Sensornets for Home Health Care

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http://www.cs.virginia.edu/wsn/medical/
http://wirelesshealth.virginia.edu/
What’s Wrong With Wires

And we don’t want a patient tethered to a bed or fixed medical device.
Outline

• Problems and Vision

• Applications

• Underlying Technology

• Summary
The Problems

• Aging Populations
• High Cost of Medical Care
• Lack of Facilities
• Quality of Life Issues

• Solution: Home Health Care
  CCRC
  Assisted Living
Vision - Smart Living Space

- Humans-in-Loop
- Heterogeneous
- Evolution
- Open
- Privacy
Large Scale Deployments

Assisted-Living Campus

- Person
- Person with Body Network
- Backbone Node
- Sensor Node

DB
Benefits

- Identify normal behaviors
- Identify anomalous behaviors
- Detect medical problems (depression) early
- Improve quality of life
- Monitor adherence to and effectiveness of treatments
- Detect dangerous situations
- Maintain privacy
- Longitudinal studies
State of Art

- UCLA, Harvard, Yale, GaTech, MIT, Univ of Washington, Johns Hopkins, Imperial College, U. of Geneva, UPenn, U Rome, UVA, Taiwan, etc.

- GE Health, Intel, Philips, Verizon, IBM, etc.

- West Wireless Health Center
- Wireless Life Sciences Alliance
Architectures

- Alarmnet
- Web based (Empath)
Applications

• Depression and general anomalies

• Dementia and incontinence

• Exercise and Epilepsy

• Circadian Activity Rhythms (general) - old
Depression Detection and General Anomalies

- Multi-modal
- Passive
- Combines Objective and Subjective Measures
Empath: Depression Monitoring

Depression Inference

Patient Display
Caregivers Display

Eating
Sleep Quality
Movement
Mood
Weight Gain/Loss

DB
Cloud

Motion and Contact
Sleep Data
PHQ-9
Acoustic
Weight

University of Virginia
Patient Health Questionnaire

In the past 2 weeks have you had any of the following problems:

Begin
Little interest or pleasure in doing things

- Not at all
- More than half the days
- Nearly every day
Caregivers Display

**Patient: Lois Peters, 83**

**Medical History:**
Chronic Major Depression

<table>
<thead>
<tr>
<th>Sleeping Quality</th>
<th>Hygiene Level</th>
<th>PHQ Score</th>
<th>Weight</th>
<th>Eating</th>
<th>Social Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>terminal insomnia</td>
<td>clean</td>
<td>22</td>
<td>123 lbs</td>
<td>3 meals/day</td>
<td></td>
</tr>
</tbody>
</table>
Dementia and Incontinence

- Bedwetting and sleep agitation relationship
- Interventions on sleep
- Sleep labs impractical
- 50 patients
Dementia and Incontinence (subsystem of Empath)

- Passive Sleep system  uva built
- UVA Tempo device uva built
- Wetness sensors – Dry Buddy off-shelf
- Acoustic sensors – Screaming off-shelf
Epilepsy Study
(subsystem of Empath)

• Linkage: between exercise, stress, sleep and epilepsy seizures

• Measure: HR, BP, sleep quality, frequency of seizures

• Intervention: qigong (Chinese healing art)
Epilepsy (cont.)

• 10 patients

• CareTaker device measures BP

• Data into Amazon Cloud via Verizon 3G

• Working with medical personnel in Center for Complementary Therapies
Many Seizures at Night

[Graph showing bed movement over time, peaking at night with multiple sharp declines and increases.]
Circadian Activity Rhythms

- 22 patients
- 3 months to 1 year
- 7 males; 15 females
- Ages 49-93
- All ambulatory
- Weekday; weekend; seasonal
- Eliminate times when not in facility
- Learning - 2-3 weeks of normal behavior
Circadian Rhythms

24 hour cycle

Circadian activity rhythm per room for 70 days
Anomalies

• Examples

  – Retroactively analyzed the anomalies
    • Detected “depression” – much more time in bed
    • Detected increased urination at night
    • Detected different behavior upon return from hospitalization

Underlying Technology

• Sleep Monitoring
• Privacy
• Semantic Anomaly Detection
• Robust Activity Recognition
Sleep Monitoring

• Sleep motion (restlessness and agitation)
  – Sleep Apnea
  – Restless Leg Syndrome
  – Incontinence
  – Epilepsy
  – …

• Sleep quality
Using Physiological Signals

- EEG: measures brain waves
- EOG: measures eye movements
- EMG: measures electrical activity of muscles

Disadvantages
- Expensive
- Uncomfortable
- Measure once/twice
Wearable Devices in Home Environments

- Actiwatch
- Headband - Zeo
- Disadvantage
  - Users need to wear the devices
Non-Wearable Solutions

• Pressure Pads
  – Disadvantage
    • Not entirely comfortable
    • Do not infer body positions

• Cell Phone Apps
  – Built-in accelerometers are used
  – Disadvantages
    • Not robust
    • Forget to use
WISP

- Combines RFID technology with sensors
- Used to sense light, temperature and acceleration
- Powered and read by RFID readers
WISP Instrumented Mattress
Body Position Inference

- For different body positions, orientations of one or more axes of the accelerometers with respect to gravity are different.
- We combine the readings from all three tags to infer body position.
- Bayesian classifier.
Controlled Experiments for Body Position Inference

- 10 subjects
- 3 different mattresses

- Each subject lies in each of the 4 body positions for 2.5 minutes each

- For each position, we use the data from the first 2 minutes for training and next 30 seconds for evaluating accuracy of body position inference
Results

• 3 settings:
  – set1: differentiate between the bed being empty or occupied
  – set2: differentiate between empty, lying and sitting
  – set3: differentiate between all lying positions, empty and sitting
Realistic Overnight Experiments

- 6 nights
- DDR pads (sense pressure) used as baseline system
- Also compare with an iPhone application: Sleep Cycle
- We also recorded the video of the 6 nights’ sleep
Evaluation by Cross Validation

• 6 Evaluation sets
• In each set, we train our system based on 5 nights of data and evaluate the performance of the remaining night
Movement Detection Evaluation

- Ground Truth
  - Validated the performance of DDR pads by comparing with 3 hours video
  - DDR pads are considered ground truth
Body Position Inference

- **Ground Truth**
  - Collected from the recorded video
  - Accurate within 5%
Privacy

Fingerprint And Timing-based Snoop attack

Activities of Daily Living (ADL)

- **ADLs inferred:**
  - Sleeping, Home Occupancy
  - Bathroom and Kitchen Visits
  - Bathroom Activities: Showering, Toileting, Washing
  - Kitchen Activities: Cooking

- **High level medical information inference possible**

- **HIPAA requires healthcare providers to protect this information**
Performance Evaluation

- 8 homes (X10 sensors) different floor plans
  - Each home had 12 to 22 sensors
- 1 week deployments
- 1, 2, 3 person homes
Privacy Results

• Violate Privacy
  – Techniques Created – 3 Tier Inference
    • K-means - time
    • DB-scan - room
    • LDA – sensor type and activity
  – 80-95% accuracy of AR

• FATS solutions
  – Reduces accuracy of AR to 0-15%
Semantic Anomaly Detection

- Sensor Level Anomalies
- Activity Level Anomalies
- Behavioral Anomalies (apply semantics)
Sensor Level Anomalies

• May be due to different types of sensor failures
  – Fail-stop failure (may be detected by Ping)
  – Stuck-at failure
  – Transient
  – Obstructed field-of-view
  – Sensor movement
Sensor Level Anomalies

• How to detect:
  – Use temporal and spatial correlation among different sensors
  – Use multiple classifiers

Activity Level Anomalies

• Point Anomalies
  – For each activity, one or more models based on training data

  – Different set of features for different activities
    • Sleep: sleep onset time, duration, number of interruptions, movement level
    • Showering: Start time, duration, water usage

  – Use statistical anomaly detection
Behavioral Anomalies

• Collective Anomalies
  – Monitor instances of same activity for \( N \) days collectively
    • Example: exercise twice per week
  – Monitor whether other activities happen before/after/during that activity in each time period
    • Example: have coffee before breakfast
  – Monitor instances of all activities for \( N \) days collectively
    • Example: every week shop, exercise, see doctor, …

• Semantics
Semantics

- Watching a pet for a few days
- Entertaining visitors
- Power outage
- Recovering from major medical operation
- Sensors died
- Extreme weather: cold/heat wave
- Social security check did not arrive: cannot purchase food or medication
- Major medication change
- Life changing events: sibling etc died, new grandchild etc.
Anomaly Detection Framework

- Normal Behavior Models
- Anomaly Detector
- Anomaly Filters
- Alarms or Warnings

User Feedback
Update over time
Correlation and Semantics
Assessment Data
Training Data
Robust Activity Recognition

- Accurate detection and summary of daily activities are essential
- Proper training and periodic retraining are necessary
- Necessary to ensure user comfort
Overlapped Activities

- Interrupted by room changes
- Concurrent in the same room
- Across rooms (not done yet)
Room Level Segmentation

- Most Activities of Daily Living have spatial regularity

In real life:
- An activity may not complete within one episode
- Within one episode, multiple activities may take place
Room Level Segmentation

• Successive Occupancy Episode Merging (SOEM)
  – to identify overlapped activities interleaved across multiple rooms

• We construct a new occupancy episode by merging two occupancy episodes in the same room that are separated by less than a time interval threshold
Many Activities are usually performed

- in the same location
- using similar set of objects
- sometimes have similar temporal characteristics
Evaluation

Public Dataset

- Single resident home
- Activity annotation by the resident using Bluetooth headset
- 26 days of data
- 4 rooms (Bedroom, Kitchen, Toilet, Shower)
- ‘Out of house’ considered as another room

List of Sensors

<table>
<thead>
<tr>
<th>kitchen_microwave</th>
<th>kitchen_groceries</th>
</tr>
</thead>
<tbody>
<tr>
<td>kitchen_cups</td>
<td>kitchen_fridge</td>
</tr>
<tr>
<td>kitchen_plates</td>
<td>toilet_door</td>
</tr>
<tr>
<td>kitchen_dishwasher</td>
<td>toilet_flush</td>
</tr>
<tr>
<td>kitchen_freezer</td>
<td>shower_door</td>
</tr>
<tr>
<td>kitchen_pans</td>
<td>bedroom_door</td>
</tr>
<tr>
<td>kitchen_washingmach</td>
<td>front_door</td>
</tr>
</tbody>
</table>
Reducing User Labeled Data

- User needs to label only 19 clusters

- Any supervised algorithm requires labeling of 291 activity instances

- With supervised algorithms, amount of user labeling proportionally increases with number of training days

<table>
<thead>
<tr>
<th>Room</th>
<th>Number of Clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bedroom</td>
<td>1</td>
</tr>
<tr>
<td>Toilet</td>
<td>4</td>
</tr>
<tr>
<td>Shower</td>
<td>1</td>
</tr>
<tr>
<td>Kitchen</td>
<td>12</td>
</tr>
<tr>
<td>Outside</td>
<td>1</td>
</tr>
</tbody>
</table>
Effectiveness of SOEM

Training Time Slice Error for Different Activities

- Accuracy of ‘Sleep’ & ‘Prepare Dinner’ detection improved
- SOEM does not reduce the accuracy for any activity
Comparison with Supervised Algorithms

- AALO performs as good as HSMM in most cases
Summary

• (Personalized) Wireless Health
  – Body Sensor Networks
  – Environmental and AR Networks

• Easy to Modify over Time
  – Incorporate new technology as it becomes available
  – Adapt as medical conditions change
“It appears to be some kind of wireless technology.”
## Example: Kitchen Clusters

<table>
<thead>
<tr>
<th>ID</th>
<th>Used Sensors</th>
<th>Mean Start Time</th>
<th>Std. Start Time (Min)</th>
<th>Mean Duration (Min)</th>
<th>Std. Duration (Min)</th>
<th>Probable Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{kitchen_fridge, kitchen_plates, kitchen_groceries}</td>
<td>9:25</td>
<td>70</td>
<td>1.76</td>
<td>1.65</td>
<td>Prep. Breakfast</td>
</tr>
<tr>
<td>2</td>
<td>{kitchen_fridge, kitchen_freezer, kitchen_microwave}</td>
<td>9:12</td>
<td>65</td>
<td>6.59</td>
<td>3.78</td>
<td>Prep. Breakfast</td>
</tr>
<tr>
<td>3</td>
<td>{kitchen_fridge, kitchen_freezer, kitchen_microwave}</td>
<td>18:50</td>
<td>45</td>
<td>30.24</td>
<td>9.25</td>
<td>Prep. Dinner</td>
</tr>
<tr>
<td>4</td>
<td>{kitchen_cups, kitchen_plates, kitchen_groceries}</td>
<td>19:20</td>
<td>60</td>
<td>40.38</td>
<td>17.84</td>
<td>Prep. Dinner</td>
</tr>
<tr>
<td>5</td>
<td>{kitchen_freezer, kitchen_groceries}</td>
<td>19:30</td>
<td>40</td>
<td>20.65</td>
<td>5.62</td>
<td>Prep. Dinner</td>
</tr>
<tr>
<td>6</td>
<td>{kitchen_plates, kitchen_pans}</td>
<td>19:25</td>
<td>45</td>
<td>10.54</td>
<td>3.29</td>
<td>Prep. Dinner</td>
</tr>
<tr>
<td>7</td>
<td>{kitchen_fridge, kitchen_cups}</td>
<td></td>
<td></td>
<td>3.98</td>
<td>2.57</td>
<td>Get Drink</td>
</tr>
<tr>
<td>8</td>
<td>{kitchen_freezer, kitchen_groceries}</td>
<td>21:54</td>
<td>90</td>
<td>1.71</td>
<td>1.28</td>
<td>Get Snack</td>
</tr>
<tr>
<td>9</td>
<td>{kitchen_microwave, kitchen_plates}</td>
<td>20:12</td>
<td>150</td>
<td>2.31</td>
<td>0.75</td>
<td>Get Snack</td>
</tr>
<tr>
<td>10</td>
<td>{kitchen_washingmach}</td>
<td></td>
<td></td>
<td>4.23</td>
<td>2.39</td>
<td>Use Wash. Mac.</td>
</tr>
<tr>
<td>11</td>
<td>{kitchen_dishwasher, kitchen_plates}</td>
<td></td>
<td></td>
<td>4.25</td>
<td>1.5</td>
<td>Use Dish. Wash.</td>
</tr>
<tr>
<td>12</td>
<td>{kitchen_dishwasher, kitchen_pans}</td>
<td></td>
<td></td>
<td>4.76</td>
<td>2.45</td>
<td>Use Dish. Wash.</td>
</tr>
</tbody>
</table>
Current (New) Research

- Data Association (multi-person homes)
- Safety
- Run Time Assurance – safety
- Scaling
- Extensible Fall Detection
- Holistic Re-design BSN
- Kinect (micro-behaviors/find objects)
- Wellness (music and heart rate)
Algorithms Research

- AR
- Anomaly Detection
- Data Association
- Data Mining
- Impact of Physical on Cyber
- Adaptable Control
Networking Research

- Multi-unit Buildings – scale
- Multi BSNs – interference
  - QoS
- Compression and Filtering
- Long term evolution
- Burst losses and guarantees
- Real-time Properties
- DTN
Realities Research

- Human behavior impact
- Environmental evolution
- Safety
- Privacy and Security
- Robust sensor processing
- Energy constraints
- RTA
- Sensing <-> Disease
- HCI
Theory Research

• Optimal locations
  – Minimum number of sensors
• Guaranteed coverage
• Maximum network capacity
  – Required bandwidth, numbers of nodes
• Limits of multi-modal approaches
## Evaluation

<table>
<thead>
<tr>
<th>Activity</th>
<th>Leave House</th>
<th>Use Toilet</th>
<th>Take Shower</th>
<th>Sleep</th>
<th>Prepare Breakfast</th>
<th>Prepare Dinner</th>
<th>Get Snack</th>
<th>Get Drink</th>
<th>Use Wash. Mach.</th>
<th>Use Dish Washer</th>
<th>Idle</th>
<th>Irregular</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leave House</td>
<td>89.9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10.1</td>
</tr>
<tr>
<td>Use Toilet</td>
<td>0</td>
<td>70.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>14.2</td>
<td>15.5</td>
</tr>
<tr>
<td>Take Shower</td>
<td>0</td>
<td>0</td>
<td>77.5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.2</td>
<td>18.3</td>
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<tr>
<td>Sleep</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>98.7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1.3</td>
</tr>
<tr>
<td>Prepare Breakfast</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>64.5</td>
<td>0</td>
<td>4.2</td>
<td>6.3</td>
<td>0</td>
<td>5.8</td>
<td>10.4</td>
<td>8.8</td>
</tr>
<tr>
<td>Prepare Dinner</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>69.8</td>
<td>2.4</td>
<td>2.9</td>
<td>0.5</td>
<td>1.3</td>
<td>13.5</td>
<td>9.6</td>
</tr>
<tr>
<td>Get Snack</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>74.3</td>
<td>4.6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>11.1</td>
</tr>
<tr>
<td>Get Drink</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>11.1</td>
<td>9.4</td>
<td>5.2</td>
<td>74.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Use Wash. Mach.</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>70.4</td>
<td>0</td>
<td>0</td>
<td>19.6</td>
</tr>
<tr>
<td>Use Dish Washer</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.6</td>
<td>29.5</td>
<td>0</td>
<td>5.5</td>
<td>0</td>
<td>69.4</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Itemset Mining

- Specific activities of daily living are performed using specific objects
- Find the groups of sensors (i.e., items) that are frequently fired together i.e., itemsets (using Apriori Algorithm)

(roomID, entranceTime, duration, usedSensors)

- Our hypothesis is that each frequent itemset represents an activity
Clustering Instances of each Frequent Itemset

• There may be multiple activities using same objects

• We cluster instances of the same frequent itemset based on their temporal characteristics (start time and duration)

• DBSCAN does not require to specify number of clusters
Output

• Set of all clusters constructed by applying DBSCAN on all frequent itemsets of all rooms separately

• Each cluster is represented by (Used Sensors, Mean_Start_Time, Mean_Duration, Neighborhood_Radius, Probable_Label)

• Example: (<Microwave, Plates Cupboard, Groceries Cupboard>, 9:25 AM, 1.76 minutes, <70 min, 1.65 min>, Prepare Breakfast)
Activity Recognition

- Construct Occupancy Episode \( e \)

- Get set of used sensors \( u_e \) in \( e \)

- Find \( \{C_j\} \) such that \( usedSensors_j \subset u_e \)

- For each \( \{C_k\} \subset \{C_j\} \) where \( C_k \)'s have same \( u_k \subset u_e \)

- Assign the time period of \( u_k \) in \( e \) the activity label of the temporally closest cluster in \( \{C_j\} \)