Using machine learning methods to predict physical activity types with Apple Watch and Fitbit data using indirect calorimetry as the criterion.

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Abstract

Background There is considerable promise for using commercial wearable devices for measuring physical activity at the population level. The objective of this study was to examine whether commercial wearable devices could accurately predict lying, sitting, and intensity level of other activities in a lab-based protocol.

Methods We recruited a convenience sample of 49 participants (23 men and 26 women) to wear three devices, an Apple Watch Series 2, a Fitbit Charge HR2, and and iPhone 6S. Participants completed a 65-minute protocol consisting of 40 minutes of total treadmill time and 25 minutes of sitting or lying time. Indirect calorimetry was used to measure energy expenditure. The outcome variable for the study was the activity class; lying, sitting, walking self-paced, and running 3 METs, 5 METs, and 7 METs. Minute-by-minute heart rate, steps, distance, and calories from Apple Watch and Fitbit were included in four different machine learning models.

Results Our dataset included 3656 and 2608 minutes of Apple Watch and Fitbit data, respectively. We tested decision trees, support vector machines, random forest, and rotation forest models. Rotation forest models had the highest classification accuracies at 82.6% for Apple Watch and 89.3% for Fitbit. Classification accuracies for Apple Watch data ranged from 72.5% for sitting to 89.0% for 7 METs . For Fitbit, accuracies varied between 86.2% for sitting to 92.6% for 7 METs .

Conclusion This study demonstrated that commercial wearable devices, Apple Watch and Fitbit, were able to predict physical activity types with a reasonable accuracy. The results support the use of minute-by-minute data from Apple Watch and Fitbit combined with machine learning approaches for scalable physical activity type classification at the population level.

Introduction

The introduction of commercial wearable devices for physical activity monitoring has been an exciting development with the potential to increase physical activity at the population level.[1,2] We define commercial wearable devices as those used primarily by individual consumers for physical activity monitoring rather than for research purposes.[1]

Research examining commercial wearable devices has primarily focused on two areas. First, examining the reliability and validity of the measures that the devices provide, including step counts, heart rate, and energy expenditure.[3–5] A systematic review found that wearable devices were accurate for tracking step count, but may be less accurate for measuring energy expenditure or heart rate.[6] The second primary research area for commercial wearable devices is how available measures, particularly steps, from commercial devices, translate to current physical activity recommendations. For example, Tudor-Locke et al., 2011, found that approximately 8000 steps/day is a good proxy for 30 minutes of daily moderate to vigorous physical activity (MVPA) and 7000 steps/day, seven days a week is consistent with obtaining 150 minutes of weekly MVPA.[7,8]

Despite the promising research examining commercial wearables, at least two important areas remain unexplored. First, commercial wearable devices tend to focus on step counts as a user goal, rather than other factors such as sedentary behaviour, and physical activity intensity which are also movement indicators of health. Yet, current physical activity guidelines are based on minutes of moderate to vigorous physical activity.[9] Second, commercial wearable devices use proprietary methods for estimating steps, heart rate, and calories, sleep, sedentary behaviour, and physical activity. Proprietary methods are unknown and make standardization between different commercial wearable devices difficult or impossible.

The purpose of this study is to examine whether commercial wearable devices (Apple Watch and Fitbit) can accurately predict sedentary behaviour and light, moderate, and vigorous physical activities and to develop indicators to assist in predictions for future studies. We hypothesize that commercial wearable devices will accurately predict moderate and vigorous physical activity, but may not differentiate well between light and sedentary behaviour. As a secondary objective, we examine whether accounting for the type of device could improve classification results. If device type is an important feature for classification, this may be an important first step in standardization between devices.

Participants

We recruited 49 participants (23 men and 26 women) to use three devices, an Apple Watch Series 2, a Fitbit Charge HR2, and an iPhone 6S. We chose Apple Watch and Fitbit for this study because they have the highest market share among wearable devices.[5] We randomly assigned the Fitbit wear location and placed the Apple Watch on the opposite wrist. Participants were given an iPhone 6S with a custom iOS App called Physical Activity, Sleep, and Sedentary Behaviour Mobile (PASS Mobile). PASS Mobile collects minute-by-minute data from Fitbit and Apple Watch. For Fitbit, the App connects to the Fitbit SDK.[10] For Apple Watch, the App connects to Apple HealthKit.[11] PASS Mobile was installed through Test Flight, the Apple development platform, and is not available publicly in the App Store. Ethical approval was obtained by the Memorial University Interdisciplinary Committee on Ethics in Human Research (ICEHR #20180188-EX). All participants provided signed informed consent.

Study Design

Participants engaged in a 65-minute protocol with 40 minutes of total treadmill time and 25 minutes of sitting or lying time. The protocol was similar to previous studies testing the reliability and validity of different physical activity monitors.[12] These studies show that changing speeds is important to ensure devices can recognize intensity changes. Figure 1 shows the study protocol. The first two phases of the protocol involve sedentary activity (i.e., lying on a cot and sitting on a chair) for a duration of 5 minutes each. Following this, participants moved to the treadmill and select a “self-paced” speed for 10 minutes. A

5-minute lying period followed. Participants then moved to the treadmill and walked at a pace of 3 METs for 10 minutes. Following the 3 MET treadmill activity, the participants lied on a cot for 5 minutes. Participants walked at an effort of 5 METs for 10 minutes, then had a 5-minute sitting period. Finally, each participant will complete a 10-minute period at 7 METs. The 5 minute rest periods were sufficient to lower participant heart rate and maintain steady state for these sedentary activities.[13] Additionally, the 10-minute treadmill periods are sufficient to estimate O_2 uptake at steady state during the specified activity (light – 3METs, moderate – 5 METs, vigorous – 7 METs) for the 10-minute durations. The information from the metabolic cart was used to create an outcome variable with seven predicted classes; lying, sitting, self-pace walk, walking at 3 METs, walking/running at 5 METs and walking/running at 7 METs.

For each stage involving a specified MET value, a VO_2 to METs calculator was used to calculate the METs of each individual. METs vary per person per specified duration of activity. This variation is related to the lean body mass and other physiological factors such as health status and age.[14–21]

Measures

The outcome variable for the study was activity classes based measures using Oxycon Pro metabolic cart. The study protocol included six classes; lying, sitting, walking self-paced, 3 METs, 5 METs, and 7 METs. The Oyxcon Pro has been shown to be a valid and reliable method for measuring energy expenditure.[22] The metabolic cart was calibrated according to manufacturer specifications every morning of data collection.

Through the PASS Mobile App we collected 1 Hz heart rate, steps, distance, and calories separately from Apple Watch and Fitbit. Apple Watch and Fitbit collected slightly different data. For calories, Apple Watch collects active calories, that do not include a constant to account for basal metabolic rate. Therefore it was plausible that during sitting or lying participants had a true value of zero calories for Apple Watch. Fitbit provides total energy expenditure using the MD Mifflin-St Jeor equation,[23,24] which means Fitbit reports energy expenditure for every minute even when the participant is sitting or lying.

Analyses

Statistical analyses were performed using R (version 3.6.1) and Weka (version 3.8.3). Data were downloaded from the metabolic cart (Oxycon Pro, Jaeger, Hochberg, Germany). We used previously published methods to convert breath-by-breath data to second-by-second MET intensity estimates.[25]. We have published the code for this analysis on GitHub (https://github.com/walkabillylab/jaeger_analysis).

Analysis was conducted separately for Apple Watch and Fitbit. We first cleaned the data and used linear interpolation on steps, heart rate, calories, and floors climbed to impute missing data. Following this, we developed a feature set that included intensity (Karvonen Formula)[26,27] which calculates individualized target heart rate parameters, steps entropy, which is a measure of predictability of step count, and correlation coefficient between heart rate and steps[28]. We developed the features in order to consider multiple physiological characteristics that could explain sedentary, light, moderate, and vigorous physical activity (See Table 1).

We used four different classification methods, Random Forest[29,30], Rotation Forest[31], Support Vector Machine (SVM)[32], and Decision Trees in our analysis.[33] Model accuracy was examined using k-fold cross-validation. Data were randomly split into 10 subsamples. For each subsample, classification algorithms were developed. Each algorithm was then used to predict the error associated with each one of the subsamples. A sum of prediction errors was calculated over all subsamples to produce a final prediction error rate.[34] In each model we included the features described in Table 1 and age, gender, height, and weight. We chose these models because SVM[35] and Random Forest models[36] are common in physical activity research using research grade accelerometers and Rotation Forest and Decision Trees are similar methods to Random Forest.

We evaluated model fit using accuracy, sensitivity, specificity, confusion matrices, and feature ranking. Finally, to answer our second research question we combined the Fitbit and Apple Watch data and added an additional feature, device type to see the difference between devices.

Results

Participants included 26 females and 23 males. The average age was 29.3 (min 18 – max 56). Table 1 shows mean and standard deviation values for continuous variables or count, and percent for categorical predictors for Apple Watch and Fitbit, respectively. The average height and weight were 1.69 m and 70.6Kg, respectively. Average heart rate was 91.1 for Apple Watch and 75.3 for Fitbit. Average steps per minute were 181.4 and 7.7 for Apple Watch and Fitbit, respectively. Table 1 also shows the feature descriptions and descriptive statistics for each feature included in the Rotation Forest model.

Table 1
Feature descriptions and descriptive statistics for each feature included in the Rotation Forest Model.

Variable	Description	Apple Watch Mean (SD)	Fitbit Mean (SD)
Steps/minute	Number of steps/minute	181.4 (270.4)	7.7 (21.8)
Heart Rate (minute)	Average heart rate/minute	91.1 (26.8)	75.3 (38.7)
Energy Expenditure	Amount of calories expended	5.8 (7.3)	40.8 (33)
Distance (metres)	Distance ran in metres	0.1 (0.1)	23.8 (58)
Heart Rate Entropy	Measure of heart rate variability	6.1 (0.2)	5 (2.3)
Steps Entropy	Measure of steps variability	6.1 (0.2)	3.9 (2.7)
Resting Heart Rate	10th percentile of HR data	68.3 (11.9)	59.1 (38.9)
Correlation Heart Rate and Steps	Correlation coefficient between heart rate and steps	0 (0.7)	0.7 (0.6)
Intensity (Karvonen Formula)	Intensity zone during activity	0.2 (0.2)	0.1 (0.2)
Steps*Distance	Product measure of total amount of steps and distance covered in metres	40.3 (113.5)	967.6 (5275.1)
SD Normalized Heart Rate	Standard deviation of normalized heart rate	8.8 (10.1)	7.7 (15.7)

Table 2
The overall percentage accuracy per each classifier for Apple Watch and Fitbit for interpolated data

	Apple Watch	Fitbit
Decision Tree	41.39	62.34
SVM	50.87	56.66
Random Forest	81.95	90.80
Rotation Forest	82.60	89.26

Table 2 shows the overall classification accuracies for the Decision tree, Random Forest, SVM and Rotation Forest models. The Rotation Forest had the best accuracy for Apple Watch and Fitbit compared to the other classifiers. Tables 3 and 4 show the confusion matrices from the Rotation Forest model for Apple Watch and Fitbit data, respectively. Table 5 shows the top 8 features from the Chi-Squared feature ranking for the Rotation Forest models for Apple Watch and Fitbit, respectively.

Table 3
The confusion matrix for Apple Watch data from Rotation Forest (values in percentage)

Predicted as ↓	**Lying**	**Sitting**	**Self Paced walk**	**Running 3 METs**	**Running 5 METs**	**Running 7 METs**
Lying	613 (78.79%)	59 (10.73%)	24 (4.66%)	51 (8.9%)	30 (4.76%)	10 (1.64%)
Sitting	48 (6.17%)	399 (72.55%)	25 (4.85%)	7 (1.22%)	41 (6.51%)	32 (5.25%)
Self Paced Walk	25 (3.21%)	28 (5.09%)	454 (88.16%)	10 (1.75%)	11 (1.75%)	1 (0.16%)
Running 3 METS	50 (6.43%)	7 (1.27%)	9 (1.75%)	493 (86.04%)	10 (1.59%)	3 (0.49%)
Running 5 METS	27 (3.47%)	25 (4.55%)	3 (0.58%)	9 (1.57%)	518 (82.22%)	21 (3.44%)
Running 7 METS	15 (1.93%)	32 (5.82%)	0 (0%)	3 (0.52%)	20 (3.17%)	543 (89.02%)

Table 4
The confusion matrix for Fitbit data from Rotation Forest (values in percentage)

Predicted as ↓	**Lying**	**Sitting**	**Self Paced walk**	**Running 3 METs**	**Running 5 METs**	**Running 7 METs**
Lying	505 (88.13%)	15 (4.05%)	24 (6.38%)	26 (6.91%)	11 (2.76%)	11 (2.14%)
Sitting	16 (2.79%)	319 (86.22%)	8 (2.13%)	0 (0%)	20 (5.01%)	15 (2.92%)
Self Paced Walk	6 (1.05%)	13 (3.51%)	333 (88.56%)	4 (1.06%)	1 (0.25%)	3 (0.58%)
Running 3 METS	25 (4.36%)	1 (0.27%)	5 (1.33%)	338 (89.89%)	7 (1.75%)	2 (0.39%)
Running 5 METS	16 (2.79%)	10 (2.7%)	3 (0.8%)	6 (1.6%)	357 (89.47%)	7 (1.36%)
Running 7 METS	5 (0.87%)	12 (3.24%)	3 (0.8%)	2 (0.53%)	3 (0.75%)	476 (92.61%)

Finally, we included the device type as a feature to the Rotation Forest model to examine the potential of device as important in predicting activity type. The results were similar to the accuracy being 85.9% with the device type variable being ranked 13th overall in terms of feature importance.

Table 5
Chi-Squared feature ranking results for Apple Watch and Fitbit from the Rotation Forest model

Ranking	Apple Watch	Fitbit
1	Heart Rate	Distance
2	Normalized Heart Rate	Steps
3	Steps	Heart Rate
4	Intensity	Normalized Heart Rate
5	Calories	Steps*Distance
6	Distance	Intensity _Low Energy
7	Steps*Distance	Calories
8	SD Normalized HR	SD Normalized HR
9	Correlation Heart Rate and Steps	Entropy Steps Per Day
10	Weight	Resting Heart Rate

Discussion

This study used machine learning techniques in an attempt to improve the accuracy of physical activity intensity classification measured via indirect calorimetry, from commercial wearable devices, Apple Watch and Fitbit. Our research differs from previous research in that we use minute by minute data collected from the commercial wearable devices.[37] New features were developed using a combination of device-based features which included heart rate, step count and calories and features sourced from existing literature.

The Rotation Forest algorithm achieved the highest accuracy for classifying sedentary, light, moderate, and vigorous activity from Apple Watch and Fitbit data; the overall percentage accuracy for all four activity intensity levels are slightly lower than previous research using research grade wearable devices.[30,38,39] The accuracy of models in studies using research grade wearables ranged from approximately 60–90%. The class specific predictive accuracies from the Rotation Forest model tended to be higher for activities greater than 3 METs and lower for low intensity and sedentary activities for both Fitbit and Apple Watch[1].

We show that the overall accuracy is slightly higher for Fitbit compared to Apple Watch. Previous studies have shown that the Apple Watch is more accurate for individual measures.[40–43] We further explored the reasons why we show differences between the devices using feature ranking. The results of feature ranking showed that for Apple Watch, heart rate was the most important, while for Fitbit, steps was more important. Among the top six most important features for both Fitbit and Apple Watch were the raw features, heart rate, steps, calories, and distance.

We developed new features based on the literature including normalized heart rate and intensity using the Karvonen formula, which were important in model accuracy. Conversely, previous features thought to be important for classifying moderate activity (100 steps/minute) were not important in our models. This is may be because our classification model includes multiple classes and features that differ from previous research.

Overall, the findings of this study achieved accuracy estimates of energy expenditure are similar to what has been published in literature. This study found that the type of activity tracker may impact accuracy, however, we only examine differences between two devices. The practical significance of differences between devices might be relatively minor when the devices and models are used in population-based samples.

Limitations

There are a number of limitations to this study. First, unlike research grade devices, commercial wearables include much more missing data. We attempted to deal with these missing data by imputation. Future research should examine imputation methods and their impact of model accuracy. Second, the devices we used for our research are now relatively old. This is common with wearable device research. We cannot know if newer devices provide less missing data or more accurate measures of the ground truth. Finally, our results show that device type was not important in predictions. However, we believe that given the unknown nature of the algorithms used to measure heart rate, steps, calories, and distance, by commercial companies, researchers should continue to develop methods to attempt to account for algorithmic differences when these algorithms are unknown.

Conclusion

This study demonstrated that commercial wearable devices such as Apple Watch and Fitbit were able to predict physical activity type with a reasonable accuracy. The results support the use of raw data from Apple Watch and Fitbit combined with our machine learning approach for scalable physical activity type classification at the population level.

Declarations

Ethical Approval and consent to participate.

Ethical approval was obtained by the Memorial University Interdisciplinary Committee on Ethics in Human Research (ICEHR #20180188-EX). All participants signed paper consent forms.

Consent for Publication

Not applicable

Availability of Data and Materials

Data are publicly available on the BeapLab Dataverse: https://doi.org/10.7910/DVN/ZS2Z2J

Analysis code is available on Github: https://github.com/walkabillylab/wearable_device_classification

Competing Interest

The authors do not have any competing interests.

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Authors’ Contributions

DF conceptualized the paper. All authors assisted with data collection. DF, JRA, BS, AB, HL conducted data analysis. All authors contributed to writing the manuscript and approved the submitted version.

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Figures

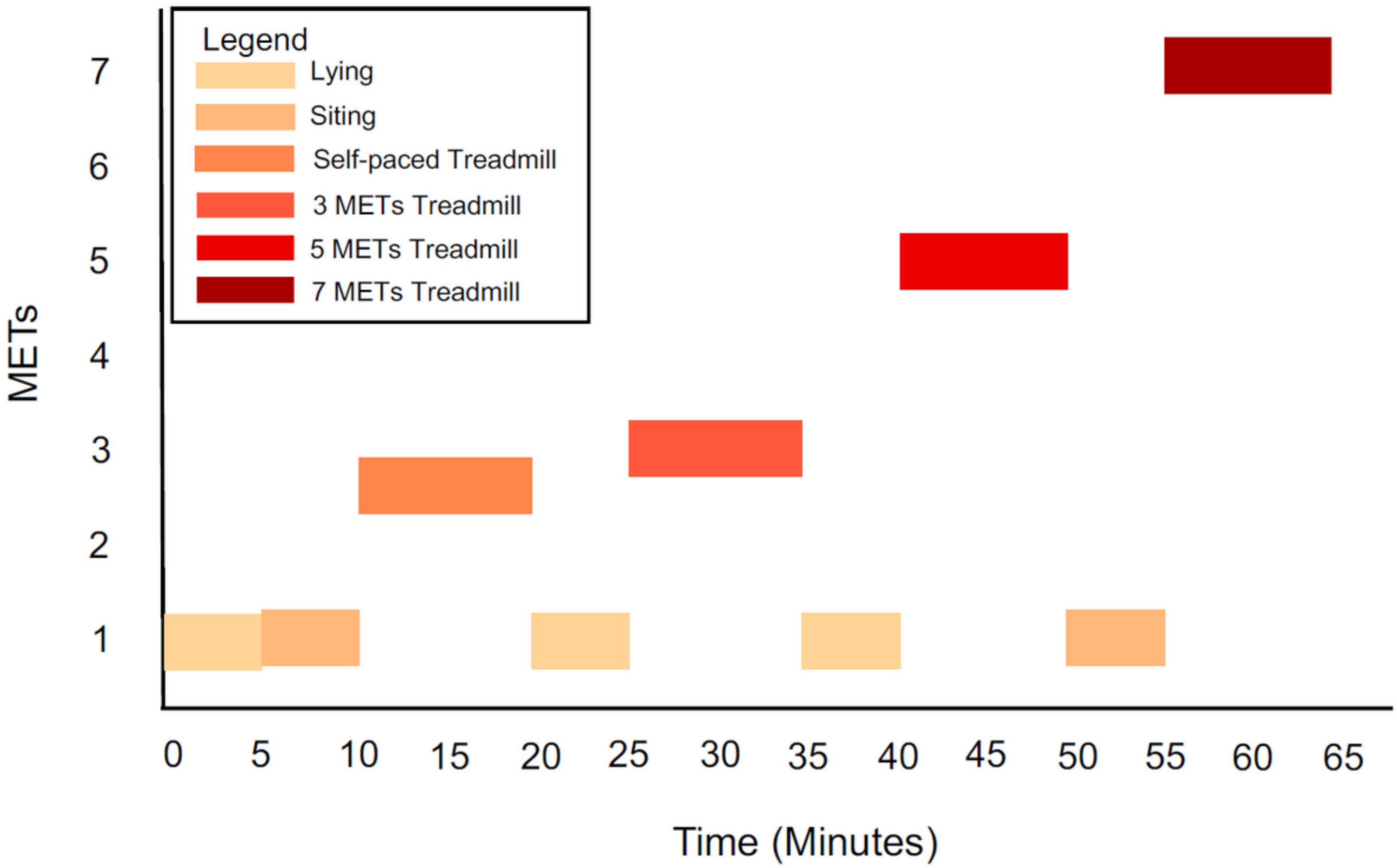

Figure 1

65-minute lab-based activity protocol

Supplementary Files

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- FitbitTreeDecisionTree.pdf
- ApplewatchTreeDecisionTree.pdf