Context-Aware Prompting From Your Smart Phone

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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. This demo illustrates the implementation of a context-aware prompting system 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.**

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

I. Introduction

Over the last decade, smart environment technologies have been providing novel solutions to improving aging-in-place issues and increasing the independence of older adults with cognitive impairments while also decreasing caregiver burden [1]. 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 this demo, we use an Android smart phone as a prompting interface for our context-aware prompting system. Context-awareness [2] 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). IADLs are not necessary for basic functioning, but are considered important for individuals to continue living independently. In order to augment context-awareness, we include subject's behavioral information by performing real-time recognition of activities such as standing, walking, and climbing stairs, that involve ambulatory movement. This is done by building a machine learning model on training data gathered from a tri-axial accelerometer in the phone.

II. System Architecture

The Center for Advanced Studies in Adaptive Systems (CASAS) smart environments are 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. The various sensor agents implement a Publish-Subscribe model for communication with the CASAS Lightweight Middleware (CLM), which utilizes XMPP for fast and timely communication.

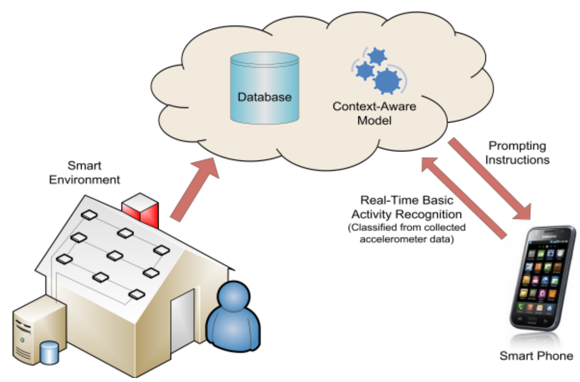

Figure 1. System Architecture

The Prompting Users and Control Kiosk (PUCK) agent on the smart phone also connects with the CLM, as seen in Figure 1, and regularly publishes the current basic activities it is recognizing from the tri-axial accelerometer. By subscribing to these activity events as well as events from the environmental sensors our context-aware model, also known as the ReminderLogic agent, can watch for patterns in the events that meet defined criteria for issuing a prompt. When the criteria are met, ReminderLogic sends a prompt to the PUCK agent running on the smart phone to be played.

A Samsung Captivate™ smart phone is what we have used as the device running Android 2.1. For the purpose of real-time ambulatory activity recognition, accelerometer data is 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. We formulate context awareness on the basis of three parameters: Temporal, Environmental and Behavioral.

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.

IV. Movement-Based Activity Recognition

Tri-axial accelerometer data are 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 [3]. 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. [4] 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*

The phone accelerometer produces time series data for X, Y and Z axes. 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.

For each axis (X, Y, and Z) three features are generated from the values collected every 5 seconds for use in our classifier: arithmetic mean, root mean square, and the difference between the maximum and minimum values.

B. *Experimentation and Results*

The experiments are conducted with four machine learning techniques, namely, Naïve Bayes Classifier, Decision Tree, Support Vector Machine and K-Nearest Neighbor, using 10 fold cross validation. With the nine different features mentioned earlier, we settled with Naïve Bayes as it gives an average performance accuracy of 98.67% and is the least processor intensive on the Android phone's 1GHz processor [5].

V. Infrastructural Requirements of the Demonstration

In the demonstration we would like to illustrate how context-aware prompting systems in smart homes could be used to help residents with activities of daily living. In order to keep the prompting interface simple and unobtrusive, we use a smart phone as the prompting device.

We plan to setup a "mini" smart home at the demo, where people can perform simple scripted activities and test the effectiveness of this technology. A subset of the sensors mentioned in Section II would be used. We request for the following from the organizers:

- **Space:** An area of 8 feet X 6 feet.
- **Table:** 6feet X 2.5 feet
- **Power:** Sufficient power outlets to run 3 systems.
- **Internet:** Wired internet connectivity.

We are very interested to demonstrate our work at the CES 2012, and therefore, we are more than willing to be present for all of the days at CES.

References

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