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Article Title: Validity of the Apple iPhone/iPod Touch® as an Accelerometer-based Physical Activity Monitor: A Proof-of-concept Study

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ABSTRACT

Background: The popularity of smartphones has led researchers to ask if they can replace traditional tools for assessing free-living physical activity. Our purpose was to establish proof-of-concept that a smartphone could record acceleration during physical activity, and those data could be modeled to predict activity type (walking or running), speed ($km \cdot h^{-1}$), and energy expenditure (METs). **Methods:** An application to record and email accelerations was developed for the Apple iPhone/iPod Touch®. Twenty-five healthy adults performed treadmill walking (4.0 $km \cdot h^{-1}$ to 7.2 $km \cdot h^{-}$1) and running (8.1 $km \cdot h^{-1}$ to 11.3 $km \cdot h^{-1}$) wearing the device. Criterion energy expenditure measurements were collected via metabolic cart. **Results:** Activity type was classified with 99% accuracy. Speed was predicted with a bias of 0.02 $km \cdot h^{-1}$ (SEE: 0.57 $km \cdot h^{-1}$) for walking, -0.03 $km \cdot h^{-1}$ (SEE: 1.02 $km \cdot h^{-1}$) for running. Energy expenditure was predicted with a bias of 0.35 METs (SEE: 0.75 METs) for walking, -0.43 METs (SEE: 1.24 METs) for running. **Conclusion:** Our results suggest that an iPhone/iPod Touch® can predict aspects of locomotion with accuracy similar to other accelerometer-based tools. Future studies may leverage this and the additional features of smartphones to improve data collection and compliance.

Key Words: Accelerometer, smartphone, free-living physical activity, energy expenditure

INTRODUCTION

The assessment of physical activity behaviours is difficult to accomplish under free-living conditions. However, this information is necessary for researchers monitoring the physical activity levels of various populations, planning and evaluating physical activity promotion initiatives, and investigating the impact of physical activity on health outcomes. Ideally, assessment should be minimally obtrusive to participants, affordable for large-scale studies, and reveal day-to-day physical activity patterns, including the volume of physical activity (duration, frequency, intensity), type, and resulting energy expenditure [1,2].

Accelerometer-based physical activity monitors are currently one of the most popular devices used by physical activity researchers to assess free-living physical activity [3,4]. Small and wearable, these monitors record bodily accelerations, which can be modeled to estimate the duration, frequency, and intensity (light, moderate, vigorous, or very vigorous) of physical activity using monitor- and calibration-specific regressions [3,5].

Using Smartphones to Assess Physical Activity

Smartphones are devices able to place telephone calls, text message, email, browse the internet, identify geographical location and headings, and capture photographic and video data[6]. A number of smartphones also have triaxial accelerometers with specifications similar to accelerometer-based physical activity monitors. Consequently, it may be possible to use the acceleration signals collected by smartphones to estimate physical activity type, speed and energy expenditure. If the accuracy of these estimates is comparable to current accelerometer-based methods, there are a number of other methodological advantages of using smartphones. These advantages include leveraging the popularity of smartphones to increase participant recruitment and compliance; transmitting data wirelessly over long distances and from remote locations without retrieval of the device; and, the ability to program smartphone software to the researcher's specifications. Multiple data types, such as questionnaires, photographs, geographical location, and accelerometer data may be recorded using a single device, allowing researchers to develop an increasingly holistic assessment of free-living physical activity behaviours[6,7].

Other researchers have recognized the potential of using smartphones as accelerometer-based physical activity monitors. Studies have investigated using smartphones to collect data from a number of bodily sensors on participants and send the data to researchers[8-10]. However, in these studies the smartphone's onboard sensors were not used. In 2009, Kawahara et al. developed a tri-axial accelerometer and low-power processor module for smartphones that recorded acceleration signals[11]. The module performed comparably to two other physical activity monitors, but needs to be installed in a smartphone and is not commercially available. Recently, Hynes et al. (2011) used smartphones to identify bouts of physical activity (walking) among elderly patients[12], and other researchers have begun using acceleration signals collected by smartphones to discriminate between different physical activities[13,14].

What is currently absent from this rapidly growing body of literature is evidence that the acceleration signals from a smartphone can be modeled to estimate a suite of physical activity behaviour outcomes, such as activity type, speed, and physical activity energy expenditure (PAEE), and the validity of these estimates in comparison to criterion measurements.

The purpose of this study was to establish proof-of-concept that a smartphone application (Apple iPhone®, Apple Inc. Cupertino CA) could be used to collect acceleration signals during physical activity, which could then be modeled to produce estimates of activity type (walking or running), speed ($km \cdot h^{-1}$), and rates of energy expenditure (metabolic equivalents, METs). This study adds to the literature by validating these estimates against known values (activity type, speed) and criterion measurements (energy expenditure), and comparing them to published values for other monitors.

As a 'proof-of-concept' study, the concept of using a smartphone as a physical activity monitor was demonstrated in a limited sense to determine the viability of additional development. This approach tested the viability of this novel technique, but does introduce some limitations to generalizability, which are discussed.

METHODS

Study Design

The study consisted of four phases. The first phase involved the development of a smartphone application to collect acceleration data during physical activity (treadmill walking and running). The second phase involved the measurement of energy expenditure via expired gas analysis and collection of acceleration data via the smartphone during treadmill walking and running. The third phase involved processing and modeling the acceleration data to yield estimates of activity type, speed and energy expenditure. Finally, the fourth phase involved comparing the accuracy of the estimates to the criterion measurements, as well as literature values for other monitors. The repeatability of collecting acceleration signals with the smartphone was also assessed.

Phase I: Development of the smartphone application

A software application, or an "app", for the iPhone® and iPod Touch® (Apple Inc., Cupertino CA) was developed using the software development kit for the iOS 4.0 operating system (Apple Inc., Cupertino CA) (see Figure 1). Upon initiation of the data collection session, the application used the device's triaxial accelerometer (LIS302DL, STMicroelectronics, Geneva) to sample and record accelerations, in multiples of g (± 2 g), at a user-defined frequency. A frequency of 64 Hz was defined for this study, producing a high-resolution acceleration signal that exceeded Sampling Theorem criteria [15]. Upon conclusion of the session, the acceleration signal was saved in a text file and emailed back to the researcher.

Due to the costliness and limited availability of the iPhone® at the time of this study, an iPod Touch® was used exclusively in Part II of this study. While it is acknowledged that the iPod Touch® does not have all of the capabilities of the iPhone® (e.g. telephone, text messaging, GPS), it possesses identical accelerometer hardware and can send and receive email over wireless Internet networks. We expect the results produced from the iPod Touch® to be applicable to the iPhone®.

Phase II: Obtaining acceleration data during treadmill walking and running

Participants

Twenty-five healthy, young adults (11 males, 14 females) participated in this study, three of whom agreed to return for repeatability testing. This sample size afforded the study a statistical power greater than 95% (see Appendix A). Participants were conveniently recruited from the Faculty of Kinesiology at the University of Calgary, and their characteristics are presented in Table 1. Participants provided written, informed consent and were screened for exercise readiness according to the Canadian Society for Exercise Physiology protocol [16]. This study was approved by the Conjoint Health Research Ethics Board at the University of Calgary, Alberta.

Data Collection

To control standardize exercise testing results, participants were given pre-testing instructions, which were to refrain from: a) consuming food or beverages other than water two hours prior to testing; b) consuming alcohol or tobacco six hours prior to testing; and, c) excessive exercise six hours prior to testing. For each participant, height (cm) using a stadiometer (HR-100, Tanita, IL), weight (kg) using a platform manual balance scale (Healthometer, Continental Scale Corp., NY), and age on the day of testing were recorded.

Using disposable adhesive material in a belt-like manner, an iPod Touch® was secured to the middle of the lower back, such that the top of the device was aligned with the supra-iliac crest. The x, y, and z axes of the accelerometer corresponded to the medio-lateral, vertical, and anterior-posterior axes of the body, respectively. Positioning the device in this manner produced an optimal acceleration signal by dampening vibrational noise, and standardized device orientation among subjects, which was necessary for data modeling.

Each participant completed two sessions of physical activity, each approximately 30 minutes in length. The two sessions were separated by a minimum of fifteen minutes. In each session, the participant wore an iPod Touch® and a heart rate monitor (FS2c, Polar Electro, NY). Participants breathed through a one-way valve mouthpiece, which collected expired gases. Expired gases were analyzed in 30-second interval mid-point averages using a metabolic cart equipped with gas analyzers for sampling from a mixing chamber (TrueOne2400, Parvomedics, UT).

The first session consisted of walking on a treadmill (Woodway 24-72, Quinton Instruments, WA) at speeds of 4.0, 4.8, 5.6, 6.4 and 7.2 $km \cdot h^{-1}$ and jogging at 8.1 $km \cdot h^{-1}$, all at an incline of 1%. The second session consisted of jogging/running on the same treadmill at speeds of 8.9, 9.7, 10.5, and 11.3 $km \cdot h^{-1}$, all at an incline of 1%. Each session began with a warm-up of walking at 3.2 $km \cdot h^{-1}$ at an incline of 1% for two minutes. Speeds were randomized within sessions, avoiding the cumulative effects of physical activity on energy expenditure, and the treadmill was inclined to 1% to compensate for the absence of air resistance. Participants exercised at each speed until their absolute rate of oxygen consumption (VO_2, $L \bullet min^{-1}$) reached a steady state, which was considered to be four consecutive absolute VO_2 measurements within 0.100 $L \bullet min^{-1}$ of each other[17]. Energy expenditure (METs) was calculated by dividing the relative VO_2 values ($mL \bullet kg^{-1} \bullet min^{-1}$) from the metabolic cart by a relative resting VO_2 value (3.5 $mL \bullet kg^{-1} \bullet min^{-1}$)[17].

Phase III: Modeling activity type, speed, and energy expenditure from acceleration data

Data Processing

Typically, acceleration signals from physical activity monitors are broken into intervals, rectified, integrated, and averaged to obtain a rate of "activity counts per minute"; however, this approach tends to underexploit the acceleration signal. We used a "feature extraction" approach in which a number of different variables that have either been shown previously or hypothesized to correlate with physical activity outcomes were calculated from intervals of raw acceleration signal (see Appendix B for the complete list).

Data collection was synchronized between the iPod Touch® and the metabolic cart. Analysis of expired gas data yielded two-minute intervals representing steady state oxygen consumption, or energy expenditure, for each walking and running speed. For each speed, the start time of the steady state interval was used to identify the start time of three non-overlapping, consecutive 30-second intervals of acceleration data (3 x 30 seconds x 64 measurements/second = 5760 acceleration values for each axis, for each speed). Acceleration data are often analyzed in

15, 30, or 60-second intervals, or "epochs"[5]. We used 30-second epochs because Bonomi et al. (2009) indicated that this interval was optimal for classifying activity types using a feature extraction approach[18]. Filtering with a Butterworth filter did not improve results, so raw data were used.

For each of the three 30-second intervals of raw acceleration data, thirteen different variables were calculated. The mean of these three values was used in subsequent analysis. Of the thirteen variables calculated, three were included in the final predictive models, and are described in detail here.

Y_{SD}, is the standard deviation of the vertical acceleration values in a 30-second interval of data (1920 values). In Equation 1, y_i is the ith acceleration value in the data interval, and μ_y is the mean of the acceleration values.

$$(1) \qquad Y_{SD} = \sqrt{\frac{1}{1920}\sum_{i=1}^{1920}(y_i - \mu_y)^2}$$

X_{RMS} is the root mean square of the medio-lateral acceleration values in a 30-second interval of data (1920 values). In Equation 2, x_i is the i^{th} value in the data interval.

$$(2) \qquad X_{RMS} = \sqrt{\frac{1}{1920}\sum_{i=1}^{1920}(x_i)^2}$$

$AU \bullet min^{-1}$, acceleration units per minute, the average of the normalized sum of the squared acceleration values in a 30-second interval of data (1920 values), multiplied by two to yield acceleration units per minute (Equation 3).

$$(3) \qquad AU \bullet min^{-1} = \frac{1}{960}\sum_{i=1}^{1920}\left(\sqrt{(x_i)^2 + (y_i)^2 + (z_i)^2} - 1\right)$$

Data processing was accomplished using customized programs with MATLAB software (R2009a, The MathWorks Inc., MA). For each model variable, up to 300 data points could be included in the calculation (25 participants x 12 speeds/participant x 1 mean variable value/speed = 300 values for each variable). However, one participant did not complete the second data collection session, and three participants were unable to reach steady state oxygen consumption while running at 11.3 $km \cdot h^{-1}$. Consequently, only 291 data points could be calculated for all model variables.

Development of Predictive Models

The same 25 participants provided sample data for each model variable. To account for the resulting inter-dependence of the sample data we used a panel regression modeling approach, part of the family of generalized linear models [19]. A binary logistic panel regression equation was developed to classify accelerometer output into walking or running states. Next, multiple linear panel regression equations were developed to estimate walking speed (125 data points per variable for speeds 4.0 to 7.2 $km \cdot h^{-1}$), or running speed (121 data points per variable for speeds 8.1 to 11.3 $km \cdot h^{-1}$). Variables that were highly correlated ($r^2 > 0.85$) with the outcome of interest (activity type, walking speed, or running speed) were modeled in a step-wise process until a model was developed that minimized the Corrected Quasi-Likelihood under Independence Model Criterion (QICC), which assesses the goodness-of-fit for panel regression models [19].

The estimates of walking and running speeds were used as input to a number of published equations for the prediction of energy expenditure (METS) from walking or running speed [20-25]. Some of these equations also used participant characteristics such as sex, height, and weight. One of the benefits of using this approach is that it cross-validated a number of equations that predict METs from speed, and allowed us to establish which equation was most accurate in this context.

Phase IV: Accuracy and repeatability of model estimates

Accuracy

The predictive models were validated using a leave-one-out (LOO) cross-validation procedure [26]. In this procedure, data points from 24 of the participants were used to build a model that was used to predict the gold-standard (true) values measured from the 25th participant. This process was repeated 25 times such that data from each participant was involved in both the modeling and testing process[26]. The mean of the twenty-five validation models is presented in the results.

In the case of the binary classification of activity type (walking or running), classification accuracy and F-scores in percentages were calculated according to the method suggested by Bonomi et al.[18]. In the case of estimating walking and running speed the difference between the known value and the estimated value from the model was calculated for each data point. However, in estimating energy expenditure, error was defined as the difference between the criterion measurement of METs and the estimated value from the models. The average error (X_{ERROR}), the standard deviation of the error (SD_{ERROR}), the limits of agreement (95% confidence intervals about the average error), and the standard error of the estimate (SEE), were also calculated to assess the accuracy of the model estimates[26]. Bland-Altman plots were constructed to assess the level of agreement between estimates and criterion measurements and to identify bias[27].

Repeatability

Three participants completed repeatability testing (2 males, 1 female; average height = 177.8 cm; average weight = 73.7 kg; average age = 26.7 yrs). To assess inter-device differences, two iPod Touch units were aligned and secured together. Participants wore the devices according to the data collection protocol in Part II, walking at 4.0 and 7.2 $km \cdot h^{-1}$, and running at 8.1 and 11.3 $km \cdot h^{-1}$, all on a treadmill at an incline of 1%. Participants walked and ran for two and a half minutes at each speed. The devices were decoupled, and the protocol was repeated two more times for a total of three trials for each participant.

After visually inspecting plots of the acceleration data versus time, three consecutive, non-overlapping 30-second intervals were extracted from the middle of the intervals for each speed. The variables used in the models were calculated from the acceleration data in the same manner as in Part II. A two-way repeated measures analysis of variance (R-MANOVA) was used to assess differences between variable values, accounting for effects by device, and by trial [26].

Statistical Analyses

The LOO validation procedure and all other statistical tests were performed using PASW/SPSS software (Version 18.0, IBM, IL). In all statistical tests, the threshold for statistical significance was 0.05.

RESULTS

On average, the male participants were both significantly taller and heavier than the female participants (Table 1). According to body mass index (BMI), 8% of the participants were underweight, 84% were normal weight, 8% were overweight, and none were obese. In contrast, this distribution among the general population of Canadian adults is: 2.0% underweight, 38.9% normal weight, 36.1% overweight, and 23.1% obese [28].

Estimation of activity type

The binary classification model for predicting activity type (walking or running) included a single variable, the standard deviation of the vertical acceleration data (Y_{SD}, Wald's X^2= 26.0, $p < 0.001$) (Table 2). The overall accuracy of the model was excellent (99.0% of intervals were correctly classified). F-Score values revealed that the model was marginally more accurate for classifying walking (99.1%) than running (98.4%).

Estimation of walking and running speed

The models developed to predict walking and running speeds from acceleration data variables are presented in Table 3. For walking, the standard deviation of the vertical acceleration data (Y_{SD}, Wald's X^2= 137.0, $p < 0.001$), the root mean square of the medio-lateral acceleration data (X_{RMS}, Wald's X^2= 16.7, $p < 0.001$), and the participant's height (m, Wald's X^2= 14.2, $p < 0.001$) were significant predictors of speed ($km \bullet h^{-1}$). On average, the model overestimated walking speed by 0.02 $km \bullet h^{-1}$. For running, acceleration counts per minute ($AU \bullet min^{-1}$, Wald's X^2= 53.9, $p < 0.001$) and the participant's sex (sex, Wald's X^2= 5.02, $p < 0.001$) were significant predictors of speed. This model underestimated running speed by 0.03 $km \bullet h^{-1}$, on average (Table 3).

Our SEE calculations indicate that the absolute variability of the estimate error for predicting running speed (SEE = 1.0 $km \bullet h^{-1}$) was nearly double that for predicting walking speed (SEE = 0.57 $km \bullet h^{-1}$) (Table 3). However, if expressed as a percentage of the average walking (5.6 $km \bullet h^{-1}$) and running (9.7 $km \bullet h^{-1}$) speeds, the variability of the error was similar, SEE = 10.1% (walking) and SEE = 10.5% (running). Bland-Altman plots confirmed that the absolute variability of the estimate error was greater for the prediction of running speed than for walking speed, as the limits of agreement were almost twice as wide for running speed (4.0 km$\bullet$h^{-1}) those for walking speed (2.2 km$\bullet$h^{-1}) (Figure 2, Panels A and B). A trend of overestimation at lower running speeds and overestimation at higher running speeds was also indicated by the Bland-Altman plot (Figure 2, Panel B).

Estimation of METs from speed

The estimates of speed produced by our predictive models (Table 3) were entered into previously published models (Table 4) to predict rates of energy expenditure (METs) for walking and running. These estimates were compared with gold-standard energy expenditure values. The cross-validation results are presented in Table 5. For all walking speeds, the average estimate error ranged from -0.19 METs to 0.54 METs, and the SEE ranged from 0.75 to 0.96 METs. Considering walking speeds individually, slower walking speeds (4.0 km$\bullet$h^{-1}, 4.8 km$\bullet$h^{-1}) produced the smallest average estimate errors (-0.01 to 0.20 METs), regardless of the predictive model (Table 5). The SEE appeared to increase as walking speed increased, regardless of the predictive model. For all running speeds, the average estimate error was -0.43 METs, and SEE was 1.24 METs. Considered individually, average estimate error appeared to increase from -1.25 to 0.48 METs as running speed increased. The SEE appeared to decrease as running speed increased, which was opposite to the trend observed for walking.

The equation by Brooks et al. (2005) produced the most favourable estimates of energy expenditure during walking with an mean error of 0.35 METs and an SEE of 0.75 METs across all walking speeds[20]. Bland-Altman plots were constructed for this model for walking, and the ACSM model for running (Figure 2, Panels C and D). The limits of agreement were wider for the prediction of energy expenditure from running speed (4.55 METs)[24] than from walking speed (2.60 METs)[20]. Trends of overestimation of energy expenditure at slower speeds and underestimation at higher speeds were indicated for both walking and running by the Bland-Altman plots.

Repeatability of acceleration measurements

The results of the R-MANOVA indicated that for the three variables calculated from the acceleration data and entered into our models to predict activity type and speed (Y_{SD}, X_{RMS}, AU • min^{-1}), there were no significant inter-device differences, nor were there significant intra-device differences between trials (Table 6).

DISCUSSION

Classification of activity type

The use of accelerometer data to predict physical activity energy expenditure is based on initial studies showing strong correlations between the magnitude of vertical trunk accelerations and energy expenditure during walking and running [29,30]. However, there is also evidence suggesting that this relationship is highly dependent on activity type [31]. Identifying activity type may allow researchers to improve estimates of energy expenditure by using activity-specific models (this study), or a compendium of physical activities [32], instead of assigning an estimated range of intensities (*eg.* light: 1-3 METs, moderate: 3-6 METs, vigorous: 6-9 METs, and very vigorous: >9 METs) to participant data. Until recently, researchers were only able to *subjectively* identify activity type, after it had occurred, using questionnaires, activity journals, and interviews [18]. Bonomi et al. [33] were able to improve estimates of daily energy expenditure by using a decision tree classifier to *objectively* estimate activity type from acceleration data, and then assigning METs values from a compendium.

Accurate, reliable classification models are fundamental to an activity-specific assessment of free-living physical activity. Previous research using single accelerometers to estimate activity type has resulted in classification accuracies of 90% to 100% for walking [18,34,35] and 100% for running [18]. Our model performed favourably in comparison, with classification accuracies of 99% for walking and 98% for running (Table 2). It should be highlighted, however, that treadmill walking and running results in more consistent movement patterns than over-ground walking and running, and thus, our model may not classify over-ground walking and running as accurately.

Another important aspect of classification models is their ability to accurately identify the start and stop times of various activities, yielding accurate estimates of time spent performing a specific activity or being physically inactive[18]. The behaviour of our activity classification model in these "boundary conditions" (*ie.* 30-second intervals of acceleration data representing two or more activities) has not yet been tested, and may result in misclassification of one or more activities.

Future research should include expanding the classification model to include different types of activities, which have been tested in more ecologically valid settings. For example, non-ambulatory activities such as cycling, sports such as golf or soccer, and daily living activities such as vacuuming, washing dishes, or gardening have been studied as other free-living physical activities[36,37].

Estimation of walking and running speed

Models using known walking speed to predict energy expenditure produce better estimates of energy expenditure than models using accelerometer output in “acceleration counts” from physical activity monitors[20]. Consequently, we developed two models to produce estimates of walking and running speed from the acceleration data collected by a smartphone, which could be entered into regressions predicting energy expenditure from walking and running speed. In a similar study, Bonomi et al. [18] produced a model to estimate walking speed with a bias of 0.32 $km \bullet h^{-1}$ (95% CI: -0.38 to 1.02 $km \bullet h^{-1}$) and a standard error of validation (SEV), a metric comparable to our SEE, of 0.47 $km \bullet h^{-1}$. In comparison, our model to estimate walking speed had a smaller bias (0.02 $km \bullet h^{-1}$), but wider limits of agreement (95% CI: -1.10 to 1.14 $km \bullet h^{-1}$), and a larger SEE (0.57 $km \bullet h^{-1}$) (Figure 2, Panel A). Two of the three variables included in our model, Y_{SD} and the participant’s height, are similar to those included in the model published by Bonomi et al. [18].

The model estimating running speed published by Bonomi et al. [33] had a bias of 0.29 $km \bullet h^{-1}$ (95% CI: -4.60 to 5.18 $km \bullet h^{-1}$), and a SEV of 2.45 $km \bullet h^{-1}$. Our model was less biased (-0.02 $km \bullet h^{-1}$), had narrower limits of agreement (95% CI: -2.04 to 1.99$km \bullet h^{-1}$), and a much smaller SEE (1.02$km \bullet h^{-1}$) (Figure 2, Panel B). Outlying points in Figure 2 may have resulted from looseness in the fixation of the iPod Touch®, resulting in higher variability in the y-axis and gross overestimation of walking speed in the three points below the 95% limits of agreement (Panel A). In the case of the points above the 95% limits of agreement (Panels A and B) improper fixation of the iPod Touch® or changes in participant posture at higher running speeds could have tilted the device, decreasing y-axis values and resulting in gross underestimation of walking and running speed.

The estimates of walking and running speed produced by our models were less biased than previously published estimates, and in the case of running speed, our model produced narrower limits of agreement and a smaller SEE than a previously published model. However, we were unable to produce estimates of walking speed with narrower limits of agreement or a smaller SEE. If estimates of walking and running speed are to be used to estimate energy expenditure, the error associated with the predicted speeds needs to be minimal. Thus, future research should focus on reducing the variability of the estimates of speed, perhaps by including other variables in the models. The Bland-Altman plots (Panel B, Figure 2) indicate an interaction between running speed and estimate error such that speed is overestimated at slower speeds and underestimated at higher speeds. This interaction effect would need to be identified and adjusted for in future research.

The iPhone® may provide researchers with an alternative to these methods of estimating activity type and speed, using location data collected by the device's GPS (Global Positioning System) unit.. Estimating speed as the distance measured by a GPS unit traveled over time produces more accurate estimates of speed, as well as location and altitude data[38,39]. Currently, participants must wear two separate devices (one accelerometer, one GPS unit), and researchers must manually synchronize the data after collection; however, the iPhone® integrates a GPS unit and accelerometer into a single device, which may increase feasibility of this method.

Estimation of METs

Previous cross-validation of the models used in this study to predict energy expenditure from walking speed, using a single self-selected walking speed, resulted in average estimate error values ranging from -0.4 to 0.1METs, and SEE values ranging from 0.4 to 0.7 METs [20]. Our values for bias and SEE are similar for walking at 4.8 $\text{km} \cdot \text{h}^{-1}$, confirming and the validity of these equations (Table 5). Not surprisingly, the values for bias and SEE are larger for all walking speeds combined (Table 5). In a recent study by Lyden et al. [40], nine models, which estimated METs from acceleration counts produced by the commonly-used ActiCal and ActiGraph physical activity monitors, were cross-validated. For walking at 4.8 km•h^{-1}, average error (bias) ranged from 0.0 to 0.8 METs, and root mean squared error (RMSE), ranged from 0.6 to 1.6 METs. For walking at 5.6 km•h^{-1}, average estimate error ranged from -0.3 to 0.7 METs, and RMSE ranged from 0.8 to 1.6 METs. For running at 8.0 km•h^{-1}, average estimate error ranged from -1.4 to 2.6 METs, and RMSE ranged from 1.5 to 3.6 METs. According to Table 5, our cross-validation results for the same walking and running speeds are similar and, in the case of walking at 4.8 km•h^{-1}, favourable. As mentioned previously, the model by Brooks et al.[20] produced the most accurate estimates of energy expenditure. This model was also the only one to include speed, weight *and* sex as predictors, indicating that other factors besides walking speed are necessary in predicting physical activity energy expenditure. Unlike the other equations in Table 4, this model did not use a quadratic approach to predicting energy expenditure.

The increasing SEE of energy expenditure estimates observed in most models as walking speed increased and as running speed decreased is possibly due to the mechanical inefficiencies of walking at higher speeds and running at slower speeds [41]. Improving the predictive models to accommodate this increase in variability during fast walking and slow running should be addressed in future research.

Another source of the error in our estimates of energy expenditure includes inputting walking and running speeds that may have been beyond the ranges originally used to develop the models in Table 4. The Bland-Altman plots, based on the model by Brooks et al.[20], suggest this source of error may have resulted in over-prediction of energy expenditure at slower speeds and under-prediction at higher speeds for both walking and running (Figure 2, Panels C and D). Outlying points in Figure 2 Panel C indicate gross underestimation of METs in some cases. A possible explanation for these points is amplification of error in the estimated speed used to estimate energy expenditure. Alternatively, some participants could have had much higher actual energy expenditures due to low fitness, especially at higher walking speeds.

Finally, it is worth mentioning that all of the equations used to predict energy expenditure, except for the ACSM equations, were developed for level surfaces and do not take into account the changes in energy expenditure that occur with changing grade. Since accelerometers alone cannot detect changes in grade, this is also one of the biggest shortcomings in predicting energy expenditure from accelerometer-based physical activity monitors[5]. Fortunately, the newest generation of smartphones has gyroscopes, magnetometers, and altimeters, which may be used to detect changes in grade and adjust energy expenditure estimates accordingly.

Repeatability

Initial inter- and intra-device repeatability appears to be acceptable, with no significant differences found for any of the variables calculated from the acceleration data (Table 6). However, the small sample (n=3) indicates that further testing should be undertaken to support this result.

Strength and limitations of this study

The major strength of this study is that a well-powered sample was used to validate estimates of activity type, speed, and energy expenditure during treadmill walking and running, which were modeled on acceleration data from a smartphone. Additionally, indirect calorimetry was used as the criterion measurement for energy expenditure in this study. To our knowledge, this is the first time estimates of activity type, speed, and energy expenditure based on acceleration data collected with an "off-the-shelf" smartphone have been validated in this manner. Using this approach, the study aims to give physical activity researchers an insight as to whether or not it is feasible to continue developing as free-living physical activity monitors.

One of the major limitations of this study is that it only included treadmill walking and running in a laboratory setting. While appropriate for a proof-of-concept study, these activities do not represent free-living physical activity. Future research could include adapting the models for free-living, over-ground walking and running, as well as other physical activities; however, these activities are likely to be more variable, and therefore, more difficult to predict from acceleration data.

Another limitation of this study is that the iPod Touch® was secured to the middle of the lower back of participants. While this position produced high quality data ideal for modeling, it does not represent a position individuals use to carry their smartphones in everyday life. In 2008, Ryu et al. published a data modeling approach in which different smartphone carrying positions (e.g. front hip pocket, back hip pocket) could be identified from the acceleration signal and used to select an appropriate model to estimate energy expenditure[25]. However, this approach required individual calibration, which was not required in this study.

This study used a convenience sample, which consisted of young, healthy, primarily normal-weight adults. The distribution of BMIs within our sample, presented as part of our results, is not reflective of the distribution of BMIs for the general population. Thus, the results of this study are not readily generalizable to the broader population of Canadian or North American adults. Overweight/obesity are commonly accompanied by low physical fitness, which may result in higher levels of energy expenditure for any given walking or running speed, and underestimation of energy expenditure by our models. Increased adiposity may also make it more difficult to fix the smartphone securely to the trunk of the body, resulting in noisier acceleration signals. A more randomized and representative sampling approach could be implemented in future research to address this limitation. However, these limitations were generally considered to be acceptable for a proof-of-concept study.

Future Directions

As have already been identified in this discussion, there are multiple directions for future research, the most pressing of which involve addressing some of the limitations of this study. Placement of the monitor in other locations and orientations either on the body or in pockets, backpacks, and handbags is a critical next step for demonstrating that smartphones can be used as physical activity monitors. This step will likely involve more sophisticated data modeling to determine the smartphone’s location and orientation, and use the information to select an appropriate prediction equation. Calibrating and validating the method for additional activities, including sedentariness is another important direction for future research, as well as expanding the sample to make it more representative of the population.

CONCLUSION

Free-living physical activity is a difficult phenomenon to assess in individuals, and accelerometer-based physical activity monitors have come to the forefront as a tool of choice. These devices are used by many researchers to estimate physical activity energy expenditure, but are not without limitations. In this study an iPhone® was used to collect triaxial acceleration data during physical activity, which were retrieved wirelessly via email and modeled to predict activity type, speed, and METs. Upon comparison to criterion measurements and known values for activity type, speed and METs, the accuracy and variability of our estimates were similar to those produced by traditional physical activity monitors.

The findings of this study constitute an important methodological advancement in this field as they indicate that state-of-the-art estimates of physical activity type, speed and METs can be produced using a widely-available, highly-valued consumer device, which individuals voluntarily carry with them as part of their daily routines. For treadmill walking and running, these estimates have equivalent accuracy when compared with traditional monitoring systems. If development of smartphones as physical activity monitors continues, it may eventually yield substantial improvements in free-living physical activity assessment methodologies.

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APPENDIX A

Statistical Power Calculation

The following calculation illustrates the statistical power present in this study to detect differences in energy expenditure measured by indirect calorimetry and estimated by a physical activity monitor, using a sample of twenty-five participants. The calculation is based on energy expenditure values obtained in this study during treadmill walking at $5.6 \text{km} \cdot \text{h}^{-1}$.

Mean METs (indirect calorimetry) = μ = 4.70 METs

Mean METs (physical activity monitor) = $\bar{x}$ = 4.80 METs

Standard deviation = s = 0.27 METs

Sample size = n = 25

$$\text{Power}(\beta) = \Pr\left(t < \frac{\bar{x} - \mu}{s/\sqrt{n}}\right) = \Pr\left(t < \frac{4.80-4.70}{0.27/\sqrt{25}}\right) = 0.9678 = 96.8\%$$

APPENDIX B

Complete List of Variables Generated From the Raw Acceleration Data.

The following are mathematical formulae and/or definitions for the additional variables calculated from 30-second intervals of raw acceleration data, collected at 64 Hz. The following variables were calculated for each of the three axes of acceleration data. Let x_i represent the i^{th} acceleration value in one 30-second interval of data in one axis (1920 values).

Mean: $\mu_x = \frac{1}{1920}\sum_{i=1}^{1920} x_i$

Median: Upon ordering the acceleration values from smallest to largest, the median (m) is the mean of the 960th and 961st values.

Mode: Upon determining the frequency of each acceleration value, the mode is the value that occurs most frequently, or the mean of the values that occur equally frequently.

Variance: $x_{VARIANCE} = \frac{1}{1920}\sum_{i=1}^{1920}(x_i - \mu_x)^2$

Minimum: x_{min}, the smallest acceleration value in the interval.

Maximum: x_{max}, the largest acceleration value in the interval.

Range: $x_{RANGE} = x_{max} - x_{min}$

Sum of squares: $x_{SS} = \frac{1}{1920}\sum_{i=1}^{1920}(x_i)^2$

Auto-correlation: The autocorrelation function of the interval, after subtraction of the mean from each value and normalization. Computed using the MATLAB function "autocorr".

Cross-correlation: The cross-correlation function between two intervals, after subtraction of the mean from each value and normalization. Computed using the MATLAB function "crosscorr".

Dominant frequency: The most powerful frequency within the signal, after fast-Fourier transformation of the signal into the frequency domain.

Magnitude of the dominant frequency: The magnitude of the power of the dominant frequency.

“Validity of the Apple iPhone/iPod Touch® as an Accelerometer-based Physical Activity Monitor: A Proof-of-concept Study”
by Nolan M, Mitchell JR, Doyle-Baker PK
Journal of Physical Activity & Health

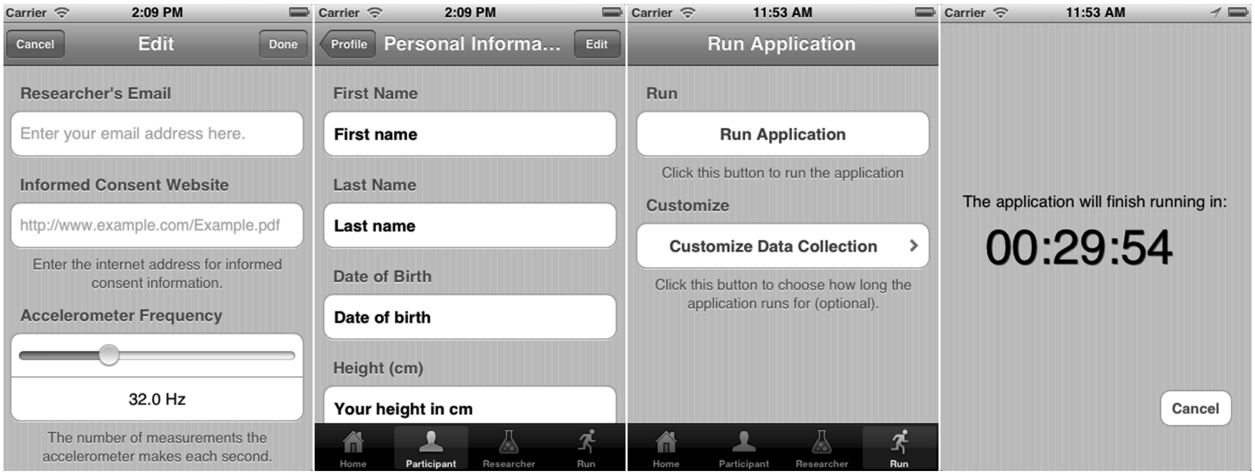

Figure 1.

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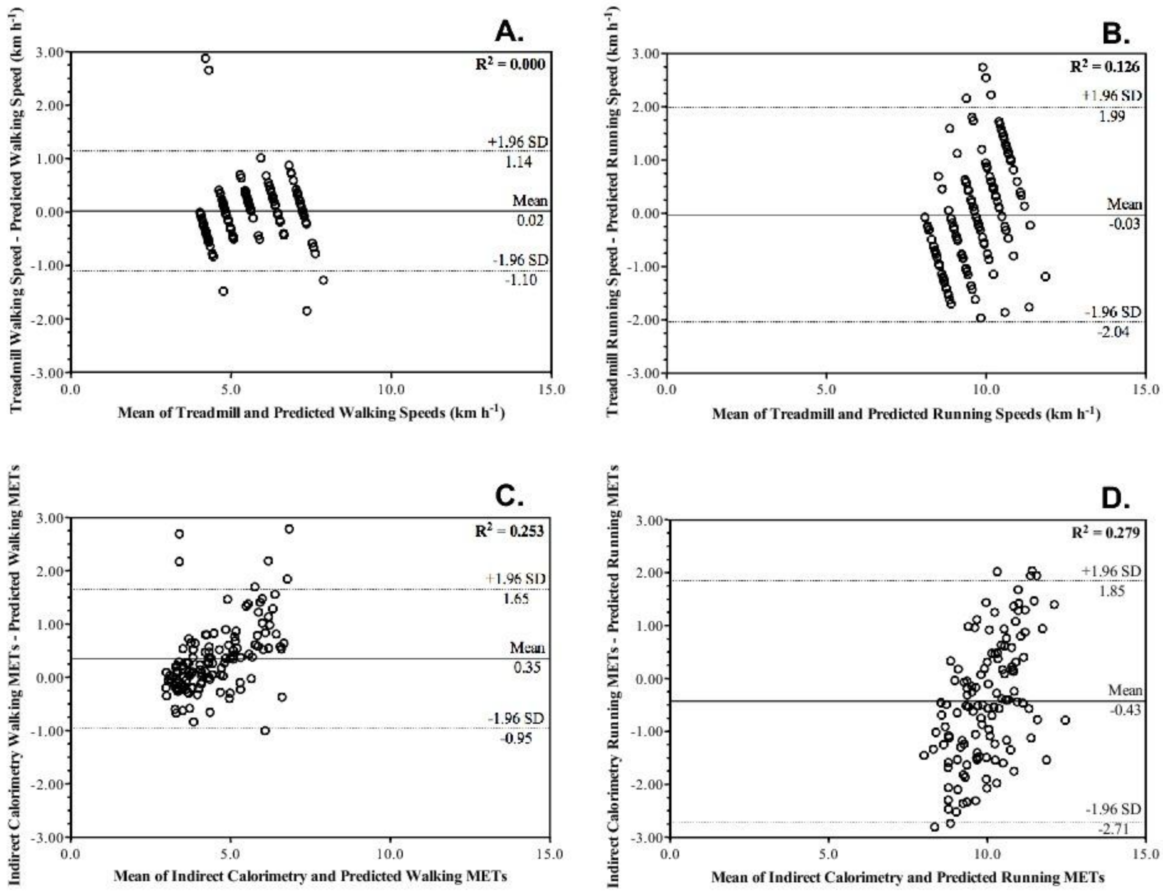

Figure 2.

Table 1. Participants' characteristics.

Parameters	**Female (n = 14)**	**Male (n = 11)**	**All (N = 25)**
Age (yr)	25 (2.6)	26 (4.1)	25 (3.3)
Height (m)	1.65 (0.06)	1.78 (0.07)**	1.71 (0.09)
Weight (kg)	59.8 (7.8)	74.6 (6.0)**	66.3 (10.2)
Body Mass Index ($kg \cdot m^{-2}$)	21.9 (1.9)	23.5 (1.6)*	22.6 (1.9)

Data presented as mean (SD).

BMI, body mass index; All, characteristics of male and female participants used for the development and cross-validation of predictive models.

* Significant difference between males and females ($p < 0.05$).

** Significant difference between males and females ($p < 0.001$).

Table 2. . Logistic panel regression model to classify activity type (walking or running), and cross-validation results.

Variable	Coefficient	Wald's C^2	P	Classification Accuracy (%)	*F*-score (%)	
					Walking	Running
Intercept	-10.76	25.2	< 0.001	99.0	99.1	98.4
Y_{SD}	14.24	26.0	< 0.001			

Model yields the logarithm of the odds of running.

Wald's C^2, relative importance of variable in panel regression model; classification accuracy, percentage of correctly classified intervals over total number of intervals (n = 291) using the leave-one-out cross-validation procedure; *F*-score, harmonic mean of sensitivity and positive predictive value of classification model.

Table 3. Models to estimate walking and running speed, and cross-validation results.

Variable	Coefficient	Wald's c^2	P	$\overline{X}_{ERROR}$ (95% CI)	SEE
Walking speed ($km \cdot h^{-1}$)					
Intercept	-1.85	2.38	0.123	0.02	0.57
Y_{SD}	6.82	132	<0.001	(-1.10, 1.14)	
X_{RMS}	3.36	16.7	<0.001		
Height	0.0003	14.2	<0.001		
Running speed ($km \cdot h^{-1}$)					
Intercept	6.94	303	<0.001	-0.03	1.02
$AU \cdot min^{-1}$	0.002	53.9	<0.001	(-2.03, 1.97)	
Sex	0.483	5.02	0.025		

Models yield walking and running speeds in kilometers per hour.

Y_{SD}, standard deviation of vertical acceleration data (0.02g to 0.68g) ; X_{RMS}, root mean square of medio-lateral acceleration data (0.04g to 0.52g); Height, participants' height in meters (1.57m to 1.88m); $AU \cdot min^{-1}$, acceleration units (counts) per minute (412.31 to 2686.40); Sex, participant's sex (female = 0, male = 1); Wald's c^2, relative importance of variable in panel regression model; SEE, standard error of estimate using the leave-one-out cross-validation procedure; $\overline{X}_{ERROR}$ (95% CI), mean over (positive) or under (negative) estimation (bias), and the 95% confidence intervals of these biases upon comparison to known speed.

Table 4. Published models used to estimate energy expenditure (METs) from walking and running speed.

Reference	Authors	Model	SEE (METs)
Walking			
16	ACSM	[0.1(Speed) + 1.8(Incline)(Speed) + 3.5]/3.5	-
2	Balogun et al.	$[0.003(\text{Speed})^2 – 0.3(\text{Speed}) + 17.8]/3.5$	0.4
4	Blessey et al.	$[0.0008(\text{Speed})^2 + 7.5]/3.5$	0.7
8	Brooks et al.	0.832(Speed) – 0.016(Weight) – 0.196(Sex) + 1.034	0.4
10	Bubb et al.	$[0.003(\text{Speed})^2 – 0.36(\text{Speed}) + 21.1]/3.5$	0.4
24	Pearce et al.	$[4.38(\text{Speed})^2 – 1.81(\text{Speed}) + 6.3]/3.5$	0.6
Running			
16	ACSM	[0.2(Speed) + 0.9(Incline)(Speed) + 3.5]/3.5	-

Speed, $m \cdot min^{-1}$, except Brooks et al., where speed is $km \cdot h^{-1}$, and Bubb et al., where speed is $m \cdot h^{-1}$; Weight, kg; Sex, 1 = Male, 2 = Female; Incline, decimal incline of surface (*eg* 1% = 0.01).

Table 5. Cross-validation results for the prediction of METs using published models.

	ACSM		Balogun et al.		Blessey et al.		Brooks et al.		Bubb et al.		Pearce et al.	
Walking	$\overline{X}_{ERROR}$ (95% CI)	SEE	$\overline{X}_{ERROR}$ (95% CI)	SEE	$\overline{X}_{ERROR}$ (95% CI)	SEE	$\overline{X}_{ERROR}$ (95% CI)	SEE	$\overline{X}_{ERROR}$ (95% CI)	SEE	$\overline{X}_{ERROR}$ (95% CI)	SEE
4.0 km·h^{-1}	-0.22 (-0.80,0.37)	0.36	-0.18 (-0.85,0.49)	0.38	-0.14 (-0.73,0.46)	0.33	-0.09 (-0.79,0.61)	0.36	0.15 (-0.45,0.74)	0.33	0.20 (-0.45,0.85)	0.38
4.8 km·h^{-1}	0.04 (-0.58,0.65)	0.31	-0.01 (-0.69,0.68)	0.34	0.11 (-0.52,0.73)	0.33	0.06 (-0.63,0.76)	0.35	0.43 (-0.19,1.06)	0.53	0.38 (-0.28,1.05)	0.51
5.6 km·h^{-1}	0.47 (-0.61,1.55)	0.71	0.14 (-1.08,1.35)	0.62	0.47 (-0.59,1.54)	0.71	0.38 (-0.99,1.76)	0.79	0.69 (-0.17,1.55)	0.82	0.65 (-0.61,1.92)	0.91
6.4 km·h^{-1}	0.77 (-0.20,1.74)	0.91	-0.32 (-2.35,1.71)	1.07	0.61 (-0.57,1.78)	0.84	0.39 (-0.73,1.50)	0.68	0.55 (-1.22,2.31)	1.04	0.54 (-0.89,1.97)	0.90
7.2 km·h^{-1}	1.62 (0.40,2.85)	1.30	-0.56 (-2.94,1.81)	1.20	1.20 (-0.24,1.64)	1.40	1.00 (-0.34,2.34)	1.21	0.56 (-1.57,2.68)	1.20	0.86 (-0.83,2.54)	1.20
All speeds	0.54 (-1.02,2.09)	0.96	-0.19 (-1.80,1.42)	0.84	0.45 (-0.91,1.81)	0.82	0.35 (-1.30,1.65)	0.75	0.47 (-0.90,1.85)	0.85	0.53 (-0.74,1.80)	0.84

	ACSM	
Running	$\overline{X}_{ERROR}$ (95% CI)	SEE
8.1 km·h^{-1}	-1.25 (-2.96,0.47)	1.51
8.9 km·h^{-1}	-0.80 (-2.87,1.27)	1.31
9.7 km·h^{-1}	-0.50 (-2.64,1.65)	1.18
10.5 km·h^{-1}	-0.07 (-2.27,2.13)	1.10
11.3 km·h^{-1}	0.48 (-1.31,2.27)	1.01
All Speeds	-0.43 (-2.71,1.84)	1.24

CI, confidence interval; SEE, standard error of the estimate.

Table 6. Repeatability of acceleration measurements.

	Y_{SD}	X_{RMS}	$AU \cdot min^{-1}$
	P	**P**	**P**
Between Devices	0.125	0.245	0.466
Between Trials	0.901[⚲]	0.066	0.073
Effect of Trial on Devices	0.905	0.297[⚲]	0.118

[⚲] Greenhouse-Gaussier corrected value. P, p-value.