Using Smart Phones for Context-Aware Prompting in Smart Environments

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The Problem

Please turn off the burner.

Sugar is in the cupboard.

It's time to take medicine.

You just picked up the wrong vessel.

You look tired, why don't you take a nap.

Sam is trying to get in touch with you.

It's John's birthday, you wanna write a card?

Please take a look at the Wattage of the light bulb.

It's time to take medicine.

Sam is trying to get in touch with you.

Sugar is in the cupboard.

It would be a good idea to take a walk.

Automatic delivery of verbal or non-verbal interventions that would help a smart home inhabitant in successful completion of daily tasks.
Our Solution

Context-Aware Prompting

On the go prompt delivery on your Smart Phone

Solution

Behavioral Context from Accelerometer Data on Phone

Movement-based Real-time Activity Recognition
System Architecture

Figure 1: System Architecture

Real-Time Basic Activity Recognition
(Classified from collected accelerometer data)
Phone Infrastructure

- **Device:** Samsung Captivate™
- **Operating System:** Android 2.1
- **Networking:** WiFi makes local connection to XMPP server.
- **Accelerometer Type:** Tri-axial
- **Frequency of Data Collection:** 20Hz
Context Model

Context Awareness

Temporal
- Time Instance
- Time Window
- Time Period

Environmental
- Location
- Sensor Sequence

Behavioral
- Basic Activity Recognition
Example of Context Awareness

• Taking medication sometime in between 7:00 AM and 8:30 AM, right after breakfast:

**Tigger Pattern**
startTime(7:00:00) \(\land\) 
dayOfWeek() \(\land\) 
triggerPattern (M013, sitting, walking- standing, M016- M017- M018) 
→ prompt(medication.wav)

**Kill Pattern**
endTime(8:30:00) \(\lor\) 
endPattern(D007, I002 ABSENT) \(\lor\) 
repeats(10) 
→ stopPrompt()
Movement-Based Activity Recognition

Figure 3:Accelerometer Data for X, Y and Z Axes for activities “running” and “climbing stairs”
### Features

<table>
<thead>
<tr>
<th>Features</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arithmetic Mean (X, Y and Z axes)</td>
<td>Arithmetic mean of the values of an axis in the time segment.</td>
</tr>
<tr>
<td>Root Mean Square (X, Y and Z axes)</td>
<td>$x_{rms} = \sqrt{\frac{x_1^2 + x_2^2 + \ldots + x_n^2}{n}}$ where, $n$ is the time segment size (same for $y_{rms}$ and $z_{rms}$)</td>
</tr>
<tr>
<td>Difference Between Max and Min Values</td>
<td>Difference between the maximum and the minimum values in the time segment on a particular axis.</td>
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Experiments

Figure 3: (left) Accuracies of Different Classifiers, (right) Accuracies for Different Activities with Naïve Bayes Classifier

Final implementation. Real-time activity recognition accuracy > 85%
Future Work

• Phone software to include user’s ability to reply to prompts.

• Asking users multiple choice questions to understand the state of the world better.

• User study to include large, unbiased sample size of clinical population (e.g. older adults with cognitive impairment).
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