

DIY Smart Home: Narrowing the gap between users and technology



Figure 1. Conceptual user interface mock-up for a sensing and control system that would enable end users to build custom, DIY (“do-it-yourself”) smart home solutions.

Amy Hwang

Graduate Dept. of Rehabilitation
Science & Intelligent Assistive
Technology and Systems Lab
500 University Avenue
Toronto, ON M5G 1V7 Canada
amy.hwang@mail.utoronto.ca

Michael Liu¹ & Jesse Hoey²

¹Faculty of Engineering
²David R. Cheriton School of
Computer Science
University of Waterloo
200 University Avenue West
Waterloo, ON N2L 3G1 Canada
m27liu@uwaterloo.ca
jhoey@cs.uwaterloo.ca

Alex Mihailidis

Intelligent Assistive Technology &
Systems Lab (IATSL)
500 University Avenue
Toronto, ON M5G 1V7 Canada
alex.mihailidis@utoronto.ca

Abstract

Over the past decade, we have been building intelligent systems to provide assistance for persons with dementia wishing to age-in-place [1]. These systems are built using partially observable Markov decision process (POMDP) controllers. While the POMDPs provide a framework for long-term model learning and reinforcement learning, they must be engineered to fit each situation and user to ensure adoption. Custom-building a smart home solution is a time-intensive exercise, in which technologists extract and encode knowledge from end users. As this process is neither easily understood by, nor accessible to, end users, we are exploring this problem from two complementary directions. From the user perspective, our research with older adults and family members has revealed the need for practical, customizable systems that can be set up and managed by “informal caregivers”. From the technological perspective, we have developed a method by which POMDP-based smart-home controllers can be specified at an appropriate level of abstraction using probabilistic relational modelling and a database schema for assistance systems. Our goal is to close the gap between these perspectives by designing *interfaces* for end-users to express contextual knowledge, needs, and preferences in a natural way to build custom smart home solutions in an organically developing, DIY (“do-it-yourself”) fashion.

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Introduction

The globally aging population and rise of dementia and other chronic illnesses have motivated substantial research in smart homes to support aging-in-place. This field has focused on technological innovation to date and must now shift to understanding users' needs and contexts to bridge solutions to real-world problems. Our research has revealed a critical need for smart homes to be customizable by end users to provide a desirable degree of user control and accommodate unique and dynamic home contexts [2]. We describe our research from two complementary perspectives and propose a DIY approach that aims to close this gap.

We argue that smart home solutions for persons with dementia will only be useful if caregivers can easily customize and manage them. Research suggests that caregivers are willing to assume such responsibilities [3; 4; 5] as long as doing so does not add extra burden or shift their focus from their care responsibilities [2]. We interpret this as the need to minimize changes to physical artefacts, interpersonal interactions, and everyday routines when devising solutions.

Effective smart home solutions should be able to sense what is happening and appropriately *intervene*. Traditional approaches involve designing a system for one particular application and its specific environment,

tasks, and users. As this would require re-engineering for every new application, our approach is to construct abstractions to represent domain knowledge in the most natural way, such that end users will be able to use sensing and control systems to build their own custom solutions.

A next-generation DIY approach

Our user-centered research aims to uncover the language by which end users can naturally and effectively specify their own situations and preferences. Our technology-centered research aims to provide a method to encode this language into a POMDP-based smart home system that will learn and adapt to users' needs over time. We use a probabilistic relational model (PRM) of assistance tasks that is based on a psychological theory of human-machine interaction. This theory provides appropriate "hooks" for end users to complete a relational model, creating a ground instance of a POMDP controller for each new situation [1]. Details of the inner workings of the intelligent sensing and control systems are hidden from end users, who only need to provide information at a high level. Our research is therefore focused on formalizing these abstractions. Our formal models can then be implemented to enable end users to build their own specific solutions.

The POMDP models encode an assistance task by defining the user goals, the environmental states, the user behaviours, the system actions, and the user's cognitive abilities. These factors are derived from a task analysis technique that arises in the human factors literature [7]. The technique involves an experimenter video-taping a person being assisted during the task, and then transcribing and analyzing the video using a

“syndetic” modeling technique. The end-result is an Interaction Unit (IU) analysis that uncovers the states and goals of the task, the user’s cognitive abilities, and the user’s actions. The abilities are broken down into recalling what they are doing, recognizing necessary objects like the kettle, and perceiving affordances of the environment. This model of cognitive abilities is defined a priori by experts in the psychology of dementia, but generalizes across tasks. The IU analysis is augmented by a small set of parameters that give the rate at which a user gains or loses abilities over time, and the likelihoods they will take certain actions in situations with multiple possibilities. Further, a set of sensors is proposed for the environment to provide evidence about task and behavior elements in the IU analysis. A POMDP controller is then automatically compiled from the IU analysis and specification of sensors and actuators for each environment [8,11]. The complete set of specifications is stored in a relational database, and we use a probabilistic relational model to unite the database and POMDP [8]. The database has an intuitive graphical interface, where users can drag-and-drop images onto the canvas to model the environment, and use interactive form controls involving canvas objects to specify actions and goals of the task (Figure 2). The user’s cognitive abilities are computed based on a specified dementia profile, and the list of sensors pertaining to the task is generated automatically. The interface also contains an ontology of objects and their usages, which can be expanded and shared across users. Therefore, it serves as not only the presentation layer of the database, but rather an abstraction of the cumbersome specifications of data that would otherwise require manual entry.

Although POMDPs are intractable in theory, there have been many recent advances in their solution and usage. In particular, Monte-Carlo methods have proven to put solutions to extremely large POMDP models within reach, allowing POMDPs for domains with up to 10^{56} states to be effectively solved [9]. We expect that progress will continue in this direction and that the use of POMDP models will evolve into a general-purpose control mechanism. Our own research has shown how to build hierarchical POMDP models for the assistance domains, and how the hierarchies follow naturally from the task analysis technique [10].

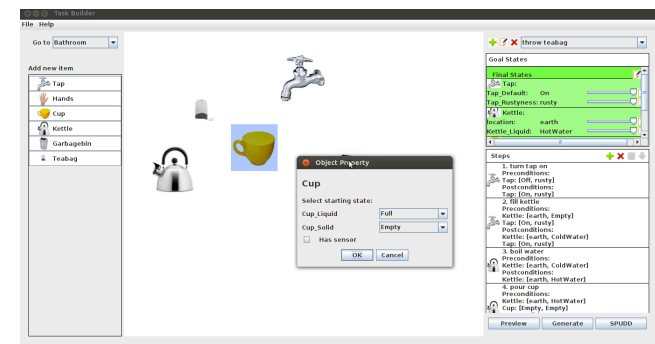


Figure 2. Current user interface prototype in development.

In the long-term, we expect the POMDP controllers to learn from interactions with end users (i.e., persons requiring assistance) over time using reinforcement learning techniques, report problem areas (where the controller is unable to help), and receive further instruction from humans (i.e., caregivers or other persons responsible for setting up the system). Reporting may also drive technological development, feeding a “marketplace” of assistive technology sensors

and actuators, thus creating an economic incentive for further development and engagement.

Conclusions and Future Work

From the user side, we are working to translate the needs expressed by caregivers [3] into the next “caregiver interface” design iteration for evaluation with new participants. Another focus is on developing a method to elicit comprehensive knowledge about users, home environments, and routines to guide and inform caregiver interface design. From the technology side, our current prototype is shown in Figure 2 and we show our proposed concept for an interface in Figure 1 and using a video demonstration at [6]. In both streams of research, we are aiming to build solutions that generalize across multiple users and applications. We are first uncovering the language through which a specific user (or group of users) express and specify smart home needs, and then developing formal models to translate this language into specifications for POMDP-based systems. In this way, we can enable users to customize and interact with smart home systems without any understanding of POMDPs and the nuances of relational models, thus making DIY smart homes possible for the widest range of users.

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