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Smart Home in a Box: A Large Scale Smart Home Deployment

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Abstract. Smart home technologies hold promise for many aspects of daily life. Research and development of these systems has matured for elder care, energy efficiency, and home safety applications. The focus of most implementations has been on single living spaces for a small number of individuals. New low-power wireless systems, inexpensive computing power, and widely available network access has reached the point where large scale ubiquitous computing technologies have become much more feasible.

The smart environments research community has few projects to explore issues and techniques for deploying large scale ubiquitous systems. This work summarizes some of the existing works and introduces the Smart Home in a Box (SHiB) Project. The upcoming SHiB Project targets building 100 smart homes in several kinds of living spaces for gathering longitudinal data from a significant number of residents. The resulting data set will provide opportunities to answer open questions in the areas of transfer learning, active learning, digital asset migration, middleware architectures, activity detection and discovery, human factors, smart home installation, and others.

Keywords. smart homes, large scale ubiquitous computing, Smart Home in a Box, crowd sourcing, active learning, transfer learning

Introduction

Since the foundation of ubiquitous computing was laid out in the early 1990s [1], the promise of ambient, smart, or calm technologies has driven work in the areas of engineering, computer science, mobile applications and health care. The application of these high density sensor platforms to behavior modeling [2], activity detection [3,4], gerontechnology [5] and adaptive environments [6] has pushed a boom in both the research and commercialization fields. Many of these tools have reached maturity on small scales, but work on large scale implementations poses new hurdles to overcome.

Part of the ubiquitous computing vision is the ability to move from one space to another, and drawing upon locally available computing resources to suit your needs. Having an intelligent environment in a home or office that learns an individual's preferences has been explored [7,8,9], but the ability to move those preferences between spaces is still

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an oft-discussed, though rarely tested goal. There is still plenty of work to be done in all areas of having spaces conform to people, especially in the case of multi-site situations.

This work summarizes some of the existing small and large-scale smart environment projects to date, and introduces the Washington State University Center for Advanced Studies in Adaptive Systems' (CASAS) upcoming Smart Home in a Box (SHiB) project. The SHiB Project is projected to include 100 new smart homes deployed at a wide range of living spaces over the next three years. The kinds of spaces SHiB will focus on are private homes and elder care facilities.

The primary goal of SHiB is to provide a massive data set with high quality annotation. The project is a multi-disciplinary, with participation from researchers in the fields of computer science, psychology, health care, and other engineering fields. The hope is to have a test bed sufficient to address issues in the areas of large-scale deployment, activity detection, transfer learning, individual preference mobility, human factors, active learning, and more.

1. Grand Challenges in Large Scale Smart Homes

There are a number of open grand challenges to be addressed in the deployment of large scale smart home systems. This work proposes upcoming tools to address some of these, and other groups are investigating solutions to others. Listed here is a partial list of challenges, in no particular order of importance.

1. A smart home system completely deployable in a home in under three hours by a non-specialist.
2. Strategies to mitigate the visible impact of the technology on the look and feel of the home, especially in a retrofitting situation.
3. Smart homes able to model residents in an unknown space and of an unknown quantity "out of the box" to a reasonable accuracy.
4. Subtle and calm prompting systems that adapt to the current home conditions.
5. A smart home user interface that may be accessed ubiquitously throughout the home and without inconveniencing most residents.
6. Methods to harness and integrate information from disparate sources: environmental sensors, smart phones, wearables, etc.

2. Related Work

To date there has been a plethora of small-scale smart home installations, such as the Aware Home [10], the iDorm [11], House_n [12], the Gator Tech Smart home [13], the Neural Network House [14], the MavHome [15], and the CASAS project [16,17]. These projects encompass one or a handful of smart environments. They have been used to understand human behavior and provide context-aware services.

Historically, there has been few multi-site, large-scale smart environment research projects. Even a single smart environment represents a significant investment in equipment, engineering time and maintenance. Keeping and maintaining numerous sites is a daunting task for most research groups. To date there have been two well known large scale smart environment projects: TigerPlace at the University of Missouri [18] and the ORCATECH Living Laboratory at Oregon Health and Science University [19].

TigerPlace is a monolithic smart home system installed in a long term elder care facility, with the sensors installed in 17 apartments, plus shared living spaces. This facility has provided numerous opportunities for developing novel approaches to elder care and behavior analysis over the years.

The ORCATECH Living Laboratory (OLL) is a distributed in-home smart environment project. To date it has gathered data from over 400 homes across the United States. The project has spanned numerous health care, sensor technology development and behavior analysis projects. Additionally, OLL has published information about the engineering and logistical problems overcome during its operation [20,21]. The sheer scale and distributed nature of the project have required innovative and strict approaches necessitated by managing so many installed testbeds and data sources.

2.1. WSU CASAS Horizon House

A more recent large-scale smart environments project is the Washington State University's CASAS Horizon House installation. This project is installed at Seattle's Continuing Care Retirement Center (CCRC), called Horizon House, where volunteer older adults have the CASAS sensor technology installed in their apartments. The project is targeting longitudinal data collection of both sensor data and biannual psychological evaluations to track individual residents' cognitive capabilities. To date, the facility has 16 running apartments with a year's worth of data each.

3. CASAS Smart Home in a Box

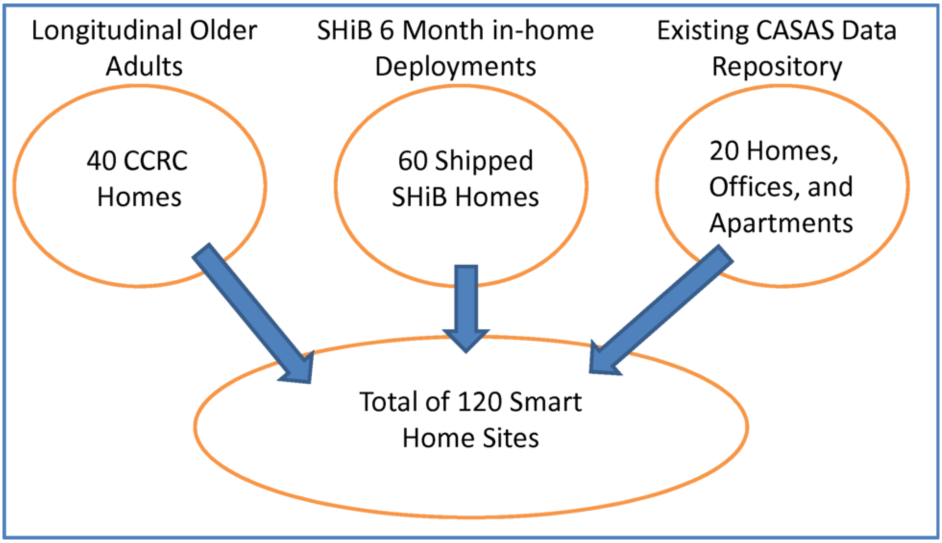
Smart Home in a Box (SHiB) is an upcoming project initiated by the CASAS research group. The primary goal of this project is to provide a large-scale smart environment data and tool infrastructure. The project will increase the number of four currently operational CASAS smart home testbeds and the 16 long-term suites at Horizon House to a much larger collection. A second goal is to provide longitudinal data that monitors behavioral patterns over months or years and allows researchers to thus examine behavioral cycles and trends. Finally, we want to include collection of smart environment data specifically targeted towards older adults with cognitive decline.

3.1. SHiB Planned Deployments

To target the older adults, the project will expand the installation at Horizon House to 25 suites, plus another 15 suites at other CCRCs around the region. These CCRC installations will run for upwards of five years each. This provides a set of longitudinal data on older adults matched with biannual psychological evaluations to give personal physical and cognitive health trends for analysis.

For the large-scale in-home deployments, SHiB will create 20 "CASAS in A Box" kits and make them available for volunteer participants to install in their own homes. These SHiB kits will run in the volunteer's home for at least six months before being shipped back to CASAS to be re-deployed somewhere else. After two years of this process, the SHiB Project plans on gathering data from 60 private homes. In total, the project

Figure 3.1. Planned categories and quantities of Smart Homes deployed for the CASAS SHiB project.



will have collected smart home data from 100 homes. All of this data will be integrated into the CASAS data repository [22], taking the total CASAS database up to 120 data sets, as shown in Figure 3.1.

The net result of CASAS' SHiB effort will be a massive data collection. These smart homes generate an average of 5,000 sensor events each day. When smart phones and power meter readings are incorporated, the volume increases dramatically. The data collection will offer unprecedented opportunities for researchers to study human health and behavior. It will also offer a large step toward the goal of scaling pervasive computing to larger population groups and settings.

As a research project, the SHiB addresses issues in a number of fields. These include how to deploy a smart home without a specialist on hand, managing large scale data gathering, dealing with annotation of exceptionally large data sets, making a resident's data available and understandable to themselves, plus core algorithms research in the areas of transfer learning, trend analysis, active learning, and activity detection.

3.2. CASAS in a Box Design

The first component of the project is the design of the "CASAS in A Box" kits. Each kit consists of a standard set of parts, plus a few optional ones. The core of the infrastructure is the computing and communications infrastructure, as shown in Figure 3.2. This box contains the power sources, networking and a Dream Plug computer to handle the computation, data collection and storage for the home.

Each of the installations will include 30–40 sensors. These are Control4 [23] and Card Access [24] ZigBee-based wireless sensors that have a proven battery life of 6 months to a year and reliable performance. This sensor package, as shown in Figure 3.3, provides motion/lighting detectors, door open/close, and temperature sensors. Each home will also optionally include a TED power meter, object shake sensors and a smart home with data collection software to capture acceleration and direction parame-

Figure 3.2. CASAS smart home components for power, networking, computation and middleware stored in a box.

ters while the phone is in the resident's possession. All of the sensors will be attached using 3M Command Strips, which allow objects to be easily attached and removed from walls without damage.

The current CASAS smart homes upload their data collection at 15 minute intervals if they have access to an Internet connection. The data is copied using an encrypted connection, checked for transmission errors and loaded into the CASAS database if the files were copied correctly. If the smart home server fails to connect to the CASAS central system it spools the new data until an uplink can be established. Because the CASAS sensor platform is event driven and the repetitive nature of the data compresses efficiently, a year's worth of data takes up around 60MB of disk. With higher resolution data from smart phones and power metering this will balloon to several hundred megabytes, which is still easily kept locally on the in-home server.

To handle the case of homes without an available Internet connection, the in-home server will be expected to keep all gathered data locally until it is shipped back to CASAS at the end of the deployment. Once the in-home server connects to the main data repository, it will upload all new data for long term storage. In the interests of protecting the data over the six month deployment, the servers will use a RAID 1 disk configuration to reduce the chance of data loss if a single disk fails.

3.3. SHiB Kit Installation

One of the key components of a smart environment is installation. Traditionally, this process is completed by specialists and may require numerous tweaks to get the system running. Since having specialists on hand to perform every install does not scale, the

SHiB Project is researching methods and tools to overcome this requirement. The goal is for laymen volunteers to install the system straight from the box without a specialist's intervention. How to achieve this is a notable project unto itself.

CASAS has built a team of experimental psychology and engineering researchers with the aim of developing the best set of equipment and instructions for the kit. Since the layout of the resident's home is unknown, the kit and instructions need to be flexible and clear to achieve the best results. There is an inherent trade off of sensor density with ease of installation, and finding the required sensor capabilities for driving the data gathering goals of the SHiB Project is currently under review.

Figure 3.3. CASAS in A Box sensor components, including motion / lighting sensors attached to the ceiling (upper left), door / temperature sensors (upper right), object shake sensors (lower left), smart phone (lower middle), and TED power meter (lower right).

3.4. Sensor Placement

Sensor placement for smart environments, especially when done by laymen, is difficult. Being able to determine which sensors are required for a given space and to communicate how to place them effectively is a crucial process. There has been very good work into where to place sensors to meet a variety of constraints [25], but also doing this in a previously unknown space to meet amorphous goals is less explored. The SHiB Project hopes to build new tools and approaches to overcome these issues, making the kits more effective data gathering platforms.

3.5. Human Factors in Smart Environments

SHiB hopes to address a number of human factors issues with smart environments. Having a large scale deployment and hands-on experience feedback from 60 homes will give significant results on several fronts:

1. Technology perception, especially regarding intrusiveness and expectations
2. Installation problems and understanding of complex instructions
3. Sensor labeling, both for installation and how that influences perceptions
4. In-home impacts on behavior, both conscious and unconscious
5. Privacy and control over personal data

To date, much of the data gathered about living and interacting with smart environments has been anecdotal. There exists some recent work on privacy in sensor rich environments [26,27], and CASAS researchers hope to leverage the large scale of the SHiB Project to formally evaluate these factors to help guide future projects.

3.6. Data Annotation

During the course of the previous CASAS smart homes, it became apparent that the value of the smart home data is increased dramatically if it is annotated. These annotations are historically done by human hand for features such as activities being performed, the identity of residents, and environmental information. Experience shows that it takes roughly 1.5 hours of labor to annotate one 24 hour period in a home. Since this hand-annotation process is expensive, the SHiB Project will use a four stage process to annotate the vast data collected:

1. Self reporting
2. External observers
3. Crowd sourced information
4. Transfer and Active Learning algorithms

3.6.1. Self Reporting

Initially, the residents will be asked to complete a form that indicates when they perform key activities. In the CCRCs with the older adults, this process will be completed with the help of the research team. SHiB participants in private homes may ask CASAS engineers for clarification and direction, but most will be expected to complete it on their own. The targeted activities include: Cook, Eat, Wash dishes, Bathe, Dress, Groom, Make phone calls, Sleep in bed, Sleep out of bed, Work, Watch TV, Read, Leave home, Enter home, Entertain guests, Exercise, and Take medicine. Optionally, the residents can specify exact dates and times when activities occurred.

3.6.2. External Observers

This stage is the classic human annotation phase for the data. People hired by the SHiB Project will view the data from homes using a graphical interface, and annotate activities by hand. Their primary guidance will be information provided by the residents about their behaviors and homes. This stage is expected to label 10 days for each home and is a requirement for many supervised and semi-supervised algorithms used for classifying events automatically.

3.6.3. Crowd Sourced Information

For this approach, people will be invited to annotate a series of sensor events in a visualization on a web page. Small segments of data and detailed instructions will allow visitors to vote on which activity is being performed. The goal is to provide reasonably accurate labels for "interesting" series of events in the data set, as well as driving the cost of annotation down. How to present the data, get involvement, and resolve inconsistencies between volunteers are open research questions.

3.6.4. Transfer and Active Learning Algorithms

There are also approaches for using transfer learning and semi-supervised algorithms for "out of the box" annotation being evaluated. Transfer learning leverages labeled data from other smart environments to begin classifying unlabeled at the new site. With the new data sets generated and labeled on the scale of the SHiB Project, these approaches can be truly evaluated for a wide variety of environments.

When using semi-supervised classifiers, the initial 10 day annotation from self reporting and external observers is used to automatically classify new data from the same site. These tools can also be boosted by an initial transfer learning stage with data from other homes. The new automatically determined labels are then used to help classification as the home runs, essentially learning more about itself to get better at recognizing the residents and their activities.

Another approach being explored is using Active Learning algorithms. The goal is to query the resident as an expert label provider. This is expected to be done through the smart phone or other interface delivered with the SHiB kit. As the classification tools operate, they will have the opportunity to ask the resident about a series of events and what activity it should be classified as. This process can happen "out of the box" or at any time later to augment an existing model provided by a transfer learning approach.

3.6.5. Digital Asset Migration

The CASAS SHiB team has begun implementing approaches to digital asset migration between varied smart home facilities. By having a wide range of living and working spaces to draw upon the migration of learned personal preferences can be well explored. We already have data sets for individuals that include both their behavior and environmental controls in homes, offices and offices within a home. Being able to identify a resident and bring their assets across from one space to another is a key step in Ubiquitous Computing. The SHiB project will enable the expansion of this work to many sites with many individuals.

4. Summary

Large-scale smart environment technology research projects are a necessary step towards realizing the ubiquitous computing concept. These projects are resource and time intensive, but offer a wealth of research opportunities. The upcoming CASAS Smart Home in a Box project is designed to support a wide range of research targets, both immediately practical, and to evaluate open ended theories.

The field of intelligent environments needs to draw upon its existing successes and begin exploring the possibilities presented by these large-scale systems. SHiB provides a solid platform with significant tools to take these next steps towards making smart technologies available to large numbers of people.

References

[1] Mark Weiser. The computer for the 21^{st} century. *Scientific American*, pages 94–104, 1991.

[2] Hui-Huang Hsu and Chien-Chen Chen. RFID-based human behavior modeling and anomaly detection for elderly care. *Mobile Information Systems*, 6(4):341–354, December 2010.

[3] Usman Naeem and John Bigham. Recognising activities of daily life through the usage of everyday objects around the home. In *International Conference on Pervasive Computing Technologies for Healthcare*, PervasiveHealth, pages 1–4, April 2009.

[4] Geetika Singla, Diane J. Cook, and Maureen Schmitter-Edgecombe. Recognizing independent and joint activities among multiple residents in smart environments. *Journal of Ambient Intelligence and Humanized Computing*, 1(1):57–63, 2010.

[5] G. Demiris and B. K. Hensel. Technologies for an aging society: a systematic review of "smart home" applications. *Yearbook of Medical Informatics*, pages 33–40, 2008.

[6] Parisa Rashidi and Diane J. Cook. Adapting to resident preferences in smart environments. In *Proceedings of the AAAI Workshop on Advances in Preference Handling*, pages 78–84, 2008.

[7] N. Kushwaha, Minkoo Kim, Dong Yoon Kim, and We-Duke Cho. An intelligent agent for ubiquitous computing environments: smart home ut-agent. In *Proceedings of the IEEE Workshop on Software Technologies for Future Embedded and Ubiquitous Systems*, pages 157–159, May 2004.

[8] Scott Davidoff, Min Lee, Charles Yiu, John Zimmerman, and Anind Dey. Principles of smart home control. In Paul Dourish and Adrian Friday, editors, *Ubiquitous Computing*, volume 4206 of *Lecture Notes in Computer Science*, pages 19–34. Springer Berlin / Heidelberg, 2006.

[9] George Demiris, Brian K. Hensel, Marjorie Skubic, and Marilyn Rantz. Senior residents' perceived need of and preferences for "smart home" sensor technologies. In *International Journal of Technology Assessment in Health Care*, volume 24, pages 120–124. Cambridge University Press, 2008.

[10] Elizabeth D. Mynatt, Anne-Sophie Melenhorst, Arthur D. Fisk, and Wendy A. Rogers. Aware technologies for aging in place: understanding user needs and attitudes. *Pervasive Computing*, 3(2):36–41, April 2004.

[11] Faiyaz Doctor, Hani Hagras, and Victor Callaghan. A fuzzy embedded agent-based approach for realizing ambient intelligence in intelligent inhabited environments. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 35(1):55–65, January 2005.

[12] A. Helal, E. Kim, and S. Hossain. Scalable approaches to activity recognition research. In *Pervasive*, volume 7040. Springer Berlin / Heidelberg, May 2010.

[13] Sumi Helal, William Mann, Hicham El-Zabadani, Jeffrey King, Youssef Kaddoura, and Erwin Jansen. The Gator Tech Smart House: a programmable pervasive space. *Computer*, 38(3):50–60, March 2005.

[14] Michael C. Mozer. The neural network house: An environment that adapts to its inhabitants. In *Proceedings of the AAAI Spring Symposium on Intelligent Environments*, pages 110–114, Menlo Park, CA, 1998. AAAI Press.

[15] Diane J. Cook, Michael Youngblood, Edwin O. Heierman III, Karthik Gopalratnam, Sira Rao, Andrey Litvin, and Farhan Khawaja. MavHome: an agent-based smart home. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communications*, PerCom '03, pages 521–524, March 2003.

[16] Aaron S. Crandall. *Behaviometrics for Multiple Residents in a Smart Environment*. PhD thesis, Washington State University, 2011.

[17] Diane Cook. Learning setting-generalized activity models for smart spaces. *IEEE Intelligent Systems*, 27(1):32–38, January–Feburary 2012.

[18] Marilyn Rantz, Myra Aud, Greg Alexander, Debra Oliver, De Minner, Marge Skubic, James Keller, Zhihai He, Mihail Popescu, George Demiris, and Steve Miller. Tiger place: An innovative educational and research environment. Technical Report FS-08-02, AAAI Fall Symposium, Washington, DC, November 2008.

[19] OHSU ORCATECH. Oregon Center for Aging & Technology (ORCATECH) at Oregon Health & Science University. http://www.orcatech.org/.

[20] Jeffrey Kaye, Tamara Hayes, Tracy Zitzelberger, Jon Yeargers, Misha Pavel, Holly Jimison, Nicole Larimer, Jessica Payne-Murphy, Eric Earl, Kathy Wild, Linda Boise, Devin Williams, Jay Lundell, and Eric Dishman. Deploying wide-scale in-home assessment technology. In *Technology and Aging*, volume 21 of *Assistive Technology Research Series*, pages 19–26. IOS Press, 2008.

[21] Tamara L. Hayes, Pavel Misha, and Jeffery A. Kaye. Gathering the evidence: Supporting large-scale research deployments. *Intel Technical Journal*, 13(3):148–167, 2009.

[22] WSU CASAS. CASAS public smart home datasets repository. http://casas.wsu.edu/datasets.html.

[23] Control4. Control4 home automation and smart home control web site. http://www.control4.com.

[24] Card Access. Card access incorporated web site. http://www.cardaccess-inc.com.

[25] Andreas Krause. *Optimizing Sensing: Theory and Applications*. PhD thesis, Carnegie Mellon University, December 2008.

[26] Predrag Klasnja, Sunny Consolvo, Tanzeem Choudhury, Richard Beckwith, and Jeffrey Hightower. Exploring privacy concerns about personal sensing. In *Proceedings of the International Conference on Pervasive Computing*, PerCom '09, pages 176–183, Berlin, Heidelberg, 2009. Springer-Verlag.

[27] George Demiris, Debra Perker Oliver, Jarod Geiger, Marjorie Skubic, and Marilyn Rantz. Older adults' privacy considerations for vision based recognition methods of eldercare applications. *Technology and Health Care*, 17(1):41–48, 2009.