Using a Live-In Laboratory for Ubiquitous Computing Research

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Abstract. Ubiquitous computing researchers are increasingly turning to sensor-enabled "living laboratories" for the study of people and technologies in settings more natural than a typical laboratory. We describe the design and operation of the PlaceLab, a new live-in laboratory for the study of ubiquitous technologies in home settings. Volunteer research participants individually live in the PlaceLab for days or weeks at a time, treating it as a temporary home. Meanwhile, sensing devices integrated into the fabric of the architecture record a detailed description of their activities. The facility generates sensor and observational datasets that can be used for research in ubiquitous computing and other fields where domestic contexts impact behavior. We describe some of our experiences constructing and operating the living laboratory, and we detail a recently generated sample dataset, available online to researchers.

1 Introduction

Technologies that can automatically detect and respond to context may permit the development of useful, novel, and user-friendly computational devices for the home setting [1]. In order to fully realize such *context-aware* user interface technologies at least three key challenges must be overcome:

1. **Need for comprehensive sensing:** Testing promising context detection algorithms that use multiple (and sometimes multi-modal) sensors in a real home is logistically difficult and costly in early stages of research. Therefore, results are often published on small test datasets acquired from "simulations" of home activity done in a laboratory setting. Even those tests done in actual homes are usually conducted for a short time with only a small portion of the environment instrumented.
2. **Need for labeled training datasets:** Some of the most robust and promising context detection algorithms for the home setting use statistical models that must be trained on example datasets – often *annotated* datasets. Datasets for people performing common domestic activities, particularly those that may take hours or days, are difficult to obtain. Accurate labels for the activity and contexts of such datasets are often dependent on participant recall or diary recordings, both of which have been demonstrated to be error-prone [2, 3].
3. **Need for complex, naturalistic environments:** Researchers developing context-aware applications for the home must ultimately evaluate how typical users will react

to a prototype technology in a representative setting. Users will be multi-tasking, experiencing interruptions, dealing with tens of objects, interacting with other people, and engaging in other complex behaviors that are difficult to simulate in the lab. Researchers need observational tools that help them study how people are reacting to novel technology in the complex home setting.

These challenges, among others, have led to a growing interest in so-called "living laboratories" for ubiquitous computing research, which are naturalistic environments instrumented with sensing and observational technologies and used for experimental evaluation (e.g., [4, 5]. Researchers thinking of developing living laboratory facilities must pick a target along two dimensions: richness of physical sensor infrastructure and behavioral realism. Ideally one would have access to many real home environments that have an extensive physical sensor infrastructure. However, the cost of more extensive sensing may limit how long data can be collected and the complex ad hoc setup may inhibit how natural the behavior observed actually is. Living laboratories require a compromise, therefore, such as having someone move temporarily into a home that is not their own. Nevertheless, the environments may be valuable when attempting to bridge the gap between traditional laboratory experimentation and small-number-of-subject studies in multiple, real homes. Living laboratories can also play an important role in iterative hypothesis generation and testing (see Fig. 1).

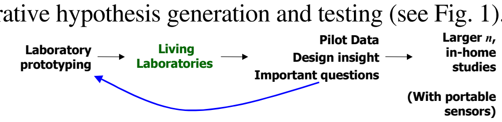

Fig. 1: Living laboratories may help researchers bridge from laboratory testing to larger studies in real homes using portable ubiquitous computing technologies.

We have developed a new live-in, apartment-scale research facility called the PlaceLab, which opened in July of 2004 in an urban neighborhood in Cambridge, Massachusetts. Volunteer research participants individually live in the PlaceLab for days or weeks, treating it as a temporary home. Meanwhile, a detailed description of their activities is recorded by sensing devices integrated into the fabric of the architecture. The PlaceLab was designed from the outset to support the collection of rich, multi-modal sensor datasets of domestic activity, which are intended to be shared among researchers in different organizations and fields, including researchers working on context-aware ubiquitous computing technology, preventive healthcare, energy conservation, and education.

In the remainder of this paper, we describe the PlaceLab facility and some of the challenges we have faced in the design, development, and early phases of operation. We aim to provide some guidance for researchers currently operating or considering the construction of residential living laboratories. We conclude by inviting other researchers interested in using our living laboratory data to study example data we have made available online and to contact the authors to learn more about how to take advantage of this resource (and more extensive datasets) in their own work. As much as is administratively possible, we would like the PlaceLab to be a community resource.

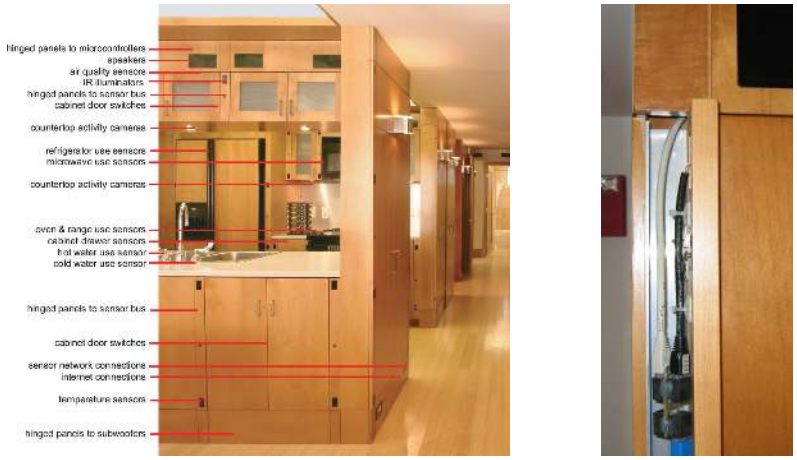

Fig. 2: Sensors are located throughout the cabinetry in a consistent way in every room of the apartment. Some sensor locations are indicated here (left). All of the observational sensing is built directly into the cabinetry. Although the sensors are ubiquitous, they become part of the design aesthetic (small black windows). Pilot volunteers have expressed that they are easy to forget. The cabinetry has been designed with channels for the sensor bus, making it easy to distribute sensors throughout the environment. The channels hinge open, allowing easy access for maintenance and sensor additions/upgrades (right). Adding a sensor simply requires adding a splitter in a channel (circled) and plugging in the device.

2 PlaceLab Overview

Fig. 2 shows the interior of the PlaceLab facility. The 1000 sq. ft. apartment consists of a living room, dining area, kitchen, small office, bedroom, full bath and half bath. Fig. 3 shows a floor plan. The interior of the PlaceLab consists of 15 prefabricated and reconfigurable cabinetry components. Each contains a micro controller, an addressable speaker system, and a network of up to 30 sensors that capture a complete record of audio-visual activity, including information about objects manipulated, environmental conditions, and use of appliances. *All* wired sensors are discreetly integrated into the cabinetry, appliances, and furnishings and fixtures. The wireless sensors utilized are small (4.5 x 4.0 x 1.75 cm) and can be placed inconspicuously on any objects of interest.

New sensors can be easily added to this network as required. The exact list of portable sensors used varies slightly from study to study, depending upon the principal goals at that time. As of December 2005, the sensors were as follows. Eighty small, wired switches detect on-off and open-closed events, such as the opening of the refrigerator, the shutting of the linen closet, or the lighting of a stovetop burner. Interior conditions of the apartment are captured using distributed temperature (34), humidity (10), light (5), and barometric pressure (1) sensors. The PlaceLab also features electrical current sensors (37), water flow (11) and gas flow (2) sensors. Wireless object movement sensors can be easily taped onto any non-wired objects. Currently 125 of

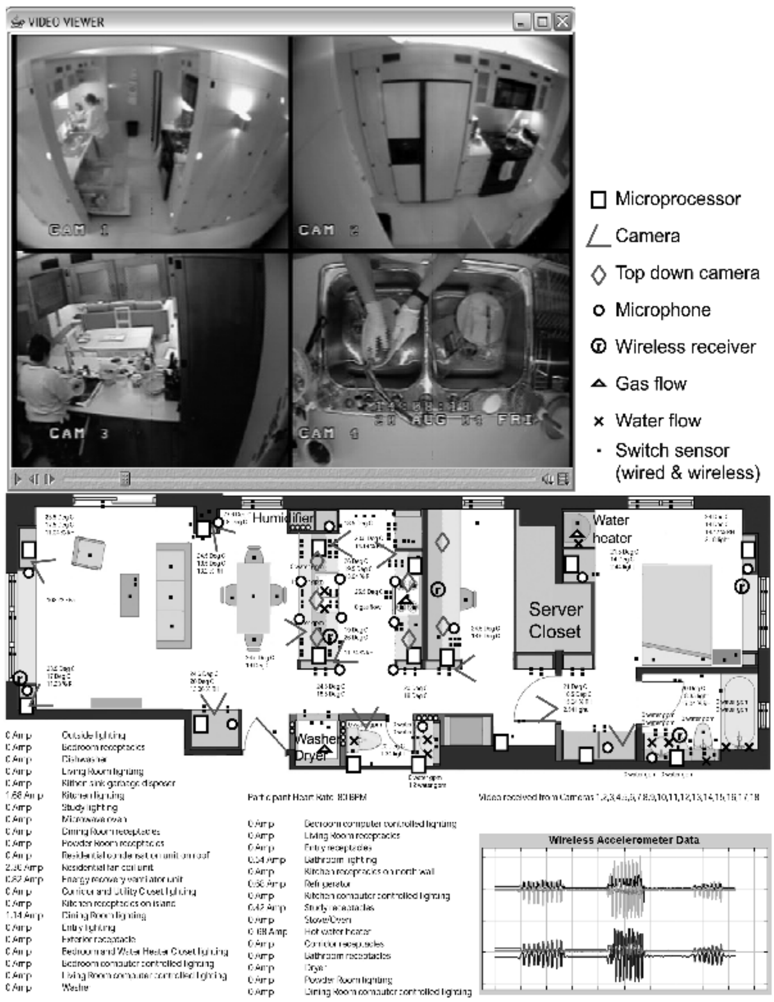

Fig. 3: A data visualization tool for the PlaceLab and a floor plan indicating the location of most sensors described in the text. Data from two wireless 3-axis accelerometers outputting data at 67 Hz is also represented. The display shows the 4 views that were automatically selected from the 18 possible video streams, using computer vision processing. An annotation tool allows researchers to click on a particular sensor and then see the rest of the data (including video and audio) at the time of that sensor's activation – this may simplify data analysis or searching for particular events of interest in multiple days of data.

such sensors are installed on objects such as chairs, tables, appliances, brooms, remote controls, large containers, and other objects people may manipulate [6]. Participants in the PlaceLab can wear up to three wireless 3-axis, 0-10 G accelerometers that measure limb motion. A wireless heart rate monitor (using a standard Polar chest strap) can also be worn. Five receivers spread throughout the apartment collect all wireless object motion, accelerometer, and heart rate data sent via the MITes wireless sensors [6]. Nine infrared cameras, 9 color cameras, and 18 microphones are distributed throughout the apartment in cabinet components and above working surfaces, such as the office desk and kitchen counters. Eighteen computers use image-processing algorithms to select the 4 video streams and 1 audio stream that may best capture an occupant's behavior, based on motion and the camera layout in the environment. Two other computers synchronize the audio-visual data streams with the other sensor data and save all data to a single portable disk drive. Fig. 3 shows the location of the sensors. More technical details of the PlaceLab's sensor infrastructure are described in the Appendix.

3 Living Labs: Complementing Existing Tools and Methods

A key motivation for the creation of the PlaceLab arose from our prior work developing context-detection algorithms in traditional laboratory settings. Controlled laboratory studies allowed dense sensor installation useful for the study of behavior and development of new context-aware algorithms, but simulated rooms or short stays severely constrained behavior variability. In response, we developed portable tools that can be installed in real homes, but practical limitations dictate that only a subset of a full laboratory system can be deployed at once. We thought that we needed a resource to bridge the (large) gap from studies in the lab to studies in real homes.

A common criticism of living laboratories such as the PlaceLab is that requiring people to move temporarily out of their own homes will reduce the complexity and variability of the home environment and may have a corresponding effect on the participant's behavior. We agree. However, just because behavior may be altered in some ways does not mean that we will not observe complex and important activity. Despite some limitations, a live-in lab still allows for more natural behavioral observation and data collection on everyday activities such as cooking, socializing, sleeping, cleaning, working from home, and relaxing than can be obtained from short laboratory visits. Our preliminary experiences using the PlaceLab suggest this to be true. Activities that present challenges for context detection algorithms – multitasking, interruption, task-switching, use of objects, context-dependent variation of behavior over time, and interaction with other people – have all been observed in the PlaceLab.

The PlaceLab does take a behaviorist approach with respect to activity recognition and annotation. Some activities or participant states of mind may not be possible to adequately annotate retrospectively by an independent observer or even the participants themselves. It can be difficult, for example, for a PlaceLab researcher to later determine if someone was "deep in thought" or simply closing his or her eyes and resting for a moment. The PlaceLab infrastructure, however, does permit researchers to employ novel self-report strategies that can help the researcher understand some of this behavior, such as context-triggered experience sampling [7]. Standard subject self-report with paper or electronic surveys can also be used.

As long as one is cognizant of the limitations of living laboratories, they can be used to complement other tools being used to study behavior in the home. Table 1 in [8] describes how living labs could be used to compliment surveys and interviews, experience sampling, direct observation, and in-home portable kits.

4 PlaceLab Design Goals

The PlaceLab was designed with “ubiquity” of sensing technology as the primary goal. Most living labs built to date consist of relatively typical homes where ubiquitous computing technologies are included, but not in a truly ubiquitous way. Typically a portion of the environment is wired with a few sensors of interest to the researchers who constructed the facility. Often different parts of the home have completely different technologies and each data type is not synchronized. In practice, individual researchers tend to tweak the highly specialized sensor subsystems as needed for specific projects (e.g. changing lighting and camera views for computer vision, installing directional microphones pointed at specific locations). The benefit of this type of approach is that specialized systems can be rapidly prototyped and tested for use on focused tasks (e.g., memory aids in the kitchen while cooking [9], testing gait recognition [10]).

We have deliberately chosen a different strategy. Each sensor subsystem is ubiquitous and consistent throughout the environment, and all data sources are synchronized and recorded in a common format. Our goal was to invest time up front to create a facility that would eventually allow researchers to spend less time custom tuning sensor subsystems in specific locations and more time studying what might be called the “whole house” problem – how can sensor fusion be used to create useful ubiquitous computing systems, and how can user interfaces that respond to multi-tasking, interruption, etc. be created and evaluated?

Another key design decision was to focus on quantity and ubiquity of sensing rather than quality of any particular sensor. In part, this decision was justified based upon our belief that many context detection tasks are simpler to solve with many distributed sensors and sensor fusion rather than a smaller number of more generalized sensors that require complex interpretation at the sensor itself. Distributed sensors may improve redundancy as well, allowing higher-level reasoning about activity structure to be more easily encoded in useful representations. For example, promising results have recently been obtained for recognizing activities in the home using RFID gloves and contact switches superseding the capabilities of most vision systems (e.g., [11-13]). If deemed necessary, the PlaceLab does allow any particular sensor to be easily replaced with a higher quality version, supporting multiple strategies of investigation simultaneously.

Our third key design decision was to create a system that would provide a single, unified, synchronized living laboratory dataset in a format that could be easily provided to other researchers and reused in multiple projects. In that spirit, we later describe an introductory dataset that we have placed online.

6 Running a PlaceLab Study

To our knowledge, the PlaceLab is the first living laboratory in which multi-day studies are run such that researchers and volunteers have no (or extremely limited) face-to-face interaction during the data collection period. This is quite unlike some prior instrumented homes inhabited by the researchers themselves (e.g., [14]) . Since opening in July 2004, three pilot PlaceLab studies and three technology evaluation studies of about 10 days each had been run by December 2005. In addition, our research team has conducted numerous short, informal test sessions. The sensor infrastructure operates and saves some data types continuously, even when an official study is not ongoing, which is useful for monitoring system status and conducting environmental condition quality studies (e.g., our partner TIAX is studying topics such as changes in dust mite populations relative to indoor humidity and load balancing among power consuming devices during power outages).

Participants

The PlaceLab is optimized for studies that would benefit from multi-day or multi-week observation of single individuals living alone or a couple. (In 2003, 26% of U.S. households consisted of a person living alone [15]). Participants for the initial studies were recruited via electronic mailing lists, posters, and word-of-mouth. Advertisements contained lines such as, "Teach Researchers about Your Everyday Life … help us design better technologies and homes …". Participants for studies were selected by questionnaires and interviews and ranged in age from 35 to 60 years. Each was compensated about $25 US per day for participation. The participants expressed that the primary reason they were participating was a belief that this research could yield long-term social and scientific benefits. A database of interested volunteers has since been created to support future work, including not only individuals but also couples interested in participating together.

There is nothing inherent in the facility that prevents data collection and experimentation on multiple people. By default the facility saves a single audio and video stream, but by simply adding an additional computer and disk space one could save additional streams. Even with the current settings, studies that investigate activity recognition algorithms for detecting activity when the home is occupied by more than one individual could be done.

Study Design

To date, three types of study designs have been employed in the PlaceLab. Our initial three pilot studies were primarily observational, where data was collected on the everyday activities of the participants for activity recognition training. Participants additionally completed surveys about their behavior for comparisons between subject report and observations using PlaceLab sensors. Two studies were designed to evaluate novel ubiquitous computing technology that used a house-wide sensor system. In one, a context-sensitive reminder strategy was compared against a traditional time-based reminder strategy. This study represented a more controlled, albeit exploratory, within-subject design where a participant was asked to follow an experimental regiment and results were compared between conditions. The second study examined participant initiated use of a sensor-driven technology for motivating behavior change in the course of everyday routines. The participant returned for two separate stays in the PlaceLab and therefore some comparison of behavior before and after introduction of the technology into the environment was made possible. Results from these and other studies will be submitted to the appropriate scientific venues as analysis is completed; at that time some anonymized datasets (including sensor activation data) will be available as well.

Participant Procedures

In each study, care is taken to ensure that participants maintain ultimate control over their data and that they recognize their right to withdraw from the study at any time for any reason. PlaceLab volunteers are informed of all the sensor locations in the apartment and how the recorded data will be used. Recordings from the PlaceLab are never observed in real-time, so the participants may choose to omit segments of audio, video, and/or sensor readings before releasing their data. Participants are asked to have visitors sign informed consent forms.

In post-stay interviews, participants expressed that they quickly acclimated to the PlaceLab and that, despite the ubiquitous sensing, it is a pleasant, comfortable space. For example, one participant offered as evidence of her quick acclimation the fact that she fell asleep on the couch at night watching TV, an activity she thought she would only do in a familiar environment. At first, she was embarrassed to have this behavior captured on video, and she logged that the data from that time should be deleted. However, by the end of her stay, she decided the only data she needed to remove was some audio during personal phone calls. Furthermore, this participant made the PlaceLab more comfortable and personal during her stay by gradually bringing in items from home, including her bedspread, placemats, flower vases, coffee mug and coffee maker, and, eventually, even her own coffee table. All PlaceLab subjects to date have expressed an interest in returning for another study; we believe this is a good sign that the facility and the experimental procedures in place establish a high level of comfort despite the ubiquitous sensing.

The behavior of our initial participants raises some issues that must be considered in future work as the PlaceLab is used for longer stays. For example, when wireless object motion sensors [6] are used in the PlaceLab and participants bring new objects, procedures must be established whereby the participants or the researchers add sensors to the new objects. Based upon the topics being studied at the time, procedures must be established to deal with visits from non-study participants and labeling the activities of multiple people.

7 Example Data

Our vision is that datasets from living laboratories such as the PlaceLab can serve as general purpose resources for the ubiquitous computing community. These datasets may become more useful over time as they are annotated in increasing detail by researchers. For instance, initially an unannotated dataset may be used by researchers interested in unsupervised learning and context-detection; only sensor activations and rudimentary labeling may be required. Researchers studying supervised learning algorithms may then invest time annotating the data using a set of activity tags organized into an activity hierarchy. Next a user interface designer may use the sensor data and the detailed annotation to qualitatively study the data, searching for specific events of interest that may support or inspire novel user interface ideas for the home setting. Later a discourse researcher may code speech utterances, further enriching the dataset. Meanwhile, the facility can be used to run new studies and generate new datasets where the sensor technology is improved and extended.

There are some serious challenges to achieving this vision. Some researchers may decide the data does not perfectly suit their needs, perhaps missing a key sensor. Other researchers may feel the participants who have been used in prior experiments are not representative of their target user group. Others may find that the activity herarchies used by past researchers do not map well onto their own needs.

Our experience, however, suggests that ubiquitous computing researchers – especially those developing algorithms that use sensor data – are intensely interested in high-quality datasets with observational and sensor data from homes. In response to our needs and those of others, we have invested over two years of planning and development in the creation of a living laboratory that can generate rich, sharable datasets. The grand challenge is whether we can operate this living laboratory so that it has value for the larger UbiComp community.

During the last several months, we have been stress testing and improving the PlaceLab infrastructure. To facilitate research community involvement, we have created an example PlaceLab test dataset that includes four hours of fully-annotated intensive home activity. We have put this 4.1 GB dataset with usage instructions online at http://architecture.mit.edu/house_n/data/PlaceLab/PlaceLab.htm. In the remainder of this section, we briefly describe this resource.

7.1 "Intensive Activity" Test Data Set

The *intensive activity* sample dataset was recorded with a member of our research team who was familiar with the PlaceLab but not a creator of the core technical infrastructure. The researcher wore two 3-axis mobile accelerometers in known orientations (one on the upper left thigh and the other on right wrist) and a wireless heart rate monitor (using a Polar chest strap). The researcher was asked to perform a set of common household activities anytime during a 4-hour period. These activities consisted of doing laundry, preparing a meal, baking, and performing light cleaning tasks. The researcher volunteer determined the sequencing, multitasking, pacing, and execution of the tasks and integrated additional home activities, such as making phone calls, watching TV, using the computer, grooming, and eating. Our intent was to have a short test dataset that showed a variety of activity types and activated as many sensors as possible, but in a natural way.

At the conclusion of the test period, each hour of the data was manually annotated using a hierarchy of 89 activity, body posture, and room/context types we have developed for PlaceLab data. Some of these are listed in Table 1. Trained (undergraduate) annotators required about 2 hours of effort for each hour of video annotated using professional annotation software (ProcoderDV). Initial annotation sets analyzed using Cohen's Kappa (a standard technique for determining inter-rater reliability) revealed some variation in labeling outcome. Body postures with extended state (e.g., standing, sitting, walking) received higher agreement between annotators than fast-action body postures (e.g., sitting down action, turning/pivoting). Activities that involved single appliances (e.g., ironing, vacuuming, using telephone) received the highest agreement between annotators. Based on these results, we are revising our annotation training procedures and the label hierarchy. We are also including "background" activities (e.g., "cooking" can continue even as someone makes a bed, if pots are on the stove). Our experiences annotating early PlaceLab datasets have also led us to develop custom annotation tools that help annotators label this unique type of dataset. Since an annotation session may last only a few hours, but a "background" activity can last much longer (e.g. an extended episode of "cooking" or "cleaning"), we have found that annotators need tools that help ensure they do not forget to mark start or end times of longer events. Using the sensors activations themselves can also help annotators spot check work (e.g., if one clicks on the microwave sensors, a tool that helps quickly check for "cooking" labels is of great value). We will provide our latest tools along with each dataset and we invite members of the community developing annotation tools to contribute as well.

Activities (out of 89) observed by annotator for an hour of intensive activity dataset
Activity: Prep. food bkgrnd (1, 85%, 3068s), Wash laundry bkgrnd, (1, 26%, 953s), Use computer (3, 14%, 171s), Hand-wash dishes (6, 11%, 65s), Meal prep. misc. (6, 8%, 49s), Make bed (1, 8%, 270s), Mix/stir (9, 7%, 29s), Laundry misc. (1, 4%, 155s), Dry dishes (2, 3%, 49s), Clean a surface (1, 3%, 96s), Retrieve ingred./cookware (7, 3%, 13s), Fold laundry (2, 2%, 27s), Measure (2, 0.9%, 15s), Put away dishes (2, 0.7%, 12s), Clean misc. (1, 0.7%, 24s), Dishwash misc. (1, 0.6%, 19s), Combine/add (1, 0.5%, 17s), Listen to music/radio (1, 0.2%, 7s), Put things away (2, 0.2%, 3s), Dispose garbage (1, 0.05%, 1s), Wash laundry (1, 0.04%, 1s), Drink (1, 0.04%, 1s)
Posture/mobility: Stand still (state) (40, 50%, 45s), Walk (45, 25%, 20s), Sit (state) (4, 15%, 132s), Walk w/ load (6, 3%, 20s), Bend (15, 3%, 7s), Kneel (3, 2%, 23s), Stand up (action) (15, 0.8%, 1s), Sit up (action) (3, 0.3%, 3s), Sit down (action) (4, 0.2%, 1s), Turn/pivot (1, 0.09%, 3s)
Location: Kitchen (13, 50%, 137s), Bedroom (6, 19%, 116s), Office (3, 14%, 177s), Out of view (6, 8%, 49s), Hallway (29, 5%, 6s), Dining area (6, 3%, 16s), Living room (1, 0.3%, 11s)
Activities (out of 89) observed by annotator for an hour during Participant 3's stay
Activity: Meal prep. misc. (2, 17%, 314s), Watch TV/movies (1,14%, 487s), Prep. food bkgrnd (1, 14%, 487), Read paper/book/magazine (1, 8%, 273s), Info/leisure misc. (3, 7%, 88), Mix/stir (2, 5%, 88), Toileting (1, 4%, 153s), Use phone (1, 4%, 139s), Put things away (4, 4%, 31s), Combine/add (6, 3%, 20s), Retrieve ingred./cookware (6, 1%, 7s), Wash hands (1, 0.8%, 28s), Clean a surface (1, 0.6%, 19s), Groom/hygiene misc. (1, 0.5%, 19s), Undress (1, 0.4%, 13s), Drink (2, 0.2%, 4s), Put away laundry (1, 0.2%, 7s), Wash ingred. (1, 0.1%, 5s),Dispose garbage (1, 0.1%, 4s), Enter house (1, 0.06%, 2s)
Posture/mobility: Sit (state) (6, 31%, 188s), Stand still (state) (56, 30%, 18s), Walk (23, 11%, 16s), Turn/pivot (50, 6%, 4s),Bend (13, 4%,11s), Sit down (action) (6,0.5%,3s), Stand up (action)(5, 0.2%,1s)
Location: Living room (3, 26%, 318s), Kitchen (5, 26%, 185s), OutOfView (3, 19%, 234s), Dining area (7, 19%, 95s), Bathroom (1, 4%, 159s), Office (1, 4%, 132s), Hallway (8, 2%, 7s)

Table 1: Activities manually annotated in the intensive activity test dataset and one waking hour (10/16/04, 7-8 PM) of PlaceLab Participant 3, with number of bouts, total percentage time, and mean time in seconds.

Table 1 is not intended as a comprehensive summary of activity, only a representation of the diversity of activities that may be observed. Researchers interested in particular topics are able to search the PlaceLab dataset for activities or times of interest. Currently most searching must be done based on one-to-one sensor activations (e.g. playing back video and audio and sensor activations just before and after the refrigerator was opened). However, as algorithms for automatic detection of activities are employed on datasets, those computationally inferred labels can and will be added to the set of annotations, ideally reducing annotation time for certain types of data analysis tasks. Researchers who are attempting to do activity recognition studies with in-home sensor systems lack access to datasets with well-annotated activities. Further, some PlaceLab studies result in other types of data than activity performed being collected, such as subject self report and subject responses to interviews with researchers pre and post study.

We are currently using PlaceLab annotations to validate the PlaceLab and wireless sensor infrastructure itself. For example, one hour of the test set has been annotated with all instances of interaction with objects or furnishings that (according to multiple annotators) should have produced a sensor activation. Fifty sensors (cabinets, appliances) were identified that should have fired. In practice, 42 sensor firings were recorded (84%). Three errors were due to a broken oven switch, one was due to a sticky cabinet door that does not close all the way, and four resulted from TINI board latency and very fast cabinet open/close events (see the Appendix for a discussion about sensor latency and how we have reduced it). The wired infrastructure of the PlaceLab is also being used to fully characterize the performance of the wireless sensors [6], which are intended for *in situ* ubiquitous computing research in the actual homes of volunteers. The cost of maintaining the PlaceLab sensor infrastructure over time is something we plan to monitor. The greatest barrier to using PlaceLab data is simply the manpower required to annotate datasets in detailed ways. We can currently generate far more data than we can annotate and analyze and therefore hope others in the community can participate in the effort.

7.2 Data from PlaceLab Volunteers

The intensive activity test set is designed to introduce other ubiquitous computing researchers to PlaceLab data. However, our ultimate goal is to have researchers productively using data from our volunteer subjects. The bottom of Table 1 lists activities observed during one waking hour of PlaceLab Participant 3. Clearly, even in this single hour, a variety of complex activity is observed. This same hour contains (as tabulated by one of our researchers) the following activities: learning behavior (using a new appliance), planning behavior (making lists), searching behavior (looking in cabinets), gesturing (purposeful and not), communication impacting behavior (talking on phone and pacing), and use of a large and diverse set of household objects. This high density of "interesting" activities in a single hour suggests that they will be quite common throughout typical PlaceLab datasets with multiple day or week stays. Although techniques such as ethnography could be used to learn more about such activities, those methods do not provide multi-modal datasets synchronized with specific examples.

Our experiences running PlaceLab studies and examining our preliminary datasets suggest that living laboratories can generate rich, multi-modal sensor datasets of activity in the home setting unlike those that can be acquired using other methods. Our group will be using the PlaceLab for studies on the development and evaluation of context detection and context-aware technologies. However, we believe that the facility can be used as a shared resource and that the data it generates will become more useful as more researchers use it in their own work. We will continue to improve the facility, our experimental methods, and the quality of the datasets we produce.

Conclusion

The technical and administrative complexity of building and operating this kind of residential living laboratory is great, and we therefore expect the number of living laboratories available to ubiquitous computing researchers to be small. However, our pilot testing has already created datasets that we could not have obtained in any other way. These datasets are a detailed record of home behavior synchronized with sensor data that simplifies the annotation of and searching for items of interest and can be used for context-detection algorithm development and evaluation. We believe that living laboratories can provide valuable datasets for the ubiquitous computing research community, and in that spirit we have described our facility and the type of data it can generate. We are making example data available to the community with the hope that researchers will report how they might use the data in their own work and what additional information would be beneficial. The PlaceLab is not intended to replace other ethnographic research tools and sensor data collection methods, but rather to fill a gap. Living laboratories may become increasingly important as researchers begin to migrate ubiquitous computing technologies from the traditional laboratory into actual homes.

Appendix: PlaceLab Infrastructure

In this section additional details of the PlaceLab's technical infrastructure are described.

Initial Fit-Out and Wiring

Prior to the installation of the custom-designed PlaceLab cabinetry, an extensive home-run wiring infrastructure was embedded behind the drywall by professional installers. Coaxial and CAT6 cables run from patch panels in the server closet directly to each of the cabinets, where gangs of coaxial and RJ45 outlets are installed in the drywall. The heads of the cabinets cover these outlets, providing researchers with easy access to hidden, robust commercial plug connections (Fig. 5a). Over a mile of coaxial and CAT6 cable run in the wall cavities. Although the coaxial wiring is insulated and the CAT6 wiring is twisted pair, we were concerned that electrical interference might compromise the PlaceLab systems. In practice, this has not been a problem.

To accommodate unanticipated wiring needs, plastic conduit (1 inch diameter, the largest possible given other wiring bundles) was run from the server room to each of the cabinet locations (Fig. 5b). We have already used the conduit on multiple occasions to add special sensors (e.g. wireless receivers). A cable television and Internet network was also installed for the resident, which operates independently of the research systems.

Cabinet Wiring and Sensors

Within the head of each of the 15 cabinets is a Dallas Semiconductor TINI networked microcontroller (DSTINIS400 with 2MB SRAM for data and 2MB of flash ROM for application storage and DSTINIM400 evaluation socket). This board runs (TINI OS and TINI SDK 1.12), a Java virtual machine with an API for 1-wire sensor operation. The 1-wire sensor network driven by the TINI board was chosen as an affordable, extensible, and robust architecture allowing data from many sensors (typically 30) in a single cabinet unit to be sent via TCP/IP to control computers aggregating and time stamping data. The 1-wire network uses a single wire (plus ground) to accomplish both communication and power transmission at speeds of 16kbps and 142 kbps.

The head, sides, and foot of each cabinet, which are locked when participants live in the PlaceLab, can hinge open to reveal the sensor infrastructure, making it easy to add new sensors when needed (Fig. 4, Fig. 5c). The 1-wire network typically uses a RJ11

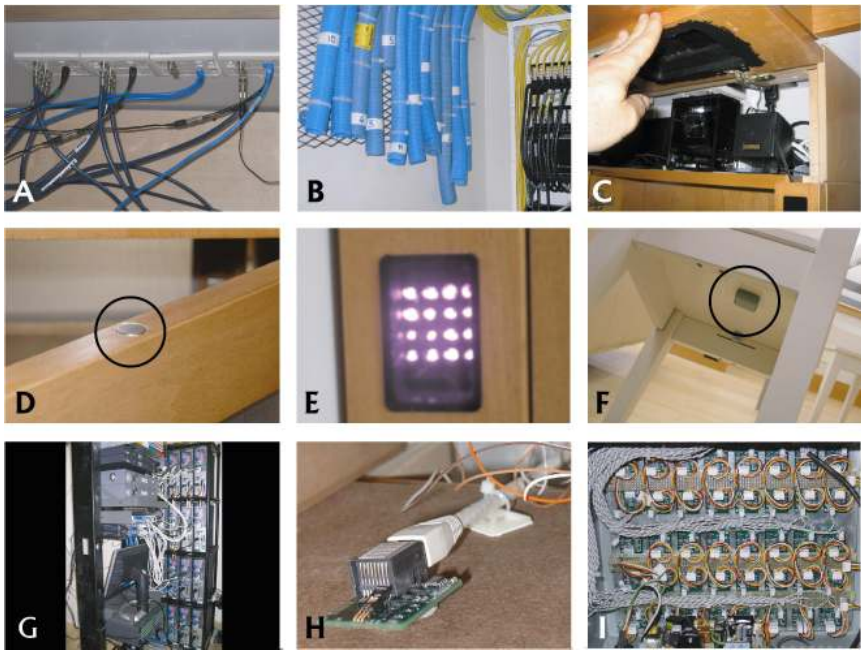

Fig 5: A) Professionally-installed coaxial and CAT6 wires terminate in gangs of outlets inside the heads of cabinets; B) Some of the 30 conduits running to all cabinetry; C) The head (shown), foot, and side channels of all cabinets open for sensor maintenance and upgrades; D) Every sensor was installed with attention to detail so that sensors would be robust and inconspicuous; switch sensors are embedded in the wood; E) The black acrylic covers many sensor types; here an infrared emitter is shown (invisible to the naked eye); emitters are scattered throughout the cabinetry; F) Wireless movement detection sensors can be placed on objects of interest, here on a chair; G) All data are sent to the server closet where 20 PCs process and synchronize all data streams; H) Custom boards were developed for some sensor types so that they can be rapidly plugged into the 1-wire network in each cabinet with a single RJ45 connection; each sensor has a unique ID; I) 37 current sensors near the circuit breaker monitor each of the circuits in the apartment.

connector and modular telephone cable, however after experiencing problems with noise in a prototype cabinet, we modified all sensors to use high-quality RJ45 connectors and CAT6 cable. CAT6 cable in convenient, short lengths can also be readily obtained. A single CAT6 cable runs from the TINI board throughout the cabinet, splitting once at each sensor. CAT6 splitters are not manufactured commercially and so our group produced approximately 400 of such splitters (Fig. 4). Further, we were adding so many sensors to the network that a small circuit needed to be designed to simplify sensor installation. This board allowed up to two reed magnet contact switches to be attached to the 1-wire network by simply plugging in a CAT6 cable. Each 1-wire device has its unique ID, however, an additional ID was burned into the EEPROM memory of sensors using ADCs (DS2438) such as light, humidity, current and flow to differentiate among them (to avoid requiring control code to have a look-up table matching IDs with sensor types, which is problematic to maintain when sensors are moved/replaced).

Similar circuits were also designed for light sensors, humidity sensors, barometric pressure sensors, flow sensors, and current sensors (Fig. 5h). Commercial 1-wire temperature sensors were purchased and hand-wired to connect directly to RJ45 wires. In some cases, short wires run from the circuit boards in the cabinetry channels to the actual sensors. For example, reed switches and magnets were carefully installed in 80 cabinets and appliances so that they were not visible and would be protected from damage during heavy use (Fig. 5d).

To minimize cabling that needed to be run in the cabinet side channels, the same CAT6 cable used for 1-wire communication in the cabinet is used to provide 5V and 12V power. When a sensor needs power, a splitter can be used and a hand-made CAT6-to-power-connector cable. This is how 85 custom-made IR illuminator boards are powered, which provide some illumination to each room even in total darkness for the IR cameras (Fig. 5e). Java code on the TINI board repetitively polls each of the sensors and reports their state back to a control computer. Overall, we have found the distributed TINI boards and 1-wire networks to be a reliable and affordable way to gather input from the wired digital and analog sensors in the apartment.

The 18 video cameras are located in the heads of cabinets or above counter surfaces and can be easily moved between studies to any part of the apartment (Fig. 5c). The IR cameras are behind visible light filter acrylic. The color cameras are behind clear acrylic that appears black from the living spaces because each camera is housed in an encasement that blocks/absorbs light. The cameras feed directly to the coaxial outlets.

Nineteen of the cabinets are outfitted to provide localized audio input and output. Small electret microphones flush-mounted in the cabinet side rails have been distributed throughout the apartment to provide complete coverage, including both washrooms. At each cabinet, a pre-amplifier boosts the signal to line-level to prevent electromagnetic crossover from adjacent 1-wire cabling. Input is run over the coaxial cables to distributing amplifiers in the server room.

Audio output is provided by commercial multimedia speaker systems that include two satellite speakers mounted behind acrylic grills in the head of each cabinet. A subwoofer is located at the foot of the cabinet. A custom RJ-45 to 3.5mm stereo headphone jack adapter allows audio to be carried over the structured cabling from the server room, where the specific output locations are selected by a matrix switcher.

Server "Closet" and Synchronization of Data

Inaccessible to PlaceLab volunteers is a 40 sq. ft. closet in the office that has been converted to the server room. This space is designed for sound attenuation and is cooled by an air conditioning unit. All data are processed by a bank of 20 2GHz PCs with running Windows XP. A key challenge has been to synchronize all data sources.

Each of the 18 video streams and 19 audio streams feed into a Kramer 1x3 video and audio amplifier/splitter and then into a particular computer. Each of the AV streams also feed into a Kramer Electronics 32x32 AV matrix switcher. Eighteen of the computers run Java code that digitizes incoming video and runs image differencing software – computing degree of motion. Another computer that integrates reports across the 18 cameras and, using heuristics about camera placement, selects the 4 views most likely to be informative at that moment. The computer routes the 4 best views using the matrix switcher into a video multiplexer in quad mode, to generate an image such as that in Fig. 3. That image stream is sent to a control computer that digitizes and saves the video in

Indeo 5.0 AVI format, with a special timestamp file.[1] The timestamp corresponds to the master PlaceLab time on the primary data archiving computer and allows for synching with other data sources later even though the video capture frame rate tends to vary with scene complexity. One of the 19 microphones is also selected, based upon the location of microphones and the primary area of motion. In practice, the microphones are extremely sensitive, and activity is generally audible as long as a microphone is on the side of the apartment near the person. The designated microphone output is switched via the matrix switcher into the computer saving the video. Video and audio are therefore automatically synchronized. The PlaceLab is currently optimized to record one participant, but actually does a reasonable job capturing activity from two. Even a single microphone can capture audio from different spaces in the apartment, and the selected microphone input switches between spaces. The infrastructure is flexible, however, so that recording of an additional audio stream (or even *all* audio streams) could easily be done with the addition of more disk space.

The data archiving computer receives data from all the TINI microcontrollers in the cabinets and immediately timestamps it and saves it to a large external disk in a logical file structure, by sensor type, day, and hour. The video and audio is saved to this same disk, in 1-hour segments with the added frame synchronization information. All data from TINI boards is synchronized once it arrives via the network at the archiving computer. In practice, the 1-wire network and TINI board introduces a latency of up to 3 seconds for many switch sensors, discussed later in this section.

Six of the computers, in addition to processing video, process data from the wireless MITes receivers, which are connected by cable home runs to the serial port. These machines filter each individual receiver data stream and remove duplicate events recorded by multiple receivers. Real-time limb motion data are saved, as well as data from object motion detectors (hundreds possible) and a wireless HR monitor.

In summary, the PlaceLab saves video (best 4 streams at 320 by 240 pixel resolution each) and audio (16kHz, 8-bit, mono stream from microphone close to activity) synchronized with 358 streams of other data. In a typical 24-hour period, approximately 24 GB of data are generated and conveniently saved onto a large portable disk drive that is picked up by a researcher at the conclusion of a multi-day study.

Latency

Although all PlaceLab data are synchronized, we have experienced latency in the 1-wire sensors. This results from our decision to use Java code on TINI microprocessors, which turns out to be slow (up to 200 ms) when querying an analog sensor. Consequently, the Java code cannot continuously poll analog sensors without introducing latency for digital switches. Until recently, the software was setup to continually poll switch sensors and only poll most analog sensors (current flow, water flow, temperature) once per minute. We have recently removed this limitation by replacing most of the TINI boards with direct 1-wire connections to the PCs in the control closet. In new datasets, latency of these sensors has been reduced to less than 100 ms.

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[1] As researchers outside of our group began to look at the test datasets, we realized that reliance on a particular video codec was problematic both when attempting to keep data synchronized and when others tried to view/use it. Newer PlaceLab datasets save static images at a high sampling rate with short synchronized audio to simplify the sharing and annotation of data.

Maintenance
The PlaceLab is a true live-in laboratory, and ideally during studies there is little or no contact between researchers and participants. There is no researcher at the site when a study is being run, and to protect the data from being compromised, we decided to physically disconnect the sensor infrastructure from the Internet during times when the unit is occupied.

In practice, it has become necessary to relax this design decision to allow for some system monitoring during a study in case a key piece of equipment malfunctions. We have therefore added a single special-purpose serial cable that connects the researcher infrastructure to a computer on the residential network (but in the server closet). That computer, the sentinel, sends an hourly report on PlaceLab systems to the researchers running a study. Each sensor in the PlaceLab, including wireless sensors, sends an "alive" ping to the archiving computer at least once per hour. The sentinel emails reports indicating whether all systems are functional as well as any anomalous values that might be cause for concern. It does not report any information about the participant's actual activity.

The sentinel has proved invaluable both for debugging PlaceLab systems as well as for protecting the system from damage. For example, a recent storm when the PlaceLab was not occupied resulted in the air conditioning unit that cools the server closet malfunctioning. Our team identified the problem within a few hours and shutdown the PlaceLab systems when a temperature of 90+ degrees was reported for the server closet. The PlaceLab can recover from power failures and runs continuously.

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