May 20th, 11:00 AM

Validating and Testing Wearable Sensors to Assess Physical Activity and Sedentary Behavior in the Center for Personalized Health Monitoring

Patty Freedson
University of Massachusetts Amherst

Follow this and additional works at: http://escholarship.umassmed.edu/cts_retreat

Part of the Biomedical Devices and Instrumentation Commons, Biotechnology Commons, Diagnosis Commons, Exercise Science Commons, Motor Control Commons, and the Translational Medical Research Commons

This work is licensed under a Creative Commons Attribution-Noncommercial-Share Alike 3.0 License.

Freedson, Patty, "Validating and Testing Wearable Sensors to Assess Physical Activity and Sedentary Behavior in the Center for Personalized Health Monitoring" (2014). UMass Center for Clinical and Translational Science Research Retreat. 7.
http://escholarship.umassmed.edu/cts_retreat/2014/presentations/7

This material is brought to you by eScholarship@UMMS. It has been accepted for inclusion in UMass Center for Clinical and Translational Science Research Retreat by an authorized administrator of eScholarship@UMMS. For more information, please contact Lisa.Palmer@umassmed.edu.
Validating and Testing Wearable Sensors to Assess Physical Activity and Sedentary Behavior in the Center for Personalized Health Monitoring

Patty Freedson, Ph.D.
Co-Chair, Organizing Committee, Center for Personalized Health Monitoring
Department of Kinesiology
School of Public Health and Health Sciences
University of Massachusetts Amherst

May 20, 2014
Outline

- Introduction
- Validation of wearable sensors
- Testing of wearable consumer activity trackers
- Capability of sensor evaluation in Human Testing Center in Center for Personalized Health Monitoring (CPHM)
Human testing facilities in the Center for Personalized Health Monitoring

- Research on wearable monitors to develop algorithms to translate sensor signals into meaningful and biologically valid output for clinical applications
  - Establishing meaning to personal biomarkers of health

- To determine the functionality and wearability of sensors

- Evaluation to determine how human movement affects brain, muscle, bone, tendons, ligaments and supporting structures and systems

- Translation: Evaluation of sensors for the commercial pipeline by establishing accuracy, effectiveness and usability of sensors
  - Usefulness of the ‘Quantified Self’
Relationship between Actigraph counts and METS

\[ r^2 = 0.82 \]
\[ \text{SEE} = 1.12 \text{ METs} \]

Freedson et al., MSSE, 1998
Activity counts and cutpoints

Counts

Clock time

Vigorous

Moderate
Minutes of moderate to vigorous physical activity: NHANES 2003-2004

Troiano et al., MSSE 2008
Traditional Data Processing of Accelerometer Data

- Provide physiological meaning to accelerometer data

- Linear regression models
  - Predict point estimate of energy expenditure
  - Classify activity intensity

- Extensively used in the literature to characterize/quantify physical activity behavior

- Numerous revised regression models
  - Confusion in the literature

- Method fails to discriminate intensity levels properly
  - Similar counts with different energy expenditure
    - Walking uphill vs walking on level ground
  - Different counts with same energy expenditure
These three time series of simulated accelerometer data have the same total or mean counts per minute. They would all be classified as “moderate” activity using typical data processing methods, but they could represent activities with substantially different energy costs.
How Can We Maximize the Information Collected?

- Use entire sequence and pattern of accelerometer signal
  - Use features of signal
  - Process with pattern recognition algorithms

- Continual ‘learning’ by example
  - Powerful
  - Flexible
Advanced Data Processing: Machine Learning

Artificial Neural Network

Input layer -> Hidden layer -> Output layer

Input #1 -> Input #2 -> Input #3 -> Input #4

Random Forest

Support Vector Machine
We tested the method on data from Crouter et al. (2006).

48 subjects did a variety of activities.

Indirect calorimetry used to estimate average PAEE for each person & activity.

Leave 1 out cross validation: method never fit and evaluated on same subject’s data.

Staudenmayer et al, JAP, 2009
Artificial neural network trained to estimate METs and applied to independent dataset

Fig. 1. Measured metabolic equivalents (METs) vs. METs predicted from neural network (nnetMET). The nnetMET was developed on University of Massachusetts (UMass) data set \((n = 277)\) and applied to University of Tennessee \((n = 65)\) data set. The bias was 0.32 METs, and the root mean square error (RMSE) was 1.90 METs.

Freedson et al, JAP, 2011
Machine learning models to detect activity types developed and tested in lab and free living settings in older adults

Sasaki, et al, In Preparation
Consumer wearable sensors to estimate activity and sleep

- Fitbit One
- Samsung Gear Fit
- Fitbit flex
- Garmin Vivofit
- Nike Fuel
- Jawbone Up
- Misfit Shine
- Basis Carbon Steel
- Polar loop

Consumer wearable sensors to estimate activity and sleep.
Accuracy of the Fitbit in estimating energy expenditure

Methods

- N = 20 college-age participants
- Performed treadmill walking and running and other activities
- Compared ee from indirect calorimetry to fitbit estimate of ee

Fitbit EE vs Indirect calorimetry

Sasaki et al., JPAH, ahead of print, 2014
Compete or share with friends
Up for a little healthy competition? Bring friends and family in on the fun so you can compare stats, share progress, and cheer each other on. Your leaderboard refreshes all day long in the Fitbit App so you know exactly how many more steps you need to rise to the top.
Fitbit output wirelessly transmitted to smart phone or computer: sleep and activity data

Calories Burned  Steps  Active score  every 5 minutes

Today's activity breakdown (excluding sleep):

- Sedentary: 13 hours 56 minutes
- Lightly active: 1 hour 19 minutes
- Fairly active: 1 hour 32 minutes
- Very active: 1 hour 13 minutes
How does this relate to the CPHM?

- This work uses off the shelf activity sensors
- We have established ourselves as leaders in the activity monitor testing and algorithm development space
- Most of our previous work is in lab settings

In CPHM we will have the capacity to:
- Test many types of sensors built in house collaborating with electrical and computer engineering, polymer science, computer science, mathematics and statistics, other disciplines
- Work with industry (e.g. medical device companies, activity monitor companies)
- Test in real world instrumented home setting
- Study clinical applications
- Use in interventions for self monitoring
- Social media for motivation and sustaining behavior change
Human testing facilities in CPHM
Human testing facilities in CPHM
Human testing facilities in CPHM
Human testing facilities in CPHM
Normalized overlaid plot for a representative participant (10-year-old boy, weight = 76.5 kg, height = 155 cm) obtained during first 600 min of the ~24-h stay in the whole-room indirect calorimeter.

AHA Scientific Statement

Guide to the Assessment of Physical Activity: Clinical and Research Applications
A Scientific Statement From the American Heart Association

Scott J. Strath, PhD, Chair; Leonard A. Kaminsky, PhD, Co-Chair;
Barbara E. Ainsworth, PhD, MPH, FAHA; Ulf Ekelund, PhD; Patty S. Freedson, PhD;
Rebecca A. Gary, RN, PhD; Caroline R. Richardson, MD; Derek T. Smith, PhD;
Ann M. Swartz, PhD; on behalf of the American Heart Association Physical
Activity Committee of the Council on Lifestyle and Cardiometabolic Health and Cardiovascular,
Exercise, Cardiac Rehabilitation and Prevention Committee of the Council on Clinical Cardiology, and
Council on Cardiovascular and Stroke Nursing

Circulation 128: 2259-2279, 2013
Decision matrix guide to selecting a physical activity measurement instrument

Acknowledgements

Collaborators

John Staudenmayer
David Pober
Scott Crouter
David Bassett
Amanda Hickey
Dinesh John
Sarah Kozey
Kate Lyden
Albert Mendoza
Jeffer Sasaki

Funding Support

NIH R01 CA121005
NIH U01 CA 130783
NIH RC1 HL0099557
Thank-you