Measuring Obesity Prevalence in Children: Possibilities

Stephen Intille, Ph.D.
Associate Professor
College of Computer and Information Science and Bouvé College of Health Sciences
Northeastern University
Boston, Massachusetts

Some projects mentioned by the NIH Genes and Environment Initiative (U01HL091737) and NIH NHLBI (R21HL108018-01)
What technology is being used and what is possible to gather data on BMI prevalence and trends of obesity in children? Want could be used to better understand variability?
Overview

• “Crazy ideas”

• More solid ideas on how technology could change measurement of mediators/moderators of obesity. Prompt some questions?
Challenge
Challenge

On hard surface, the base bends, effectively shortening distance between the fulcrum and the loading point.

Carpet supports base, so distance between fulcrum and loading point is larger.

Why we weigh more when the scales are on a carpet.
Disclaimer

- Technology may not do much better than what you have now (e.g., NHANES, BRFSS)
- You really want EHR integration and data sharing (who doesn’t?)
- And, ideas I can think of require either:
  - Policy change
  - Substantial resources
  - Buy-in from a tech giant (e.g., Google)
  - Intensive coordination among researchers
Partner with scale makers

Challenges:

- Buy-in
- Sampling bias
- Cost
- Measurement error
- Reach
- Wireless contract
Regular self-report via phones

- App sits in background

- Auto-detects locations where good measurement possible (school, gym, home w/ scale)

- Prompt for measurement 1/year

- Incentivize to facilitate engagement
text4BMI

- Phone number only; No app

- Data requests data 1/year

- Incentivize to facilitate engagement
Crowdsourcing: individuals

- Mobile/web app to incentivize measurement entry
  - Child to child
  - Parent to child
- Send data to national repository

- Challenges:
  - Incentives
  - Unique ID
  - Reach
Crowdsourcing: community HW

- People management software – citizens gathering data on other citizens in the neighborhood (similar to software used in political campaigns or census)

- Requires infrastructure, publicity, incentives
Kiosks

• Sampling people passing by using computer vision
  – Size
  – Height

• Expensive to create/maintain
• Highly localized
• Noisy measure
Crowdsourcing: pediatricians

- Website to incentivize measurement entry
  - Incentive for pediatrician
  - Incentive for child

- Send data to national repository

- Challenges: similar to other ideas
EHRs

- Pediatrician office EHR export
- Similar to “Blue Button” but for research

About Blue Button

The Blue Button lets you go online and download your health records so you can use them to improve your health, have more control over your personal health information and your family’s healthcare.

- Do you want to feel more in control of your health and your personal health information? Do you have a health issue?
- Are you caring for an elderly parent?
- Are you changing doctors?
- Do you need to find the results of a medical test or a complete and current list of your medications?

Blue Button may be able to help.
Crowdsourcing: schools

- Website to incentivize measurement entry
  - Incentive for school
  - Incentive for nurse
  - Incentive for child

- Send data to national repository

- Challenges: similar to other ideas
Leverage fitness app data

- Sampling bias
- Quality of info

• Need industry buy-in (e.g., Google, Apple)
Leverage research data tools

- Perhaps slightly easier than fitness apps, but similar challenges
- Partner with Apple?
Precision Medicine Initiative

LONGER TERM GOALS

Create a research cohort of > 1 million American volunteers who will share genetic data, biological samples, and diet/lifestyle information, all linked to their electronic health records if they choose.

Pioneer a new model for doing science that emphasizes engaged participants, responsible data sharing, and privacy protection.

Research based upon the cohort data will:

- Advance pharmacogenomics, the right drug for the right patient at the right dose
- Identify new targets for treatment and prevention
- Test whether mobile devices can encourage healthy behaviors
- Lay scientific foundation for precision medicine for many diseases
Single day blitz / incentive

Enter your child’s weight and height. Win 4 Million Dollars.
Instrumentation

- Could instrument
  - Bed (weight, height)
  - Home (height)
  - Toilet (weight)
  - Entry area/floor (weight)

- Probably not cost effective for this use only

http://ercim-news.ercim.eu/en87/special/the-intelligent-bed
Embed assessment

- Partner with game manufacturers
- Children provide data
“Simple” alternatives to BMI

- Waist circumference
- Waist-to-hip ratio
- Skinfold thickness
- Bioelectric impedance

If building specialized devices, perhaps some opportunities here
Small data

“Big data” at the individual scale will transform science and healthcare.

Mobile devices and sensing will play a key role.
A big opportunity

Today

• Surveys
• Behavior snapshots
• Limited information about context
• Limited information about dynamics
• Costly recruiting
• Limited info on the “why” of decision-making

Soon

• Open source phone apps (with optional add-on sensors)
• Months of continuous, dynamic data
• Citizen scientists donating info
• Context/purpose info
Behavior measurement

Today
Hypothesis driven investigations to understand correlations

Soon
+ Data driven, incremental and interactive discovery that can support not only new science, but also intervention design
## Two important opportunities

<table>
<thead>
<tr>
<th>Medical “big data”</th>
<th>Behavioral “small, big data”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital data sets from visits/EMR</td>
<td>Personal sensors and devices</td>
</tr>
<tr>
<td>Data relatively homogenous</td>
<td>Many heterogeneous data sources</td>
</tr>
<tr>
<td>Quality control by experts (sort of)</td>
<td>Data “digital footprints”; entered by laypersons</td>
</tr>
<tr>
<td>Few data points from relatively large numbers of people</td>
<td>Huge numbers of data points from relatively small numbers of people</td>
</tr>
<tr>
<td>Temporally sparse (every few months or longer)</td>
<td>Temporally dense (days, hours, seconds, milliseconds)</td>
</tr>
<tr>
<td>Time and context not that important</td>
<td>Time and context critical to interpretation</td>
</tr>
<tr>
<td>Population models</td>
<td>Individual models</td>
</tr>
<tr>
<td>Useful for medicine, not much else</td>
<td>Could drive innovation in many areas of life</td>
</tr>
<tr>
<td>More healthy → less data, and less interesting</td>
<td>All data provides insight into important behaviors</td>
</tr>
<tr>
<td>Controlled by hospitals and medical providers</td>
<td>Controlled by individuals</td>
</tr>
<tr>
<td>Datasets exist and easy to use (sort of)</td>
<td>Datasets coming … get ready</td>
</tr>
</tbody>
</table>

Until they are huge…
## Digital footprints (sensor fusion)

<table>
<thead>
<tr>
<th>Out bed time</th>
<th>First contact time</th>
<th>First beverage time</th>
<th>Breakfast time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time outside home</td>
<td>Start work time</td>
<td>Lunch time</td>
<td>Proximity to snacks</td>
</tr>
<tr>
<td>Dinner time</td>
<td>Exercise time(s)</td>
<td>Exercise intensity</td>
<td>Evening snack time</td>
</tr>
<tr>
<td>Watching news</td>
<td>Screen time</td>
<td>Return home time</td>
<td>Get in bed time</td>
</tr>
<tr>
<td>Texting</td>
<td>Emailing</td>
<td>HVAC settings</td>
<td>Water consumption</td>
</tr>
<tr>
<td>Info from EHR</td>
<td>In a phone call</td>
<td>Phone proximity</td>
<td>Phone use</td>
</tr>
<tr>
<td>Weight measurement</td>
<td>Advertising exposure</td>
<td>Time to acquire food</td>
<td>Smoking behavior</td>
</tr>
<tr>
<td>Face-to-face social</td>
<td>Location</td>
<td>Sedentary behavior</td>
<td>Posture (sit or stand)</td>
</tr>
<tr>
<td>Mood</td>
<td>Caffeine intake</td>
<td>Medication intake</td>
<td>Daily rhythms</td>
</tr>
<tr>
<td>Activity before bed</td>
<td>Quality of sleep</td>
<td>Body/limb movement</td>
<td>Heart rate</td>
</tr>
<tr>
<td>Inferred stress</td>
<td>Drive time</td>
<td>Galvanic skin response</td>
<td>Self-reported stress</td>
</tr>
<tr>
<td>Spouse eating patterns</td>
<td>Child eating patterns</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Example

Heading towards population-scale, longitudinal activity sensing on mobile devices

Started with physical activities
Vision: population-scale

- Participant has flexibility in how to wear/use sensors
- New surveys/interventions remotely loaded & administered; remote software updates w/ new capabilities
- Data sent to server for analysis & remote administration
- Real-time feedback to encourage compliance
- 24/7 Real-time activity detection and context-sensitive self report with sensors (GPS, phone)
- Years?
Activity monitors abound
A day in the life of a participant

- In the morning, swap & select locations
- Wear sensors under clothing
- Go about day; use phone normally
- Phone detects activities each minute
- At night, plug in phone next to bed
- Data transmitted to lab
- Phone also used for self-report
In meetings...
Lab validation experiments

- Lab and everyday activities
- “Obstacle course” datasets

- Wockets
- Mobile phone
- MITes
- Oxycon Mobile
- GPS
- Zephyr
- Actigraphs
- Sensewear
- RTI environmental
- Columbia environ.

Approximate locations
### Lab performance: Activity rec

<table>
<thead>
<tr>
<th>Activities to recognize</th>
<th>Random Guess (%)</th>
<th>Subject Dependent Total Accuracy (%)</th>
<th>Subject Independent Total Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All (51)</td>
<td>1.9%</td>
<td>87.9</td>
<td>50.6</td>
</tr>
<tr>
<td>All with no intensities (31)</td>
<td>3.2%</td>
<td>91.4</td>
<td>72.0</td>
</tr>
<tr>
<td>Postures, ambulation and two MET intensity categories (11)</td>
<td>9%</td>
<td>96.5</td>
<td>81.3</td>
</tr>
<tr>
<td>Postures and Ambulation with no intensity (8)</td>
<td>12.5%</td>
<td>98.4</td>
<td>92.9</td>
</tr>
<tr>
<td>Postures (4)</td>
<td>25%</td>
<td>99.3</td>
<td>98.0</td>
</tr>
</tbody>
</table>
Note: Activities manually labeled ... 

Working on real-time detection of some activity types and context (posture, ambulation, structure exercise, etc.)
This type of info, plus social interaction, location, and more ... for long time periods ... might change research methods and research questions and lead to new interventions
# Wrist vs. ankle

Recent data (33 subjects) wrist vs. ankle ambulation detection

<table>
<thead>
<tr>
<th>Actual label</th>
<th>Ambulation</th>
<th>Cycling</th>
<th>Other activities</th>
<th>Sedentary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wrist</td>
<td>Ambulation</td>
<td>2263 (90.6%)</td>
<td>79 (3.2%)</td>
<td>60 (2.4%)</td>
</tr>
<tr>
<td></td>
<td>Cycling</td>
<td>72 (6.9%)</td>
<td>672 (64.5%)</td>
<td>20 (1.9%)</td>
</tr>
<tr>
<td></td>
<td>Other activities</td>
<td>66 (6.9%)</td>
<td>10 (1.0%)</td>
<td>806 (83.9%)</td>
</tr>
<tr>
<td></td>
<td>Sedentary</td>
<td>45 (1.5%)</td>
<td>150 (5.0%)</td>
<td>61 (2.0%)</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy</td>
<td>= 86.5%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Actual label</th>
<th>Ambulation</th>
<th>Cycling</th>
<th>Other activities</th>
<th>Sedentary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ankle</td>
<td>Ambulation</td>
<td>2547 (99.6%)</td>
<td>5 (0.2%)</td>
<td>6 (0.2%)</td>
</tr>
<tr>
<td></td>
<td>Cycling</td>
<td>8 (0.8%)</td>
<td>993 (94.8%)</td>
<td>26 (2.5%)</td>
</tr>
<tr>
<td></td>
<td>Other activities</td>
<td>6 (0.6%)</td>
<td>15 (1.5%)</td>
<td>817 (82.4%)</td>
</tr>
<tr>
<td></td>
<td>Sedentary</td>
<td>1 (0.0%)</td>
<td>11 (0.4%)</td>
<td>89 (2.9%)</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy</td>
<td>= 95.5%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Reinventing self-report

Passive sensing is excellent, when it works

But we also need new ways to gather data that requires self-report
Experience sampling (EMA)

How MAD OR ANGRY were you feeling just before the phone went off?
- Not at all
- A little
- Quite a bit
- Extremely

What were you DOING just before the phone went off? (Choose all that apply)
- Reading/Computer/Homework
- Using technology (TV, phone)
- Active Play/Sports/Exercising
- Eating/Drinking
- Going somewhere
- Sleeping
- Something else

Since the last survey you answered, have you had too many things to do?
- Yes, and caused very much stress
- Yes, and caused some stress
- Yes, and caused a little stress
- Yes, but not at all stressful
- No
Context-sensitive EMA

Prompted just after inhaler used:

Teen asthma measurement with Genevieve Dunton at USC

Prompted after 60 min of phone motion or no motion:

What have you been DOING for the past hour?
(Choose all that apply)

- Reading or doing homework
- Using technology (TV, phone)
- Eating/Drinking
- Sports/Exercising
- Going somewhere
- Other
Major activity chunk
Assisted self-report
Walking (adjust timing)
Can we completely change how we measure behavior using sensing and emerging computing devices?
“Glanceable” health

How can we use new interfaces such as smartwatches and Google Glass for health behavior measurement and intervention?
uEMA

[18:51] Feel excited right now?
- Yes
- Just a little
- No

[19:03] How excited are you?
- Moderately
- Quite a bit
- Extremely
For more information

• Send me email: s.intille@neu.edu

• http://mhealth.ccs.neu.edu

• Northeastern’s transdisciplinary Ph.D. in Personal Health Informatics http://phi.neu.edu