Unobtrusive Assessment of Mobility and Cognitive Function
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Overview

• ABC for Technology for Aging (Applied, Basic and Clinical)
  – Serious challenge
  – Multidisciplinary
  – Model-based
• Modeling the time course of cognitive decline
• Basic system: Unobtrusive Technology + Sophisticated Algorithms
• Examples
  – Mobility: Gait velocity
  – Medication adherence
• Technical Challenges
  – Localization
  – Identification
Current Global Age Distribution

2002

Percentage of Population over 60 years old
Global Average = 10%

Source: United Nations • “Population Aging • 2002”
Projected Global Age Distribution

2050

Sweden (>65)
2005 ~ 17%
2030 ~ 23%
2050 ~ 24%

Percentage of Population over 60 years old
Global Average = 21%

Source: United Nations • “Population Aging • 2002”
Sweden Demographics

Life Expectancy

<table>
<thead>
<tr>
<th></th>
<th>2005</th>
<th>2050</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>83</td>
<td>86</td>
</tr>
<tr>
<td>Men</td>
<td>78</td>
<td>84</td>
</tr>
</tbody>
</table>

Facts about Elderly in Sweden, Ministry of Health and Social Affairs, September 2007
Cognitive Changes with Healthy Aging

![Graph showing mean T-scores for various cognitive abilities across different ages. The y-axis represents mean T-scores ranging from 30 to 60, and the x-axis represents age from 25 to 88. Different lines and markers correspond to different cognitive abilities, including Inductive reasoning, Spatial Orientation, Perceptual Speed, Numeric Ability, Verbal Ability, and Verbal Memory.](image-url)
Technology in Care for Elders and Chronically Ill

• Improving efficiency and quality of care
• Relieving burden on formal and informal caregivers
• Reducing cost by avoiding acute emergency care
• Early detection and monitoring of cognitive function
  – Developing and evaluating drug therapies
  – Neuro-protection techniques
  – Remediation methods (Dr. Jimison)
  – Adopting proper care level
  – Developing better diagnostic techniques, e.g., imaging

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Multidisciplinary Problem

- Clinicians – problem identification and workflow issues
- Caregivers
- Pharmacists, social workers, etc.
- Embedded sensor systems
- Wireless and wired networks
- Data management
- Pattern detection, data mining, visualization
- Modeling cognitive, motor and social systems
- Mechanical systems and assistive devices
Brain Loss Trajectory Predicts Aging Outcome

Prior to CI onset the yearly rate of increase is higher in those who developed CI (p=0.049)

At onset there is a further increase in the yearly rate of ventricular volume increase compared to those who have not developed CI (p=0.012)

Alzheimer’s Disease Dynamics

(Consortium to Establish a Registry for Alzheimer’s Disease, 1986-96)

Estimate MMSE as a function of time

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Modeling Dynamics of Alzheimer’s Disease

- Assumptions:
  - Define the number of affected neurons $N(t)$:
  - Test performance is proportional to the number of affected units, $N_0 - N(t)$

$$\frac{dN(t)}{dt} = rN(t)\left(K - N(t)\right)$$

- Data fit with Logistic + linear

$$S(t) = S_{\text{max}} \left[ 1 - a_1(t-a_2) - \frac{a_3}{1 + e^{-a_4t+a_5}} \right]$$

- Slow decline starts more than 10 years earlier

$$S(t) \approx S_{\text{max}} \left[ 1 - \frac{(t-13)}{64} - \frac{0.01}{1 + e^{-t+1}} \right]$$
Data From Ashford 1995

![Graph showing MMSE Score over Time (Years)](image)

- Logistic Model
- Data

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Oregon Brain Aging Study (OBAS) MMSE Data

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Modeling Cognitive Decline: MMSE and Verbal Fluency

![Graph showing MMSE and Verbal Fluency scores over time relative to diagnosis (Dx). The graph compares Logistic Model, Oregon Brain Aging Study (OBAS) Data, Logistic Model, and MMSE scores.](image-url)
Can we detect the onset of a decline?
What’s Wrong with Current Ways of Assessment of Elders?

- Short-term variability (mood, recent events, etc.)
- Short-term compensation – fear of nursing home
- Population norms applied to individuals
- Caregiver interview – biases and memory effects
- Difference between ability and performance
- Family and caregivers denial
- Compliance vs. report of compliance
- Subjectivity in the assessment of impairment level
- Insensitivity to slow changes
- Reporting biases: hypochondria vs. stoic
- Speed-accuracy tradeoff
Detection of Slow Changes in Behavior

Aliasing Errors + Noise

<table>
<thead>
<tr>
<th>Test Score</th>
<th>Time [months]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mr. Green</td>
<td>&quot;GOLD&quot; STANDARD</td>
</tr>
<tr>
<td>R ~ 0.7</td>
<td>Test - Test Reliability</td>
</tr>
<tr>
<td>R² ~ 0.5</td>
<td></td>
</tr>
<tr>
<td>Mrs. Rosen</td>
<td></td>
</tr>
</tbody>
</table>
Continuous Unobtrusive Monitoring

Fusion
Home-based scalable assessment platform
Empirical Studies

- Laboratory experiments with the sensor systems
- Pilot study of the sensors in homes Parkinson’s disease patient/control
- Social health monitoring system
- Medication adherence tracking
- Context aware medication prompting
- Living laboratory
- Longitudinal study of healthy aging

Take home message:

Study elders at home
Assessment and Monitoring of Mobility and Activities of Daily Living
Individual Sensor Data: Looking for Patterns

Total Activity for Sun Day No. 11

Total Activity for Tue Day No. 13
Daily Sensor Activity: At stand alone home

Green – Bedroom
Pink   – Kitchen
Red    – Bathroom
Yellow – Living Room
Black  – Door Sensors

Subject 5A

Change in Sleep Pattern

Meal Preparation
Daily Sensor Activity: Residential Facility (CCRC)

Out of the apartment (Meals, Social Activities?)

Green – Bedroom
Pink – Kitchen
Red – Bathroom
Yellow – Living Room
Black – Door Sensors
Assessment of Gait Velocity

• Why Gait Velocity?
  – Indicator of mobility
  – Related to cognitive function

• Existing approach: In clinic

• Approach: Unobtrusive assessment
  – Using accelerometers
  – Using passive sensors

• Technical problems:
  – Estimation of gait velocity and variability from the raw sensor data
  – Identification of the walking individual

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Assessment of Gait Velocity
Simplified Approximation to the Identification Problem

- Simple Markov Model to characterize constraints and dynamics

- Compute the likelihood of an individual $X = A$ walking through the test area, given RSSI process $\bar{R}$ and motions sensors $\bar{M}$

- Non-causal

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Parkinson’s Patient and Healthy Control

66A: Control

Walking time (s/m)

80 percentile
50 percentile
20 percentile

66A: PD

Walking time (s/m)

80 percentile
50 percentile
20 percentile

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Validation – Ground Truth – Gait Mat

- Mat with dense pressure sensors placed on a hard floor
- Measures instantaneous plantar pressure and absolute location
Laboratory Validation of the Sensor Passive IR Sensors

- Raw330: Raw Data Display with Pressure Measurement

- Distance versus Time

- GAIT MAT vs Motion Sensor
Comparison of Field Gait Velocity Measurements

- Gait Mat range  
- Clinical  
- Sensor Line

Walking time (secs/m)

Subject

Slow

Fast

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Variability in walking speed increases with early cognitive impairment

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Oregon Brain Aging Study/ORCATECH
Medication Adherence

• Problem: Assessment of medication-taking behaviors and possible intervention

• Prior Approach to Assessment:
  – Self-reports
  – Off-line measurements

• Approach:
  – Development of a wireless medication tracker
  – Installation of sensor suite
  – Schedule for medication taking (vitamin C): 2x daily

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Medication Adherence: Good Performance

Percentage of time vitamins were taken as planned: 87.2% (morn), 83.3% (eve), 90.3% (overall)
Number of missed morning doses: 1 (For 0 of these you were out of the house)
Number of missed afternoon doses: 6 (For 0 of these you were out of the house)
Percentage of days in which you took 2 pills as prescribed: 83.3%

OHSU Vitamin Study: Data for: AUM
Medication Adherence: Typical Performance

Percentage of time vitamins were taken as planned: 88.6% (morn), 45.7% (eve), 67.1% (overall)
Number of missed morning doses: 4 (For 4 of these you were cut of the house)
Number of missed afternoon doses: 19 (For 19 of these you were out of the house)
Percentage of days in which you took 2 pills as prescribed: 77.1%
Context-Aware Medication Prompting (with Intel)

- Existing Prompting: Time based alerts
- Problems
  - Patient is busy at the time of alert
  - Patient is away from the medication dispenser
- Approach: Context-Aware Prompting
  - Detect and/or predict the probability of not taking the medication
  - Detect location – proximity to medication dispenser
  - Detect interfering activity: Sleep, on the phone, about to leave
  - Generate alerts with the highest “expected utility”
Context-Aware Prompting: Results
Context-Aware Prompting: Results

The diagram shows box plots comparing average weekly adherence (in %) across different conditions:
- No prompting
- Time-based prompting
- Location-based prompting

The adherence is measured for morning, evening, and overall periods.
Current Exercising in Senior Residential Facilities

Based on “Able Bodies” project

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The doctor said he needed more activity. So I hide his T.V. remote three times a week.
System Configuration

- CCD
- CPU
- NTSC/IO
- TV

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Exercise Coach

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Elders’ Exercise – Movement in Coronal Plane
Modeling the Human Body

- 3D Model
- Body parts represented by cylinders
- 14 segments
- 12 joints
- Projection of the model into 2D image plane
Modeling the Human Body

- 3D Model
- Body parts represented by cylinders
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Resulting Inference: Perpendicular Plane
Activity Monitoring – Key Technical Issues

• Multi-person dwelling  Distinguishing among the occupants of dwellings
• Localization: Minimally obtrusive localization
• Identification: Identification of a small number of individuals and recognition of new persons
Recursive Bayesian Estimation (Eric Wan)

- Probabilistic approach for estimating an unknown state probability density function recursively over time using incoming measurements and a mathematical process model.

\[
y_k = h(x_k) + w_k
\]

State: position, velocity

\[
p(y_k | x_k) \quad \text{and} \quad p(x_k | x_{k-1})
\]

Unobserved

Observed

Observation Model(s)
- Mapping from position to RSSI
Recursive Bayesian Estimation

- Probabilistic approach for estimating an unknown state probability density function recursively over time using incoming measurements and a mathematical process model.

\[ p(y_k | x_k) \]

**Observed**

\[ y_k \]

**Unobserved**

\[ x_{k-2} \rightarrow x_{k-1} \rightarrow x_k \]

state: position, velocity

\[ p(x_k | x_{k-1}) \]

**Process model - Random Walk**

\[
\begin{align*}
x_{k+1} &= F_k x_k + V(x_k) + w_k \\
F_k &= \begin{bmatrix}
1 & 0 & T \\
0 & 1 & 0 \\
0 & 0 & .95
\end{bmatrix} \\
x_k &= \begin{bmatrix} x_k \ y_k \ v_{xk} \ v_{yk} \end{bmatrix}
\end{align*}
\]

where

\[ w_k = \text{white gaussian noise} \]

\[ T = 1 \text{ second} \]

**Potential field**

\[
\begin{bmatrix}
10 & 0 & 0 & 0 \\
0 & 10 & 0 & 0 \\
0 & 0 & .95 & 0 \\
0 & 0 & 0 & .95
\end{bmatrix}
\]
Recursive Bayesian Estimation

- **Probabilistic approach** for estimating an unknown state probability density function recursively over time using incoming measurements and a mathematical process model.

\[ x_{k-2} \quad y_{k-2} \quad x_{k-1} \quad y_{k-1} \quad y_k \quad p(y_k \mid x_k) \]

Observed

Unobserved

state: \textit{position, velocity} \quad p(x_k \mid x_{k-1})

Sigma-Point Kalman Filters

- Approximate Recursive Bayesian Estimation with Gaussian state distribution
- Superior to Extended Kalman Filter (EKF)
- \textit{Noncausal} (smoother) Implementation
Ekahau Positioning Software
Tracking Performance: Point of Care Lab (CHH)

Sigma-Point Kalman Filter
Tracking Performance: Point of Care Lab (CHH)

Sigma-Point Kalman Filter + IR Sensors

SPKF: RSSI+IR
Real-time Image-Based Localization: Work in Progress

- Ceiling-mounted fish-eye camera
Real-time Image-Based Identification: Work in Progress
Other Projects that would benefit from embedded systems

- Augmented Cognition: Assessment of an individual’s cognitive state using EEG
- Diagnosis/triage of vocal cord diseases using acoustic measurements
- Assessment of cognitive functions using computer interactions and interactive games
- Assessment of sleep quality using bed sensors, e.g. load cells
- Reconciliation of medication lists
Medication Reconciliation: RxSafe

**Critical Questions:**
- What medication is the patient taking?
- What should he be taking

**Existing Records**
- Clinic and family practitioner
- Pharmacy record
- Residential facility: Medication adherence record
- RxSafe: Tools for medication reconciliation

**Missing**
- Reliable embedded systems for the assessment of medication taking behaviors

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Summary

- Continuous, unobtrusive in-vivo assessment is possible and is likely to reduce the variability of the assessment.

- Sensitive real-time monitoring can provide critical information for intervention.

- Context-sensitive intervention appears to be an effective way to improve health-related behaviors.

- But, there are many technical challenges ahead.

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Technical Challenges

• Unobtrusive sensing of behaviors and physiological variables
• Unsupervised calibration and maintenance
• Power management and harvesting
• Integration and synchronization
• Localization
• Identification/authentication
• Adaptation of sensor systems to each individual and context
• Recognition of activities, e.g., activities of daily living
• Detection of subtle changes, e.g. cognitive decline
• Prediction of adverse events, e.g. falls
• Development of assistive cognition devices
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