Using Smart Phones for Context-Aware Prompting in Smart Environments

Barnan Das[1], Adriana M. Seelye[2], Brian L. Thomas[1], Diane J. Cook[1], Larry B. Holder[1], Maureen Schmitter-Edgecombe[2]

[1]School of Electrical Engineering and Computer Science, [2]Department of Psychology
Washington State University, USA
{barnandas, aseelye, bthomas1, djcook, holder, schmitter-e}@wsu.edu

Abstract—**Individuals with cognitive impairment have difficulty successfully performing activities of daily living, which can lead to decreased independence. In order to help these individuals age in place and decrease caregiver burden, technologies for assistive living have gained popularity over the last decade. In this work, a context-aware prompting system is implemented, augmented by a smart phone to determine prompt situations in a smart home environment. While context-aware systems use temporal and environmental information to determine context, we additionally use ambulatory information from accelerometer data of a phone which also acts as a mobile prompting device. A pilot study with healthy young adults is conducted to examine the feasibility of using a smart phone interface for prompt delivery during activity completion in a smart home environment.**

Keywords: context-aware prompting; smart phones; smart homes; activity recognition

I. INTRODUCTION

The world's population is aging. By 2040, 23% of the US population will be age 65+ [1]. The number of individuals who will be unable to live independently and need assistance due to cognitive impairments, will rise rapidly [2]. Older adults with cognitive difficulties experience impairments in daily functioning [3, 4]. When activity difficulties are encountered, individuals typically receive prompts from family members to help them initiate or complete the activity accurately. The amount of prompting caregivers offer to older adults and individuals with Mild Cognitive Impairment increases as cognitive impairment progresses, which increases the amount of caregiver responsibility and burden [5]. Functional impairment in these individuals may lead to negative consequences for individuals, caregivers and society [6]. Caregivers report offering prompts to individuals with cognitive impairment to assist them with IADLs [7], and prompting likely increases as cognitive impairment progresses.

Over the last decade, smart environment technologies have been providing novel solutions to improving aging-in-place and increasing the independence of older adults with cognitive impairments while also decreasing caregiver burden [7]. Automated prompting technologies may assist these individuals with activity completion in order to keep them functioning independently in their homes longer and decrease caregiver burden. Furthermore, using smart phones to deliver prompts "on the go" have benefits over traditional interfaces such as stationary computers or touch screens.

In the current work, we use an Android smart phone as a prompting interface for our context-aware prompting system. Context-awareness employs temporal and environmental parameters for identifying a useful context. However, this information is not sufficient for the smart environments domain where prompts are issued in complex situations that involve Activities of Daily Living (ADLs) and Instrumental ADLs (IADLs). In order to augment context-awareness, we include subject behavioral information by performing real-time recognition of *basic activities* that involve ambulatory movement, such as standing, walking, and climbing stairs. This is done by building machine learning models on training data gathered from a tri-axial accelerometer in the phone.

In order to facilitate the development of assistive technologies to help older adults with cognitive difficulties in completing IADLs, a pilot study is conducted with a healthy younger adult population to explore the feasibility of smart phone prompting technology to assist with IADLs in a smart home environment. Specifically, we examined perceived prompt usefulness, appropriateness, timing and realism. No studies known to us have focused on these parameters of smart phone technology acceptance.

II. SYSTEM ARCHITECTURE

A. Smart Environment Testbed

The Center for Advanced Studies in Adaptive Systems's (CASAS) smart environment smart apartment testbed is located in an on-campus town house apartment at Washington State University. Younger adults, healthy older adults, and older adults with various levels of dementia are brought in to perform Activities of Daily Living. The data collected from these experiments are used to train classifiers in identifying these ADLs. The smart apartment also serves as a proving ground for new sensor systems and techniques before they are integrated into systems that are deployed in private residences.

The current sensor system is composed of several sensor types for motion, ambient light level, temperature, doors, light switches, item presence, vibration-based object movement, water flow, and power use. A majority of the sensors are now wireless, utilizing a low-cost, low power wireless mesh network standard: ZigBee, provided by Control4.

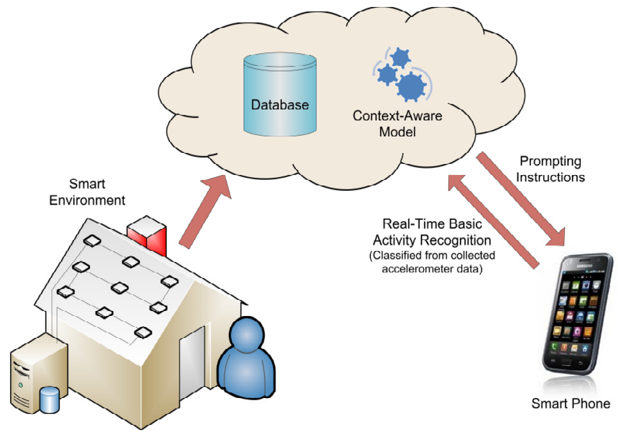

Figure 1. System Architecture

A. *Middleware Architecture*

The CASAS Lightweight Middleware utilizes XMPP for fast and timely communication between the various agents that comprise the smart environments. We replicate a Publish-Subscribe model where agents can publish and/or subscribe to channels of information. By using XMPP, we can take advantage of the ability to communicate over networks and easily integrate data sources and sinks across multiple computers and agents.

The Manager manages the event channels, accepting events from various agents and adding a timestamp to the event (this is done to prevent issues of clock skew across different computers), then sending the event to all subscribers of that channel. The Scribe agent records the events to disk before securely transferring them to the main CASAS database every 15 minutes. The Control4 agent publishes events as they occur. The agent can also receive standardized commands for controlling relays and actuators, and in turn send the command through the Control4 ZigBee mesh network to the requested device. The ReminderLogic agent watches for patterns in the sensor events from the smart environment. When it sees a pattern that meets the defined criteria for issuing a prompt, it sends messages to the Prompting Users and Control Kiosk (PUCK) agent on the smart phone. The Experimenter Reminder Control allows experimenters to send prompts to a specific device to be played in the smart apartment.

B. *Smart Phone Infrastructure*

A Samsung Captivate™ smart phone is used as the device running Android 2.1. Due to the security configuration of the smart apartment only a local network connection could be made to the XMPP server, so we could only use the phone's WiFi connection for connecting to the local CLM. For the purpose of real-time basic activity recognition, accelerometer data was collected at 20 Hz from the phone's accelerometer.

III. CONTEXT MODELING

Providing time-based rules for reminders is not enough as everyday life involves many other complex activities with which people would need help. Therefore, taking overall context of the smart home inhabitant under consideration is a better solution to the problem. Context-awareness as defined by Schilit and Theimer [8], is synonymous to location awareness. Dey et al. [9] proposed a definition of context which considers context to be any information that can be used to characterize the situation where an entity could be anything relevant to the interaction between a user and an application, not excluding the user and application themselves. Over the last decade, context-awareness has found a wide spectrum of applications in health care, pervasive games, middleware, semantic webs, user interfaces, and information retrieval.

With an increased growth of smart environment technologies for health monitoring and assistive living, context aware computing has found its place in this area as well. There have been some projects focused primarily on context-aware prompting such as Cybreminder [10] and ComMotion [11]. These systems use temporal and complex location-based contextual information to determine when and how to deliver the prompts. The HYCARE system [12] of the CogKnow project is a hybrid context-aware reminding framework based on a scheduling mechanism. Chang et al. [13], on the other hand, emphasize on increasing accuracy of contextual unique-to-the-user prompts.

A. *Context Model*

In the current work, we hypothesize that temporal and location-based contextual information is not sufficient to represent complicated contexts of daily life. Therefore, behavioral information of an individual based on ambulatory movements could be valuable contextual input for customized prompts. We have not found any work that uses sophisticated environmental and behavioral information to determine prompt situations in a smart environment. As shown in Figure 2, we formulate context awareness on the basis of three parameters: Temporal, Environmental and Behavioral.

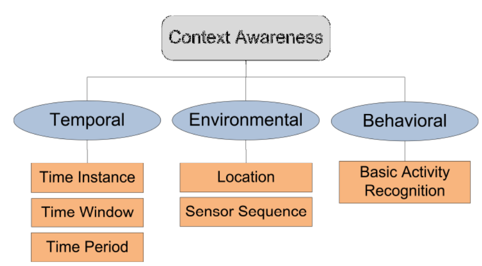

Figure 2. Context-Awareness for Determining Prompt Situation

Temporal Context: In a smart environment, temporal contexts can be crucial to set reminders. Daily life can include activities like taking medication, doing laundry, paying utility bills, or writing letters to friends. Time can refer to a specific time in a day, week, month, year; a time window; or, a duration of time, for example 5 minutes.

Environmental Context: Location in a smart home is a vital environmental context for complicated daily activities like cooking and housekeeping. In addition, specific sensor patterns derived from motion, object interaction, door and temperature sensors in the smart environment and different states of these sensors are also crucial. A prompt situation can be determined by formulating a sensor pattern that either includes or strictly follows a certain sensor sequence.

Behavioral Context: Behavior context can be derived from ambulatory movements. Raw data collected in real-time from a phone, when it is carried by the individual, is used to predict basic activities like sitting, standing, walking, running and climbing stairs. Predictions done with the help of a machine learning model can be helpful in situations where the smart environment has multiple inhabitants or pets. This can ensure that the target pattern is not triggered by somebody other than the individual for whom the prompts were designed.

As there can be an innumerable number of context combinations for a prompt situation contextual rules need to be defined from which caregivers can make choices. Here are examples of some prompt situations:

- *Taking medication everyday at 8:00 AM.* This is an example of purely temporal context.
- *Taking medication some time in between 7:*00 *AM and 8:30 AM, right after breakfast.* This is a combination of temporal (time window based) and environmental (target pattern indicating breakfast is over) context.
- *Notifying individuals that they have met their evening walking goal.* The basic activity recognition from the phone can be used to recognize that the subject has been continuously walking for a certain period of time in the evening and may head back home.

B. Low Level Representation

The higher level prompt situations explained above are represented by a key-value-based formalism. Every rule is represented by a combination of a predetermined set of key-value pairs. The keys represent different types of contextual information such as time of day, day of week, and context. Every prompt rule is implemented with the help of a pair of logic functions:

- stTime(t) ∧ dayOfWeek(d) ∧stPattern(p) → prompt(f)
- endTime(t)∨endPattern(p) ∨ repeats(r) → stopPrompt()

The first function issues a prompt upon identifying the prompt situation as per the triggering pattern. The second function stops issuing the prompt on the basis of an end pattern and ensures that the prompt is repeated until the end pattern is identified. Thus the examples given in the previous sub-section can be represented in a logical format as the following:

- *Taking medication at 8:00 everyday.*

```
stTime(8:00:00) ∧ dayOfWeek() ∧ stPattern() →
prompt(medication.wav)

endTime() ∨ endPattern() ∨ repeats(1) → stopPrompt()
```

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

```
startTime(7:00:00) ∧ dayOfWeek()∧
triggerPattern(M013,sitting,walking-standing,M016-
M017-M018) → prompt(medication.wav)

endTime(8:30:00) ∨ endPattern(D007, I002 ABSENT) ∨
repeats(10) → stopPrompt()
```

- *Notifying individuals that they have met their evening walking goal.*

```
startTime(4:00:00) ∧ dayOfWeek()∧
triggerPattern(walking-running,30mins) →
prompt(evening_walk.wav)

endTime(7:00:00) ∨ endPattern(D001 OPEN, D001 CLOSE)
∨ repeats(2) → stopPrompt()
```

IV. MOVEMENT-BASED ACTIVITY RECOGNITION

Tri-axial accelerometer data can be exploited to determine patterns of an individual's ambulatory movement, which can in turn help in recognizing activities such as sitting, walking, and running. Accelerometers have been successfully used for achieving this goal [14]. The major issue involved with this approach is the obtrusive nature of so many additional devices on the body. As a solution, commercial mobile devices, like cell phones equipped with tri-axial accelerometer and a gyroscope, are being used. Some groups used the Nokia N95 to recognize ambulatory activities in real time but trained the model separately for each user. Kwapisz et al. [15] improved this approach by forming a universal model for six activities performed by 29 participants.

In our work, an approach similar to that of Kwapisz is considered. We perform real-time activity recognition on 5 activities: sitting, standing, walking, running and climbing stairs. As our model runs on an Android smart phone platform, we use a lightweight classifier and a minimum number of features that can be easily extracted in real-time.

A. Building Machine Learning Model

Data Collection

The data was collected at the CASAS Lab with a lab member. It has been found that accelerometers placed close to the thigh [16] give better classification accuracy for activities that are mainly related to lower body movement. Therefore, the phone was placed in pants pocket. The lab member performed all the basic activities for *4 mins* and the time stamp for the beginning and end of each activity performance was recorded. The accelerometer data collected from the phone was stored and all activities were parsed according to the time stamps.

Feature Generation

The phone accelerometer produces time series data for X, Y and Z axes, as shown in Figure 3. However, this data cannot be directly used by the classification algorithms. Therefore, the data is converted into training examples with additional features that can help the learning models classify the different activities accurately. In order to do that, we consider *5 secs* time segments of the data at a time and generate features on that. The length of the time segment has been considered as *5 secs* because of its significance in prompt situation identification. While other works have considered different time segments, *5 secs* is suitable for our goal. As the activity recognition runs in real-time we ensure that the features are generated fast enough in real-time. Table I summarizes the features that have been used for this work.

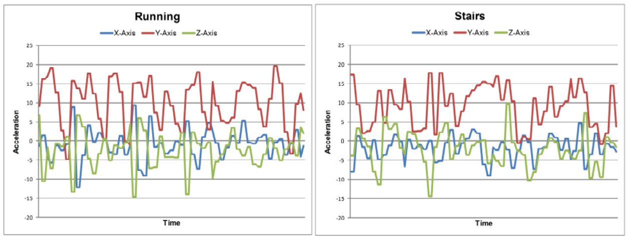

Figure 3. Accelerometer Data for X, Y and Z Axes for activities "running" and "climbing stairs"

TABLE I. GENERATED FEATURES

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

Machine Learning Models

Four machine learning techniques are considered for experimentation and determining the model that would be suitable for real-time activity recognition on the phone. In the following, we give a brief overview of the four models, for better understanding.

Naïve Bayes: A naïve Bayes classifier is a simple probabilistic classifier that assumes each feature of a class to be unrelated to any other features. It applies Bayes' theorem to learn a mapping from the features to a classification label.

Decision Tree: A decision tree classifier uses a statistical property that measures how well a given attribute separates the training examples according to their target classification, to create a classification model.

Support Vector Machine: A Support Vector Machine (SVM) [17] is a training algorithm for data classification which maximizes the classification margin between the training examples and the class boundary.

K-Nearest Neighbor: The k-Nearest Neighbor is an instance based learning method in which algorithm assigns a class label to a data point that represents the most common value among the k training examples which are nearest to the data point.

B. Experimentation and Results

The experiments are done with the machine learning techniques mentioned above, using 10 fold cross validation. Figure 4 (left) shows the average performance accuracy of the learners. With the nine different features mentioned earlier, naïve Bayes gives an average performance accuracy of 98.67%. SMO and K-star perform comparably, while J48 is around 92%.

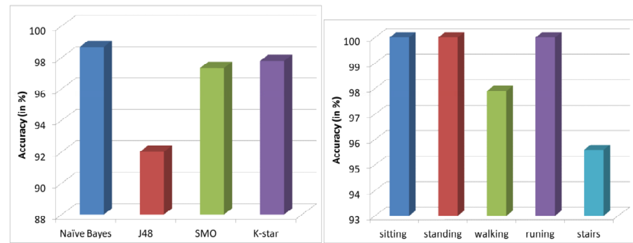

Figure 4. (left) Accuracies of Different Classifiers, (right) Accuracies for Different Activties with Naïve Bayes Classifier

SMO and K-star require a substantial amount of computation, which is difficult to achieve with an Android phone that has a 1Ghz processor. Among the less computationally expensive classifiers, Naïve Bayes performs better and therefore it is chosen to run on the phone. Figure 4 (right) shows the performance accuracy of the five different activities separately with Naïve Bayes classifier. We also tested the performance of Naïve Bayes for real-time activity recognition and the average accuracy is more than 85%.

V. USER STUDY

A. Method

Two healthy younger adults participated in this study. Participants were given a smart phone to carry in their pocket and received two questionnaires that assessed prompt helpfulness, appropriateness of timing, and natural feeling using a 5-point Likert scale, along with open-ended feedback to improve the technology.

Participants completed six IADLs in the smart environment testbed: sweeping, filling a medication organizer, cooking, watering plants, hand washing, and cleaning kitchen counters. In the smart apartment, a bedroom was used as a control room to monitor live video feed of the participants from the installed web-cams. The prompts were pre-recorded by the experimenters, preprogrammed into the server, selected by the experimenter to be delivered when an activity occurred, and delivered through the smart phone. When an error in activity completion occurred, the experimenter typed a code into the main computer to initiate prompt delivery. Timing of prompt delivery was determined by the experimenter's clinical judgment. Participants performed each activity four times. The first time, participants completed the activity accurately. The next three times, participants made one or more specific errors to test the prompting technology (e.g., skip a step). Audio prompts were delivered through the smart phone interface. After completing the activities, participants offered feedback on the usability and effectiveness of the technology.

B. Results

To evaluate the perceived helpfulness, appropriateness of timing, and natural feel of the smart phone prompts, descriptive statistics were analyzed (Table II). As an example, participants rated the prompts delivered during the sweeping task as very helpful (M=5), somewhat to very appropriately timed (M=4.5), and somewhat to very natural feeling (M=4.5). Participants rated the prompts delivered during the medication task as very helpful, appropriately timed, and natural feeling (M=5). Feedback from participants focused on improving the timing of prompts and shortening the task instructions. Both participants commented on the volume of the prompts for one of the tasks and indicated that environment noise (i.e., running water) interfered with understanding the prompt.

TABLE II. MEAN RATING OF PROMPTS

	Helpfulness	Appropriate Timing	Natural Feeling	Likelihood of Use
Sweeping	5	4	4.5	-
Medication	5	5	5	-
Water Plants	5	5	5	-
Cooking	5	5	5	-
Hand Washing	4.5	4.5	4.5	-
Countertop Washing	5	4	5	-
Overall	4.5	3	4	3

C. *Discussion*

The study findings indicate that the smart phone prompts were generally natural and useful. Qualitative data gathered from participants indicates that the main areas for improvement of the prompting technology are timing and better audio clarity of the prompts. Specifically, prompts that are delivered, immediately after an error occurs, will be most helpful for older adults with cognitive impairment. These individuals may forget quickly what they are supposed to be doing between the time that they make an error and receive a prompt. Appropriate timing of prompt delivery represents a challenge in this area of research because there are individual differences in activity step completion and length of time to complete activities. Appropriate volume of prompts is particularly important for older adults who may have hearing impairments.

VI. CONCLUSION AND FUTURE WORK

In the current work, a context-aware approach is taken to identify prompt situations in a smart home environment setting and issue audio prompts on an Android smart phone. We augment context-awareness by including ambulatory information of individuals captured by a phone. To receive user feedback on usability of smart phone technology as a prompting system interface, a user study is conducted in which pre-recorded audio prompts are initiated by an experimenter and delivered to participants through a smart phone when errors are committed on IADLs in a smart apartment.

Future versions of the smart phone software will include the ability for a user to reply to prompts (e.g., I will do it now, I will do it later, I will not do it). Additionally, the context-aware system can ask the user limited multiple-choice questions to help clarify its understanding of the state of the world. User studies will be conducted with larger, non-biased sample sizes of clinical population (e.g. older adults with cognitive impairment) and will address the comments for technology improvement made by participants in the current study, such as prompt timing and volume.

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