Technology for Long-Term Care:
Scaling Activity Recognition to the Next Billion

Matthai Philipose
Intel Research

November 3, 2008
Care and Machines
The Role of Machines in Care

Long-Term Care Defined

Hands-on assistance with fundamental daily activities

“[Jean Gavrilles] was in good condition for her age, but she faced everything from advancing arthritis to what might be metastatic colon cancer...

The single most serious threat she faced was not the lung nodule or the back pain. It was falling. So [her geriatrician] referred Gavrilles to a podiatrist, whom he wanted her to visit once every four weeks, for better care of her feet.”

The Role of Machines in Care

How We Care Today

- High touch
- High presence
- High cost

elder

family

case manager

provider
The Demographics Don’t Favor Us...

- 2 billion over 60 in 2050 (1 billion today) [UN]
- Caregivers per elder falling
  - 5:1 today, 3:1 2035 (USA), 2:1 Japan
  - 1 in 3 US adults does informal care annually [HHS]
The Role of Machines in Care

... Nor Do the Economics

- Costs increase exponentially
- Budget will flatten
- Strategy
  - Reduce care needs
  - Support informal care
  - Reduce care cost

Total US Long-Term Care Expenditure on Elderly (Medicaid + Private Pay)
(source: Congressional Budget Office, 2003; LaPlante et al., 2002)
The Role of Machines in Care

Machines are Not of Much Help

Keep an Eye Open
- Logging: What did they do?
- Rating: How well?
- Troubleshooting: What was wrong?
- Trending: How have they changed?
- Notification: Call me when they need me
- Prompting: Walk them through it

Act
- Mechanization: Automate structured tasks
- Prosthetics: Help with physical functions
- Assistance: Interact in unstructured tasks
- Automation: Do these tasks autonomously

Connect emotionally

difficult (for computer)

extremely difficult
Case Study:
Context-Aware Medication Prompting
A Case Study

Context-Aware Medication Prompting

Hypothesis

Automated context-aware reminding can significantly improve medication adherence relative to state of the art reminding

Remind low-adherence elders *when appropriate*
- Leaving home at medication time
- Close to medications
- Not when sleeping or on the phone

Joint Oregon Health & Science University/Intel effort
- 10-12 health researchers, engineers, ethnographers
- Planned 1 yr study took roughly 2 years
A Case Study

The Results are Promising...

<table>
<thead>
<tr>
<th>Participant</th>
<th>Baseline%</th>
<th>Time-Based%</th>
<th>Context-Aware%</th>
</tr>
</thead>
<tbody>
<tr>
<td>HP05</td>
<td>33.3</td>
<td>69.1</td>
<td>54.2</td>
</tr>
<tr>
<td>HP52</td>
<td>75.8</td>
<td>70.2</td>
<td>84.9</td>
</tr>
<tr>
<td>M26</td>
<td>65.8</td>
<td>71.3</td>
<td>81.6</td>
</tr>
<tr>
<td>M32</td>
<td>47.7</td>
<td>77.0</td>
<td>93.1</td>
</tr>
<tr>
<td>M44</td>
<td>N/A</td>
<td>45.7</td>
<td>48.0</td>
</tr>
<tr>
<td>M45</td>
<td>58.3</td>
<td>46.1</td>
<td>81.8</td>
</tr>
<tr>
<td>avg.</td>
<td>56.2</td>
<td>63.2</td>
<td>73.9</td>
</tr>
</tbody>
</table>

>=6 week baseline, 3 week time-based, 3-week context-aware

Started with 14 elders, ended with 6
  - All dropouts before baseline ended
  - Unexpected extensions of baseline a major factor
A Case Study

...But at What Price?

Very hard to re-target or even improve solution

models encode “common sense”, but hard for novices to specify, tough to re-use

**custom labeling rules**

- Location given by last motion sensor
  - confused if you see other sensors e.g. door/bed
- Leaving false by default, true if “door open” && at “door”
  - confused if only one of “door open” or at “door”
- Ask user if confused

**resort to ad-hoc rules to speed labeling**

integrating, modeling custom sensors
A Case Study

The Target

<table>
<thead>
<tr>
<th>Activity Class</th>
<th>Rating (1-5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal Appearance</td>
<td></td>
</tr>
<tr>
<td>Oral Hygiene</td>
<td></td>
</tr>
<tr>
<td>Toileting</td>
<td></td>
</tr>
<tr>
<td>Washing up</td>
<td></td>
</tr>
<tr>
<td>Appliance Use</td>
<td></td>
</tr>
<tr>
<td>Use of Heating</td>
<td></td>
</tr>
<tr>
<td>Care of clothes and linen</td>
<td></td>
</tr>
<tr>
<td>Making a snack</td>
<td></td>
</tr>
<tr>
<td>Making a drink</td>
<td></td>
</tr>
<tr>
<td>Use of phone</td>
<td></td>
</tr>
<tr>
<td>Leisure Activity</td>
<td></td>
</tr>
<tr>
<td>Infant Care</td>
<td></td>
</tr>
<tr>
<td>Medication Taking</td>
<td></td>
</tr>
<tr>
<td>Housework</td>
<td></td>
</tr>
</tbody>
</table>

shaving, brushing teeth, combing hair, flossing, gargling, applying make-up, bathing, using microwave, baking, blending, watching TV, doing laundry, mending, folding, putting away laundry, adjusting thermostat, making a sandwich, making a chocolate cake, making a martini, making a milkshake, getting a glass of water, phoning friends, phoning family, phoning caregivers, knitting, watching videos, going for a walk, walking the pet, putting grandson to bed, taking blood-pressure medication, taking vitamins, taking calcium, dusting, tidying, cleaning toilets, vacuuming, cleaning blinds, removing cobwebs, ...
Scaling Human Activity Recognition
Scaling Human State Recognition

Watching a Pot Boil
Scaling Human State Recognition

### Bottlenecks in Human State Recognition

- **Low-level sensing**
  - Recognizing similar things across settings

- **Interfacing levels**
  - Picking the right symbols

- **High-level sensing**
  - Incorporating all relevant rules

- **Labeling**
  - Getting enough examples from end-user

#### Diagram:

- **Hidden state**: `take medications`
- **Symbols**: `bottle`, `lift to mouth`
- **High-dim data**: `sensors`
- **Closest Example Match**
- **Soft Rules**
- **Low-level sensing**
- **Interfacing levels**
- **High-level sensing**
- **Labeling**
Scaling Human State Recognition – Picking the right symbols

What You Use Determines What You Do
Activity Models Become Lists of Symbols

- `<Activity>`
  - `<Title>`making tea</Title>`
  - `<StepList>`
    - `<Step>` `<ObjectList>` `<Object name="kettle" />` `<Object name="water" />` </ObjectList></Step`
    - `<Step>` `<ObjectList>` `<Object name="cup" />` `<Object name="teabag" />` `<Object name="kettle" />` </ObjectList></Step`
    - `<Step>` `<ObjectList>` `<Object name="milk" />` `<Object name="sugar" />` `<Object name="cup" />` `<Object name="spoon" />` </ObjectList></Step`
  - `</StepList>` `</Activity>`
Detecting Object Use: Ultra-Dense Sensing

- 30 cents, tiny, no batteries
- 10s per sq ft possible
- insensitive to environment

ID # 1287678087889343
[accel = (1.1,2.2,0.7)]
## What Object-Use Sensing Buys You

### Activity

<table>
<thead>
<tr>
<th>Activity</th>
<th>Prior Work (Past 15 yrs, evaluated on any non-researcher)</th>
<th>HAR (3 mos prep, 14 subjects)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal Appearance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oral Hygiene</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toileting</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Washing up</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Appliance Use</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of Heating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Care of clothes and linen</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Making a snack</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Making a drink</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of phone</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leisure Activity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infant Care</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medication Taking</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housework</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Legend

- General solution
- Point solution

### 70/90% average precision/recall

### Caveat [UbiComp07]
- RFID often ineffective:
  - Objects not tagged/taggable
  - Antenna gets detuned
Case Study: Technology for Long-Term Care
TLC Study Goals

Show that activity monitoring technology can help maintain elders’ independence by:

- Monitoring activities accurately
- Reducing perceived burden of care
- Satisfying elders, family and caregivers
- Triggering positive interactions between elders and caregivers

3-month, 20-elder + formal/informal caregiver, in-home deployment

Joint Intel, Veterans Administration, UW Health Sciences
Case Study

Deployed System

WiMax

home PC computes:
- data transport (Pelican Bay)
- inference (HomeWare)

web/DB server computes:
- backup,
- maintenance,
- visualization,
- web service

family display shows:
- ADL info, alerts

maintenance display shows:
- system metrics

WiMax Sensors

iBracelet detects:
- RFID tags, acceleration

shake sensor detects:
- vibration

Data Analysis + Storage tracks 8 activities
Case Study

TLC is Useful

I think it’s a marvelous thing... my sister will call me up say “I don’t have any apples, why haven’t you eaten?”

It reminds me—"hey, I didn’t take my vitamins today." It gets me in a better habit. Sometimes I'll forget to brush my teeth at night after having a snack, but I can see that I didn't brush my teeth on the screen and then I'll go do it.

It’s helpful... every shift, I have to sign off that he took his medications. When I sign his form I know for sure —before he would just tell me he took his meds [note: TLC only monitors vitamin taking, not meds]

He brushes his teeth more often now because I can keep track. That wasn’t something I really did before.

It’s like a huge night light lighting up the living room... before I’d call to check in on her. Now I can ask her why she hasn’t eaten

Now, there’s footprints all over it—so she wasn't sleeping last night. There's a break from about 3 to 4 in the morning. So, I won't bother her for awhile.
Another Scaling Challenge

TLC installation overhead

<table>
<thead>
<tr>
<th>Component</th>
<th>Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obj Inventory</td>
<td>60</td>
</tr>
<tr>
<td>Sensor ID</td>
<td>30</td>
</tr>
<tr>
<td>Sensor/Inf config</td>
<td>120</td>
</tr>
<tr>
<td>In-home PC/Net</td>
<td>20</td>
</tr>
<tr>
<td>In-home Sensors</td>
<td>30</td>
</tr>
<tr>
<td>backend setup</td>
<td>15</td>
</tr>
</tbody>
</table>

110 / 275 min
Making Tea

Activity Recognition

P(object|Activity) = \frac{\text{google(object+Activity)}}{\text{google(Activity)}}

(and a small bag of clean-up tricks)

Mined models quite good:
\sim 70\% Precision/Recall over 26 activities

Can bootstrap semi-supervised learning:
accuracy increases by up to 25\% on unlabeled data
Scaling Human State Recognition – Creating Models

Using Common Sense Databases

• Much effort spent collecting common sense
  – OpenMind Indoor Common Sense (OMICS), OpenMind, Cyc

• OMICS collected from internet users via fill-in-the blanks
  – “When people ____ they ___”

• Easily translated into logical formulas
  – personInState(X) => actionPerformed(Y)
  – actionPerformed(X) => objectUsed(y)

• Use web-scale mining to add quality numbers
  – personInState(hungry) => 0.9 actionPerformed(“eat”)

• Convert weighted logic into giant Markov Random Field
  – 50,000 nodes/time slice, 30% of nodes are about object use

• 80%/40% precision/recall on 24 kinds of context from RFID data
  – e.g., locationInferred(“bathroom”), actionPerformed(“eat”)

AAAI06, NIPS06, AAAI07
Common Sense Assisted Sensor Labeling

- Easily get to 50-80% Precision/Recall [IJCAI07]
- Trick works for vision too [ICCV07]
Scaling Human State Recognition

The Self-Sustaining Reaction...

ultra-dense sensing

the web

machines that read, observe, understand and get better at all three

statistical [logical] reasoning
The Road Ahead
The Road Ahead

Intel Everyday Sensing & Perception Initiative

Mainstreaming is the ultimate scaling trick

Understand 90% of your day with 90% accuracy

Location & Navigation
Location-based security
Finding lost & hidden objects
Fitness tracking
Auto trip report
Smart scrap booking
Virtual tour guide
Home automation
Context-aware Interruptions
Home security monitoring
Real time energy awareness
Smart appliances
Entertainment integration
In-situ recommender systems
“Visual Google”
Personal Health Monitoring
Smart shopping assistant
Social networking
Context-aware filtering
Pre-destination / route prediction
Affecting Clinical Care

Technology can make behavioral monitoring a valuable clinical tool, similar to physiological monitoring.

Clinical Behavioral Metrics Project:
- Sensor-based data can provide metrics of wellness significantly better correlated with outcomes than current standards.

Generalized Adherence Monitoring:
- Delivering regimen adherence information to patients and care givers will improve compliance rates and outcomes.
Public policy can affect perceived value of technology

Problem: Fixed-time, fixed-cost reimbursement hides tech benefits

- E1: It hasn't changed anything she does for me, she still does all of the same things.
- E2: She does everything like she always did. I've been doing everything by myself before this came up. It's no different now.
- FCG1: He brushes his teeth more often now because I can keep track. That wasn't something I really did before.
- FCG2: Every shift I have to sign off that he took his medications.

Proposal: Need-based care

- Care worker visits less if elder performs more tasks
  - fewer visit == lower up-front cost
- Elder receives incentives to self-perform task
- Sensors provide objective measure of need
- Partner with org controlling service plan e.g. VA to validate?
The Pieces of the Puzzle

- technology
- service delivery
- medicine
- financing
- architecture + design
- housing
- social change
- public policy
- your work here
In the story of Jean Gavrilles and her geriatrician, there’s a lesson about frailty. [Aging] can occur in two ways. One is early and precipitately, with an old age of enfeeblement and dependence, sustained primarily by nursing homes and hospitals. The other way is more gradual, preserving, for as long as possible, your ability to control your own life.

Thank You

Collaborators:

B. Gutmann, A. Mani, D. Patterson, W. Pentney, A.-M. Popescu, E.-M. Tapia, S. Wang, D. Wyatt, D. Wilson, B. Ziebart

J. Bilmes, G. Borriello, D. Fox, S. Intille, H. Kautz, M. Pavel, J. Rehg