mHealth Apps for Tracking Patients In-situ

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Linking patient behavior and their health

• Patient behavior is inexorably linked to their health

• Understanding the behavior ⇔ health relationship would allow us to:
  • **diagnostic techniques**
    • e.g., changes of memory, mood, activity level are precursors to Alzheimer’s
  • **evaluate efficacy of medical treatment**
    • e.g., measure the impact of cognitive behavior therapy over time
  • **support for clinical interventions interventions**
    • e.g., deliver interventions for smoke cessation
The “gold” standard

- Manual data collection is the gold standard...
  - subjective (e.g., memory bias, Hawthorne effects)
  - poor scalability
    - low temporal resolution
    - cannot monitor many subjects
  - people are expensive!

- ... but, our tools fundamentally limit our understanding

We need better measurement tools!
The mHealth alternative

• **Assesses behavioral states**
  • with objective metrics
  • in real-time
  • in-situ

• **mHealth enables**
  • longitudinal studies with large patient populations
  • interventions delivered just-in-timed
  • empower patients to participate in their care
A word of caution ...

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Source: Gartner (July 2011)
The rest of the talk

**Clinical monitoring:** delivers 100x more data than possible through manual collection

**Emergency response:** reliable data delivery to many responders

**Rapid mHealth App development:** reduce the burden of developing mHealth Apps
Detecting clinical deterioration in general hospital units

- Early detection of clinical deterioration
  - clinical deterioration is often preceded by changes in vitals
- Real-time patient monitoring is required
  - wired patient monitoring ➞ inconvenient
  - wireless telemetry systems ➞ too expensive for wide adoption
  - most general hospital units collect vitals manually and infrequently

Goal: **reliable** and **real-time** wireless clinical monitoring for **general** hospital units
Clinical deployment

Step-down cardiac care unit
41 patient monitored
System reliability

- Network reliability per patient: 99.68% median, range 95.2% - 100%
- Sensing reliability per patient: 80% median, range 0.46% - 97.69%
  - 29% of patients with sensing reliability < 50%
- System reliability dominated by sensing reliability!
Sources of sensing errors

- Hand movement
- Improper placement

Heart Rate vs. Time (min)

- Hand movement
- Improper placement
Sensor reliability

- Automatically notify a nurse after receiving no valid data for a time
  - balance nursing effort and reliability gain
  - at 15 min timeout
    - ➡ 1.55 interventions per patient, per day
    - ➡ 100x more data per day

Sensing reliability with different timeouts

<table>
<thead>
<tr>
<th>Timeout</th>
<th>Fraction of patients (%)</th>
<th># of alarms per patient, per day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 min, no alarm</td>
<td><img src="#" alt="Graph showing fraction of patients with different timeouts" /></td>
<td><img src="#" alt="Graph showing # of alarms per patient, per day" /></td>
</tr>
<tr>
<td>1 min, alarm: 5 min</td>
<td><img src="#" alt="Graph showing fraction of patients with different timeouts" /></td>
<td><img src="#" alt="Graph showing # of alarms per patient, per day" /></td>
</tr>
<tr>
<td>1 min, alarm: 10 min</td>
<td><img src="#" alt="Graph showing fraction of patients with different timeouts" /></td>
<td><img src="#" alt="Graph showing # of alarms per patient, per day" /></td>
</tr>
<tr>
<td>1 min, alarm: 15 min</td>
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</tr>
</tbody>
</table>
Infusing technology into emergency response workflow

- Mobile technology improved information quality
  - identical time to triage patients
  - reduced the rate of missing/duplicate patients
Reliable communication

• **Initial approach: required deployment of infrastructure**
  - poor performance due to incomplete coverage
  - **as little as 10% of the data delivered**

• **Peer-to-peer communication architecture:**
  - requires no infrastructure, mobile phones communicate directly
  - epidemic propagation of information
Deployment

• Drill exercise at UCSD
  • 19 responders
  • 41 victims

• Deployed devices
  • responders - 16 phones
  • commanders - 3 tablet PCs

• Time synchronization via NTP
  • accuracy < 1s
Application performance

- **Reliability:**
  - median reliability 98% per source
- **Delay:**
  - 90% of data delivered with 5 minutes, max delay 10 minutes
- **Shows the feasibility of DTN-based techniques**
Understanding the impact of technology
mHealth apps

Data collection

Feature extraction

Data upload

Data analysis
Rapid development of mHealth systems

• mHealth systems are difficult to develop
  • requires diverse expertise: embedded, web apps, machine learning, and domain experts
  • tedious management of resources on embedded sensors and phones

• Current systems are stovepipe lacking flexibility and reuse
  • impossible to reuse software
  • difficult to integrate with existing legacy software

• Our research:
  • develop a toolkit to simplify the development of mHealth systems
  • focus on developing reusable components
  • flexible mechanisms to integrate with legacy software

• Applications:
  • ecological momentary assessment for audiology
  • EgoSense - monitoring social interactions
Measuring hearing aid performance in-situ

• A fraction of people with hearing loss do use hearing aids due to high cost
  • unclear which features of the hearing aids make them effective in the real world

• Laboratory hearing performance is not predictive of that in the real world

• Develop a new methodology for measuring auditory performance in the real world
  • deliver surveys to users via mobile phones to minimize memory bias
  • record the auditory context in which surveys are completed
  • evaluate correlations between user-provided scores and auditory contexts

• Collaboration with Yu-Hsiang Wu
  (Dept. of Communication Sciences and Disorders)
• Delivers surveys to users according to a predetermined schedule

• Collects sensor data contemporaneously with administering surveys

• Uploads the collected data to a server for real-time analysis over cellular network

• You can develop new surveys to be administered within minutes!
EgoSense system

• **Components:**
  - mobile phones carried by patients: accelerometers + proximity + sound
  - environmental sensors: notebooks with proximity + sound

• **Social interaction:** inferred using proximity and speaker identification

• **Physical activity:** measured using accelerometers
Speaker recognition problem

Recognition Phase
(e.g. Verification)

“It’s me!”

Feature Extraction ➔ Model Training ➔ Model for each speaker

Text

Feature Extraction ➔ Verification Decision ➔ Accepted/Rejected

Training speech for each speaker

credit: Nikki Mirghafori
Performance of speaker recognition systems

- **Text-dependent (Combinations)**
  - Clean Data
  - Single microphone
  - Large amount of train/test speech

- **Text-independent (Conversational)**
  - Telephone Data
  - Multiple microphones
  - Moderate amount of training data

- **Text-dependent (Digit strings)**
  - Telephone Data
  - Multiple microphones
  - Small amount of training data

- **Text-independent (Read sentences)**
  - Military radio Data
  - Multiple radios & microphones
  - Moderate amount of training data

Increasing constraints
Sensor fusion can improve performance

• Detection performance can be improved using other sources of information
  • select the most informative audio stream from microphones
  • track conversations over long periods of time
  • limit the candidate speakers to one’s social network
  • leverage on proximity information

• Manage sensors for energy efficient operation
  • turn on sensors as necessary to track social information
  • => preferential use of environmental sensors that are plugged in
Conclusions

• Mobile technology and sensors will transform behavioral studies
  • enable large-scale longitudinal studies
  • open new venues for diagnostic, measurement of patient outcomes, QOL

• Significant engineering challenges remain:
  • reliable wireless communication
  • coping with sensor failures
  • sensor fusion and adaptation

• Developing mHealth systems require engineers and clinicians to collaborate:
  • understand what are the clinically relevant information that must be collected
  • develop a minimally invasive system to collect these measurements
Acknowledgements

• **Students:**
  • Farley Lai, Syed Shabih Hasan, Austin Laugesen

• **CS Collaborators:**
  • Chenyang Lu, Washington University in St. Louis
  • William G. Griswold, University of California San Diego
  • Alberto Segre, University of Iowa

• **AMBI Collaborators:**
  • Michelle Voss (Department of Psychology),
  • Nazan Aksan, Steven W. Anderson, Matthew Rizzo (Department of Neurology),
  • Melissa Duff (Department of Communication Sciences and Disorders)
  • Marianne Smith (College of Nursing)
  • any many others

• **Funding Agencies**

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...in...

...smart environments