Context-Aware Mobile Computing: Learning Context-Dependent Personal Preferences from a Wearable Sensor Array

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● Context-Aware Mobile Phone
● Four states: Meeting, High-Energy, Idle, Normal
● Thresholds from accelerometers and microphones trigger state transitions

● Problems
  ● Threshold values do not generalize well
  ● Preferences vary widely among people
Goals

- Enable a wearable computer to learn about \textit{individual} user states using sensors
- This process should not require supervision by the user
- Let the computer learn to \textit{associate} user states with user preferences

\textbf{ARIUS}

Adaptive Reflection of Individual User States
ARIEUS Two Step Approach

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>User’s attention</strong></td>
<td>Not required</td>
</tr>
<tr>
<td><strong>Availability</strong></td>
<td>Abundant</td>
</tr>
<tr>
<td><strong>Values</strong></td>
<td>Continuous</td>
</tr>
<tr>
<td><strong>Dynamics</strong></td>
<td>Time series</td>
</tr>
</tbody>
</table>
Learning User’s Preferences

User State

Learning structure / dependencies

System

Preferences

• Ringer volume
• Accept calls

Interactions (conscious)

Location

Activity

Schedule

Physiology

Learning typical patterns

State

Context

Learning structure/dependencies

• Motion
• Speech

• GPS
• WiFi

• Time cycles
• Calendar

• GSR
• Heat flux
• Temperature

Sensors (unconscious)
Accomplishments

- Development of methods for
  - Context Identification
  - Preference Learning
- Design and implementation of a wearable study platform realizing these methods
- Evaluation in several experiments
Wearable Sensors
Context Identification

- Unsupervised, dynamic identification of locally-constant contexts
- Issues:
  - Preprocessing / Feature Extraction (RA, SAD, FFT, PCA, Normalization, …)
  - Clustering (KSOM, $k$-Means)
  - Identifying the number of classes (context abstraction)
Offline Data Classifier

Preprocess.

Context classifier

Map training

Clustering

Transition probabilities

Context abstraction

Construction of Classifier

Wearable device

Sensors
Example Clustering Results
Context Abstraction
Online Data Classifier

Sensors on armband

Time

Buffer (t-1) Buffer t

| t-2 | t-1 | Buffer t |

KSOM

Clustering (t)

Transition probabilities

Old model used for update

Clustering (t-1)
Location-Awareness

● Combination of two complementary sensors
  ● Outdoors: Global Positioning System
  ● Indoors: 802.11b signal strength triangulation

● Clustering Approach to identify
  ● indoor locations
  ● outdoor locations
  ● entrances

● Scaling problems!
Preference Learning

- Creating a generative model relating the context- and system variables

- Technique: Bayesian Networks
  - Efficient method to compute joint PDF
  - Can handle incomplete data
  - Can incorporate dynamics

- Issues
  - Algorithms for parameter- / structure learning
  - Hidden variables
  - Priors
Experimental Design

- Motivation of machine learning approach
  - Survey among college phone users (preliminary)
  - Threshold analysis
- Evaluation of Context Identification method
  - Self-report study
  - Real-time movement identification / classification
- Evaluation of Preference Learning method
  - SenSay training
  - Self-report study
Clustering ⇔ Self-reports

work walk cook eat work

sleep

read walk Off.
# Self-report Study Results

<table>
<thead>
<tr>
<th>Sample</th>
<th>Size</th>
<th>Annotated Contexts</th>
<th>Clusters</th>
<th>Time-stamps</th>
<th>Transitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-1</td>
<td>20h / 2d</td>
<td>C,E,H,O,S</td>
<td>6</td>
<td>9</td>
<td>11</td>
</tr>
<tr>
<td>A-2</td>
<td>25h / 2d</td>
<td>C,E,F,H,O,R,S</td>
<td>6</td>
<td>9</td>
<td>14</td>
</tr>
<tr>
<td>A-3</td>
<td>29h / 2d</td>
<td>C,E,H,O,S</td>
<td>5</td>
<td>8</td>
<td>17</td>
</tr>
<tr>
<td>B-1</td>
<td>57h / 6d</td>
<td>B,C,H,M,O,S</td>
<td>4</td>
<td>26</td>
<td>35</td>
</tr>
<tr>
<td>B-2</td>
<td>17h / 3d</td>
<td>M,O</td>
<td>2</td>
<td>20</td>
<td>25</td>
</tr>
<tr>
<td>B-3</td>
<td>26h / 4d</td>
<td>C,M,N,O,S</td>
<td>4</td>
<td>18</td>
<td>24</td>
</tr>
<tr>
<td>B-4</td>
<td>22h / 3d</td>
<td>C,D,E,L,O,M</td>
<td>4</td>
<td>25</td>
<td>27</td>
</tr>
<tr>
<td>B-5</td>
<td>46h / 5d</td>
<td>C,E,L,M,O</td>
<td>3</td>
<td>37</td>
<td>35</td>
</tr>
</tbody>
</table>
## SenSay Training

<table>
<thead>
<tr>
<th>Activity</th>
<th>Audio</th>
<th>Phone action</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working</td>
<td>Talking</td>
<td>Silent</td>
<td>9.2</td>
</tr>
<tr>
<td>Working</td>
<td>Whistling</td>
<td>High</td>
<td>9.0</td>
</tr>
<tr>
<td>Working</td>
<td>Silence</td>
<td>Medium</td>
<td>14.0</td>
</tr>
<tr>
<td>No motion</td>
<td>Talking</td>
<td>Silent</td>
<td>6.5</td>
</tr>
<tr>
<td>No motion</td>
<td>Not talking</td>
<td>Medium</td>
<td>8.5</td>
</tr>
<tr>
<td>Walking</td>
<td>Talking</td>
<td>Low</td>
<td>10.2</td>
</tr>
<tr>
<td>Walking</td>
<td>Not talking</td>
<td>Maximum</td>
<td>11.0</td>
</tr>
<tr>
<td>Driving</td>
<td>Talking</td>
<td>Vibrate</td>
<td>8.2</td>
</tr>
<tr>
<td>Driving</td>
<td>Not talking</td>
<td>Low</td>
<td>9.0</td>
</tr>
</tbody>
</table>
Self-Report Network Structure
System Initialization

Cluster 1

Factory defaults

Cluster 1’

Learned context-dependent personal preferences
ARIUS Software Architecture

- Sensor fusion process modeled as a directed acyclic graph
  - Sensors and User Interactions are sources
  - Preprocessing steps are internal nodes
  - Clustering / Learning algorithms are sinks
  - Configurable using XML
  - Object oriented implementation (Java)
  - Extendable with new sensors / preprocessing steps
ARIUS Software Architecture II

- Event based communication
  - Distribution of events over the network or streaming into a database (different speeds)
  - Infrastructural sensors can connect upon availability
  - High level of concurrency

- Maintenance / Reliability
  - Acoustic feedback in case of error
  - Tap into sensor fusion graph
  - Runs 10+ hours without recharging
ARIUS running...
Results & Future Work

- Learning context-dependent personal preferences possible, at least for
  - Limited number of study participants
  - Locally-constant contexts from low-level sensors
  - Mobile phone application
- Method can be realized on wearable hardware
- Other applications of the presented method
- Extended studies
- Further hardware integration