Measurement of Physical Activity Behavior

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Physical Activity and Disease Prevention: Identifying Research Priorities
Dec 13-14, 2012
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Outline

- Current methods to assess physical activity and sedentary behavior
  - Self-report
  - Wearable sensors
- Calibration and validation of methods
  - Laboratory
  - Natural settings
- GIS/GPS
- Consumer devices
- Future research needs

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Many different self report tools

How tool is to be used should determine choice of self report
Strengths

- Low cost
- ‘Easy to administer’
- Can assess context
- Can assess history
- Low burden to participant
- Most practical for surveillance research
Weaknesses

- Measurement error/recall bias
- May not assess one or more dimensions of behavior
- May also miss certain activities
- Lack of validation for assessment of change in behavior following interventions
- Many types of self report – lack of standards to match need with appropriate tool
### Types of self-report tools

**Table 1** Traditional Categorization of Approaches to Self-Reported Physical Activity

<table>
<thead>
<tr>
<th>Category</th>
<th>Level of detail</th>
<th>Time frame</th>
<th>Common uses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diaries</td>
<td>High: recording of duration of all activities, sedentary behaviors, and sleep throughout a 24-hour period</td>
<td>Real time, often maintained for several days or a week</td>
<td>Validation of less burdensome measurement approaches</td>
</tr>
<tr>
<td>Logs</td>
<td>High: recording of requested details of specific activities of interest</td>
<td>Real time, past day, may be maintained for many weeks</td>
<td>Adherence to interventions</td>
</tr>
<tr>
<td>Recalls</td>
<td>Medium: recall of varying levels of detail (duration, frequency, intensity) of specific activities or categories of activities</td>
<td>Past 24 hours, past 7 days</td>
<td>Effects of interventions, assessment of current activity</td>
</tr>
<tr>
<td>Quantitative questionnaires</td>
<td>Medium: estimate varying levels of detail (duration, frequency, intensity) of specific activities or categories of activities</td>
<td>Usual week, past month, past year, lifetime</td>
<td>Assessment of longer-term activity, usual activity</td>
</tr>
<tr>
<td>Global surveys</td>
<td>Low: general categorization of activity level</td>
<td>Current, not specified</td>
<td>Ranking of usual activity</td>
</tr>
</tbody>
</table>

[Sternfeld and Goldman-Rosas, *JPAH, 2012* (suppl.)]
Primary concerns

- Not matching aims of study with appropriate self report instrument
- Lack of broad acceptance of use of measurement error models to ‘correct’ activity misclassification from self report tools
- Uncertainty about validity of self report tools to assess behavior change
- Missing certain behaviors for certain populations
Finally, there is no need to be apologetic about assessing PA or SB with self-report. The self-reported methods are not “second choice” methods when so-called objective methods cannot be used. Rather, they are valid methods in their own right and the optimal choice in certain circumstances.

Sternfeld and Goldman-Rosas, JPAH, 2012 (suppl.)
Wearable Sensors
Strengths

- Objective measure
- Assess behavior continuously over extended periods of time
- Obtain estimates of multiple measures (e.g. kcals, minutes, MET hrs, breaks from sitting, bouts of activity or inactivity)
- Provide real-time feedback to users or researchers
- Adaptable to mobile technology
Weaknesses

- Lack of standards of practice
  - Placement of sensors
  - Sampling frequency
  - Defining wear time
  - Defining ‘valid day’
- Different devices
- Different algorithms for translating output
- Compliance by user
- Data management/processing
  - Validity in natural settings
Early results of wearable monitor calibration/validation

- Freedson et al. 1998

\[ y = m(\text{counts} \cdot \text{min}^{-1}) + b \]

- Small Sample not representative of the population
- Only 3 treadmill activities

1. Point Estimates of Energy Expenditure (EE)
2. Cut-Point Method
   - Determine time spent in light, moderate or vigorous intensity activity

![Graph showing METS vs. Counts · min⁻¹](image)
Over 30 Prediction Models

- Brooks et al. 2005
- Hendelman et al. 2000
- Leenders et al. 2003
- Yngve et al. 2003
- Brooks et al. 2005
- Hendelman et al. 2000
- RT3 Proprietary
- Heil et al. 2006
- RT3 Proprietary
- Brooks et al. 2005
- Leenders et al. 2003
- Klippel et al. 2003
- Eston et al.
- Rychols et al. 2000
- Puyau et al. 2004
- Leenders et al. 2003
- Klippel et al. 2003
- Treuth et al. 2001
- Freedson et al. 2005
- Evenson et al. 2008
- Yngve et al. 2003
- Heil et al. 2006
- Brooks et al. 2005
- Heil et al. 2006
- Puyau et al. 2004
- Yngve et al. 2003
- Heil et al. 2006
Simple, rigid relationship between counts and EE

Freedson et al.
METs = 1.439008 + (0.000795 x cnts\cdot min^{-1})

Swartz et al.
METs = 2.606 + (0.0006863 x cnts\cdot min^{-1})

Klippel and Heil et al.

Crouter et al.

Using counts.min$^{-1}$ as the regression input ignores valuable information from the acceleration signal.
Artificial Neural Network

- Artificial Neural Network (ANN) – Non-linear statistical modeling tools
  - Very sophisticated, adaptive modeling technique that can change its structure based on internal and external information
  - Two step process
    1. Using representative data, invokes training algorithms to learn structure of data
    2. After “training phase” ANN can be applied to independent data sets to predict the output from known inputs
  - Often used in prediction and classification models
    - Predict medical condition
    - Stock market prediction

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ANN Development

- Staudenmeyer et al. (2009)

**Input**
- Neural Network Regression
- Neural Network Regression

**Output**
- METs
- Activity Type

- 48 subjects – variety of household and sporting activities
- Indirect calorimetry – measure energy expenditure for each person and activity
- Model Development – Leave 1 out cross validation
  - Never fit and evaluated on same subject’s data
ANN vs. Simple Regression

<table>
<thead>
<tr>
<th>Model</th>
<th>rMSE (METs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>1.22</td>
</tr>
<tr>
<td>Crouter</td>
<td>1.61</td>
</tr>
<tr>
<td>Swartz</td>
<td>1.77</td>
</tr>
<tr>
<td>Freedson</td>
<td>2.09</td>
</tr>
</tbody>
</table>

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Identification of Activity Type

- Average time correctly identified: 88.8% (95% CI: 86.4-91.2%)
  - Sedentary, Locomotion, Lifestyle (ADL) or Vigorous Sport
- Several subjects with 100% correct classification
How does the neural network perform on independent dataset with different activities?
Neural Network: Laboratory Calibration and Validation

**Input**
1. Temporal Dynamics
2. Distribution of Counts

Lab-Nnet

**Output**
METs

ANN rMSE = 1.22 METs
Freedson et al. *JAP*, 2011

rMSE = 1.90 METs
Staudenmayer et al. *JAP*, 2009

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ANN developed and validated in lab did not work well in natural conditions

Developed ‘sojourn’ method

- Decision tree before applying ANN
  - One of 5 signal patterns
  - Then apply ANN

\[ N = 13 \]

- Trained on \( n = 6 \) (3, 10 hr observations)
- Validated on 18, 10 hr observations
Lyden et al, unpublished data
Wearable Monitors to Assess Sedentary Behavior

- Actigraph accelerometers secured to waist to assess physical activity
- Pedometer secured to waist to assess physical activity
- ActivPAL secured to thigh to assess sedentary behavior
- Natural setting
- Direct observation as criterion
Sedentary Minutes for ActivPAL and Actigraph in Comparison to Direct Observation

Kozey-Keadle et al., MSSE, 2011
Detection of change in percent time sedentary

Kozey-Keadle et al., MSSE, 2011
GIS/GPS Tools
Why measure *where* PA occurs?

• Knowing where PA occurs is important to understand
  – What PA resources are being used?
  – What PA resources are needed where?
  – What disparities exist in use/need?
  – Does use of resources change with interventions?
How to measure where PA occurs?

- GPS devices matched with accelerometer data can indicate where PA occurs
  - Early studies have shown much PA occurs outside of our home neighborhood
- Programs like PALMS exist to help match GPS and accelerometer data
- Data are still messy & hard to aggregate into meaningful variables
- Need GIS expertise

![Map showing typical neighborhood buffer and actual GPS exposure by weekday & weekend]
A study in Denmark in teens demonstrated most PA occurs in shared yards
GPS can also improve PA measures

• If we invest in transportation infrastructure improvements e.g. bike lanes, sidewalks
  – We need to measure whether people use these new facilities
  – We need to better measure increases in biking, walking, and decreases in car driving due to these facilities
    • Laboratory studies don’t help us much with these free living behaviors
• Combining features of the GPS e.g. speed, satellite connectivity etc. can improve our assessment of biking, driving, walking.
UCSD TREC findings using Machine Learning, GPS, & accelerometer
92% accuracy in predicting transportation mode

<table>
<thead>
<tr>
<th>Known</th>
<th>Bike</th>
<th>Bus</th>
<th>Car</th>
<th>Sit</th>
<th>Stand</th>
<th>Walk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bike</td>
<td>140</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>Bus</td>
<td>2</td>
<td>86</td>
<td>25</td>
<td>5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Car</td>
<td>1</td>
<td>5</td>
<td>364</td>
<td>4</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>Sit</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>126</td>
<td>17</td>
<td>0</td>
</tr>
<tr>
<td>Stand</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>243</td>
<td>7</td>
</tr>
<tr>
<td>Walk</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>15</td>
<td>466</td>
</tr>
</tbody>
</table>
SenseCam for more specificity?

- As GPS increases our accuracy in locating activities, we also see deficiencies in the GIS data available.
- SenseCam images can provide more detail of where specific behaviors occur.
- Specificity will help with intervention design.
Summary

• GPS Pros
  – Accurate information on location (devices improving constantly)
  – GPS data can help predict key transportation behaviors
  – Knowledge in this area is growing & efforts at standardization being made (e.g. PALMS)
  – Participant compliance fairly high

• GPS Cons
  – Data requires smoothing
  – Algorithms to identify behaviors are complex & not available to everyone
  – GIS expertise required to map locations and match resources
    • GIS data may not match resolution of GPS data
Future research needs

- Further development and validation of self-report tools and data processing methods for wearable devices
  - Establishment of evidence-based practices need to address relative vs absolute intensity

- Evaluation of performance of self report tools and wearable devices for detecting change in activity and sedentary behavior

- Evaluation of effectiveness of tools for real-time self-monitoring of behavior using wearable sensors and mobile phones

- Evaluation of consumer devices

- Integration of self-report and sensor measures of physical activity
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SAVE THE DATES FOR ICAMPAM 2013 AMHERST

Website: [http://www.umass.edu/sphhs/icampam2013.html](http://www.umass.edu/sphhs/icampam2013.html)

Dates: June 17-19, 2013

Where: Amherst, Mass on the campus of the University of Massachusetts

Conference Themes: Physical Activity, Sedentary Behavior and Sleep Measurement

Topics
- Behavior and Health Outcomes
- Data Processing, Statistics, Computational Methods
- Validation and Calibration
- Engineering and Tool Development
- Clinical Applications

Session Format
- Keynote/Invited Lectures
- Symposia
- Oral Presentations
- Poster presentations

Key Dates
- Call for Abstracts/ Symposia Proposals: August 20, 2012
- Abstracts/Symposia Submission Deadline: November 19, 2012
- Registration Opens: December: December 2012

Mark your calendars!