duration and rate of toxin exposure rates in high risk environments and occupations may lead to the formulation of better safety and protection standards.

5. Conclusion

A focus area of NIH's GEI program was to identify the environmental basis for various diseases (<http://www.nhlbi.nih.gov/resources/geneticsgenomics/programs/gei.htm>). Under this initiative, several researchers aimed to develop valid and reliable devices to measure personal-level exposure to chemical and biological toxins. The use of accelerometers to estimate VE is now being recognized as a useful and important step to understand the relationship between inhalation exposure and disease development (Kawahara et al., 2011; Rodes et al., 2012). This study addresses the need for valid and advanced techniques to process accelerometer data to predict VE. Our techniques may be most applicable in occupational environments where workers typically engage in moderate intensity physical activity and are at risk for inhalation exposure to toxins. VE estimation may be used in combination with devices that measure toxin type and concentrations to improve the understanding of the dose–response relationship between inhalation exposure of toxins and disease development. Future research needs to examine if the performance of our prediction techniques to predict low and high VEs can be improved by training the algorithms on a larger sample size for low and high VE activities. Additional research is required to explore the potential of these techniques to model raw multi-axial acceleration from advanced accelerometers and determine the possibility of improving the prediction performance of low, medium and high VEs.

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HIGHLIGHTS

- We developed simple and complex methods to predict breathing from accelerometers.
- Simple multiple regression and complex random forest techniques performed comparably.
- Accelerometry can be used to predict breathing volume, duration and frequency.
- The methods may improve the understanding of how toxin exposure impacts disease.

Fig. 1. Percent correct classification for the three techniques for predicting low (<19.3 L/min), medium (19.3 to 35.4 L/min), and high (>35.4 L/min) VE.

Fig. 2. ROC curves to determine cut-points to define medium (A) (>19.3 l/min) and high (B) (>35.4 L/min) VE. The data-point 'closest to ideal' were selected as the cut-point for the two breathing categories.

Table 1

Confusion matrices for the random forest (A) multiple regression (B) and ROC (C) techniques. Bolded numbers indicate the number of correctly classified breathing volume categories.

Breathing categories	Low (<19.3 l/min)	Medium (19.3 to 35.4 l/min)	High (>35.4 l/min)
<i>(A)</i>			
Low	124	86	2
Medium	31	1131	106
High	1	195	509
<i>(B)</i>			
Low	121	89	2
Medium	46	1084	138
High	4	187	514
<i>(C)</i>			
Low	170	37	5
Medium	201	744	323
High	18	181	506