Mobile Measurement of Behavioral and Social Health at Population Scale

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Contributors & Collaborators

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  The Ohio State University

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- Kenzie Preston
  Intramural Research Program
  National Institute on Drug Abuse

In collaboration with

- CMU, Georgia Tech, UCLA, UMass Amherst, Pittsburgh, Johns Hopkins, NIAAA, and Giner Inc.
Healthcare in 2012

- Withings Blood Pressure
- Lucas lensfree microscopy
- NETRA vision assessment
Mobile Health in 2050

- **Ubiquitous Healthcare**
  - **Personal lab in the pocket**
    - Cell phone continuously assesses health and fitness
      - Physiology, lifestyle, risky behaviors, environmental exposures
    - More complex Health monitoring tools embedded in vehicles, home, and other public infrastructure (e.g., airport scanner)
      - Examples: Echocardiogram, MRI
  - **Personal medical assistant/therapist on the phone**
    - Knows of latest health research and best practices
    - Personalizes them and intervenes when and where needed
    - Shares and consults with health practitioner when in doubt

- **Healthcare research results in months vs. years**
  - Instantaneous data collection
  - Real-time analysis and instantaneous dissemination
  - Life Expectancy: 100+ years
Where to Focus Mobile Health Efforts

- Heart disease, cancer directly cause 53% deaths
  - Modifiable behaviors are the strongest determinant
- Stress & addictive behaviors lead to or worsen diseases of slow accumulation (e.g., cancer)

(Minino, et. al., Natl Vital Stat Rep, 2002)  
(McGinnis & Foege, JAMA 1993)

Percentage of all Deaths

0 5 10 15 20

Tobacco

Poor Diet & Phy. Inactivity

Alcohol

Microbial Agents

Toxic Agents

Motor Vehicles

Firearms

Sexual Behavior

Illicit Drug use

Stress costs $300 billion/yr

Smoking costs $193 billion/yr

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Need Population Scale Assessment

- Our team’s current focus
  - Physiological Health – Cardiac health, respiratory health
  - Behavioral Health – Stress, addictive behaviors
  - Social Health – Conversations

- Desired characteristics for target assessments
  - Operator independent – to have large-scale voluntary adoption
  - Continuous – to provide maximum visibility into health status
  - Mobile – to capture events of interest as and when they occur
  - Self-calibrating – to personalize it for each individual
  - Transparent – to make measurements actionable

- To achieve population scale
  - Measurement device should be convenient for long-term monitoring
    - Eventual integration on mobile phones
Outline

- Continuous Assessment of Physiology in Field
  - AutoSense wearable sensor suite
  - FieldStream mobile phone framework
  - Week-long mHealth field studies with addictive populations
- Automated Assessment of Behavioral and Social Context
  - Stress from ECG and respiration
    - Physiological stress
    - Perceived stress
  - Smoking puffs from respiration
  - Conversations from respiration
- Open Research Challenges for mHealth
  - Modeling and Analytics of continuous mHealth measures
  - Invisible Sensing
AutoSense Wearable Sensor Suite

10 wireless sensors (151 samples/s; 32 packets/s)  |  Lifetime: 10+ days

Used in 3 studies (n=60) for automated modeling of stress, conversation

Being used in 4 ongoing studies (n=85, 1-4 weeks of field wearing) for automated modeling of smoking, drinking, drug usage, and craving

(Ertin, et. al., ACM SenSys 2011)
FieldStream Mobile Phone Software

Sony X8

Sensor pairing with phone via UI

Lab session administration via customizable UI

Self-report items and trigger mechanisms are customizable
Monitoring and Improving Compliance

Sensor Connection Status

Review Data Quality & Quantity

Live signal visualization

Field Report Page

<table>
<thead>
<tr>
<th>Day</th>
<th>Data</th>
<th>EMA</th>
<th>SMK</th>
<th>DRN</th>
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<tr>
<td>03/30/12(Fri)</td>
<td>0 h 4 m</td>
<td>0(0)</td>
<td>0</td>
<td>0</td>
</tr>
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<td>0(0)</td>
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<tr>
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<td>0(0)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>03/27/12(Tue)</td>
<td>0 h 0 m</td>
<td>0(0)</td>
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<tr>
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<td>0(0)</td>
<td>0</td>
<td>0</td>
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<td>03/25/12(Sun)</td>
<td>0 h 0 m</td>
<td>0(0)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>03/24/12(Sat)</td>
<td>0 h 30 m</td>
<td>0(0)</td>
<td>0</td>
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</tr>
<tr>
<td>03/23/12(Fri)</td>
<td>0 h 0 m</td>
<td>0(0)</td>
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<td>0</td>
</tr>
<tr>
<td>03/22/12(Thu)</td>
<td>6 h 13 m</td>
<td>12(12)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>03/21/12(Wed)</td>
<td>10 h 17 m</td>
<td>12(12)</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Field Study Starts from:
Mar 19, 2012 4:23 PM

So far, you've earned: $16.25

Select a sensor
- Respiration
- GSR on RIPECG mote
- Chestband Accelerometer X value
- Chestband Accelerometer Y value
- Chestband Accelerometer Z value
- Alcohol Consumption

Interview break from 03/22/12 04:07 pm until 03/22/12 05:07 pm

Data collection ends at 03/22/12 11:30 pm, begins again at 03/23/12 10:08 am
Week-long Field Studies with AutoSense

- **Memphis Study**
  - 40 daily smokers and social drinkers
  - One week of AutoSense wearing in the field
    - Stress, drinking, smoking, and craving for cigarettes are reported

- **National Institute on Drug Abuse (NIDA) Study**
  - 20 active drug users
  - Two lab sessions and 4 weeks of wearing AutoSense in the field
    - Smoking, craving, and stress events are marked in the lab
    - Craving, smoking, and drug usage are reported in the field
## Data Collection Statistics

<table>
<thead>
<tr>
<th>Item</th>
<th>Memphis Study</th>
<th>NIDA Study</th>
</tr>
</thead>
<tbody>
<tr>
<td># of participants in protocol</td>
<td>22</td>
<td>6</td>
</tr>
<tr>
<td># of person days worth of data</td>
<td>153 days</td>
<td>68 days</td>
</tr>
<tr>
<td># of dropouts</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td># hours worth of data</td>
<td>1,505 hours</td>
<td>745 hours</td>
</tr>
<tr>
<td>Good-quality data contributed/day</td>
<td>9.84 hours/day</td>
<td>11 hours/day</td>
</tr>
<tr>
<td>Wireless Data Losses (With Recovery)</td>
<td>9.5% (0.25%)</td>
<td>4.92% (&lt; 0.25%)</td>
</tr>
<tr>
<td># of self-report prompts received/day</td>
<td>15</td>
<td>7.4/day</td>
</tr>
<tr>
<td>% of self-report prompts answered</td>
<td>94%</td>
<td>90.43%</td>
</tr>
<tr>
<td># of Smoking self-report</td>
<td>1,236 (or 8/day)</td>
<td>259 (or 3.8/day)</td>
</tr>
<tr>
<td># of Drinking/Drug Use self-report</td>
<td>111 (5/week)</td>
<td>18 (1.8/week)</td>
</tr>
</tbody>
</table>
Data Contribution Pattern - Memphis

Number of Person Days by Time of Day

AM
00:00 - 34
01:00 - 40
02:00 - 27
03:00 - 31
04:00 - 49
05:00 - 40.5
06:00 - 49
07:00 - 60
08:00 - 59
09:00 - 56
10:00 - 59
11:00 - 60

PM
12:00 - 58
01:00 - 60
02:00 - 60
03:00 - 59
04:00 - 60
05:00 - 60
06:00 - 60
07:00 - 60
08:00 - 59
09:00 - 56
10:00 - 56
11:00 - 56
Data Contribution Pattern – NIDA

The graph shows the number of person days per hour of the day, with AM and PM indicated separately. The data is represented in a bar chart, with the x-axis showing the time of day in hours and the y-axis showing the number of person days. The peak contribution is observed in the late afternoon and early evening, with the lowest contributions in the early morning hours.

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Scaling Data Collection

- Using ANT radio on the phone allows 12h with GPS
  - Using Bluetooth or microphone or intense processing will reduce the time between successive charge on the phone
  - Need higher energy-efficiency to get 14+ hours of life

- Get good compliance (10+ hours/day, 91%) from subjects with risky behavior
  - But, have daily meeting with subjects to review compliance
  - Need to investigate HCI mechanisms (e.g., UI, incentive) to get same or better compliance without daily face-to-face

- Can we get good compliance from volunteers without cash compensation?
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  - Invisible Sensing
Stress Modeling with AutoSense

- We conducted a study with a validated stress protocol
  - 21 participants, 2 hour lab study,
    - Public speaking – psychosocial stress
    - Mental arithmetic – mental load
    - Cold pressor – physical stress
  - 2 day field study
    - 10-14 hours in the field (20 self-reports per day)

- Developed two new self-calibrating stress models
  - Physiological stress model (binary: stressed or not)
    - To measure adverse physiological effects of stress
  - Perceived Stress Model (continuous rating)
    - To measure perception of stress in mind as accumulation & decay process
    - Predict self-reported stress rating (Plarre, et. al., ACM IPSN 2011)
Identified 22 Features from Respiration

**Basic Features**
- Inhalation Duration
- Exhalation Duration
- Respiration Duration
- Insp./Exp. Ratio
- Stretch
- Breathing Rate
- Minute Ventilation

**Statistical Features**
- Mean
- Median
- 80th Percentile
- Quartile Deviation

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Computed 13 Features from ECG

**Basic Features**
- RR Intervals
- RSA

**Statistical Features**
- Variance
- Power in low/medium/high frequency bands
- Ratio of low frequency/high power
- Mean
- Median
- 80th Percentile
- Quartile Deviation

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Classification Accuracy on Lab Data

Overall Prediction Accuracy = 90%

Features:
- Selected (S)
- All (A)
- RIP (R)
- ECG (E)

Stressors:
- All
- Instruction
- Speaking
- Mental Arithmetic (Standing)
- Mental Arithmetic (Seated)
- Cold Pressor
Perceived Stress Model

- Use a binary Hidden Markov Model
  
  \[ s_t \in \{0, 1\} \text{ is perceived stress} \]

  \[ \pi_t = P[s_t = 1 | x_1, \ldots, x_{t-1}] \text{ is perceived stress value} \]

- To reduce number of parameters, we approximate \( \pi_t \) by

  \[ \hat{\pi}_t = \alpha \hat{\pi}_{t-1} + \beta x_t, \]

  - \( \alpha \) models the gradual decay of stress with time
  - \( \beta \) models the accumulation of stress in mind due to repeated exposures to stress

- Both \( \alpha \) and \( \beta \) are person dependent and are learned from self-reported ratings of stress
Evaluation of the Model

Lab Session

Median Correlation = 0.72
n=21

Field Session (2 days)

R=0.71
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Automated Assessment of Smoking

- Existing devices can measure and display/store CO levels in a single breath exhaled through a mouthpiece.
- CReSS can provide smoking topography.
  - If subjects smoker through CReSS.
- These devices require users to remember to use for each smoking.
- They may also cause embarrassment.
Detecting Smoking from Respiration

Data: 161 puffs from 10 daily smokers

Evaluation: Each puff is detected with 86.7% accuracy

Research: Need to develop models for detecting entire smoking episodes

- By leveraging smoking topography, and
- By using other contexts (e.g., activity)

(Ali, et. al., ACM IPSN, 2012)
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Body worn microphones are reliable
- Examples: Sociometer, LENA
- But, involve subject burden

Microphone embedded in phones
- Provide population level scalability
- But, are prone to microphone occlusion

Additional issues with microphone
- Energy drain of microphone sensor
  - Needs high sampling (at 8 KHz) and data processing
- Privacy concerns due to audio capture
- May lack speaker specificity
Measurement of Conversation - Respiration

- Respiration measure provides
  - Speaker specificity
  - Privacy preservation
  - Integrated assessment of stress & addictive behavior

Confusion Matrix

<table>
<thead>
<tr>
<th></th>
<th>Quiet</th>
<th>Listening</th>
<th>Speaking</th>
<th>Classified as</th>
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</thead>
<tbody>
<tr>
<td>Quiet</td>
<td>0.9005</td>
<td>0.0706</td>
<td>0.0353</td>
<td>Quiet</td>
</tr>
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<td>Listening</td>
<td>0.1207</td>
<td>0.8275</td>
<td>0.0517</td>
<td>Listening</td>
</tr>
<tr>
<td>Speaking</td>
<td>0.0238</td>
<td>0.0833</td>
<td>0.8929</td>
<td>Speaking</td>
</tr>
</tbody>
</table>

(Rahman, et. al., ACM Wireless Health, 2011)
Modeling & Analytics of mHealth Data

- Continuous measures from field have rich information, but
  - Mobile environment introduces measurement variability
    - Displacement/detachment of wearable sensors, movements artifacts
    - Physiology is affected by stress, speaking, walking, smoking, eating, etc.
    - Data losses in the wireless channel
  - Need to estimate the quality of data in a live stream
    - Without insisting on access to the associated ground truth

- Good progress in modeling intense longitudinal data, but
  - How do we model variability and error in continuous measures of physiology collected in the field?
  - How do we model behaviors obtained by applying imperfect machine learning models to sensor measurements?
Invisible mHealth

- Physiological sensing of health today requires wearing of sensors
  - Does not scale well to voluntary usage
- Can obtain some scale by using
  - GSR phone jackets, GSR steering wheel covers
  - Audio capture on the mobile phone
- But, true population will require invisible sensing of health state
  - Contactless physiological sensing
  - Ubiquitous sensing (home, car, office, malls)
- Ideal if our phones can reliably sense various physiological states while being in pocket or purse
Conclusions

- Physiological sensing can provide continuous assessment of
  - Stress, addictive behaviors, and social interactions
  - Complemented by activity, GPS, proximity, audio, and camera sensing on the phone

- Three major challenges in scaling to population level
  - Assessment of data quality and modeling of variability
  - Develop robust and validated inference methods that can work in the presence of mild confounders and are self-calibrating
  - Obviate the need for wearing sensors
    - Ideally integrated in mobile phone

- **Vision 2020:** Safe, effective, and efficacious interventions on mobile phone to address stress and addictive behaviors
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- Dr. Mustafa al’Absi, UMN
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- Dr. Satish Kedia, Memphis
- Dr. Kenzie Preston, NIDA, NIH
- Dr. Marcia Scott, NIAAA, NIH
- Dr. Saul Shiffman, Pittsburgh
- Dr. Annie Umbricht, Johns Hopkins
- Dr. Kenneth Ward, Memphis
- Dr. Larry Wittmers, UMN

Engineering

- Dr. Anind Dey, CMU
- Dr. Emre Ertin, Ohio State
- Dr. Deepak Ganesan, UMass
- Dr. Greg Pottie, UCLA
- Dr. Justin Romberg, Georgia Tech
- Dr. Dan Siewiorek, CMU
- Dr. Asim Smailagic, CMU
- Dr. Mani Srivastava, UCLA
- Dr. Linda Tempelman, Giner Inc.
- Dr. Jun Xu, Georgia Tech
# Students & Postdocs

<table>
<thead>
<tr>
<th>Memphis</th>
<th>CMU, OSU, UCLA, Georgia Tech., UMN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dr. Andrew Raij (now at USF)</td>
<td>Dr. Motohiro Nakajima, UMN</td>
</tr>
<tr>
<td>Dr. Kurt Plarre</td>
<td>Patrick Blitz, CMU</td>
</tr>
<tr>
<td>Dr. Karen Hovsepian</td>
<td>Brian French, CMU</td>
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<td>Amin Ahsan Ali</td>
<td>Scott Frisk, CMU</td>
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<tr>
<td>Santanu Guha</td>
<td>Nan Hua, Georgia Tech</td>
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<td>Monowar Hussain</td>
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<td>Mahbub Rahman</td>
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<tr>
<td>Sudip Vhaduri</td>
<td>Nathan Stohs, OSU</td>
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<td>Zainul Chabriwala, UCLA</td>
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Further Reading


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