How Smart are our Environments? An Updated Look at the State of the Art

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Abstract

In this paper we take a look at the start of the art in smart environments research. The survey is motivated by the recent dramatic increase of activity in the field, and summarizes work in a variety of supporting disciplines. We also discuss ongoing challenges for continued research.

1 Introduction

Designing smart environments is a goal that appeals to researchers in a variety of disciplines, including artificial intelligence, pervasive and mobile computing, robotics, middleware and agent-based software, sensor networks, and multimedia computing. Advances in these supporting fields have prompted a tremendous increase in the number of smart environment projects. Because of the rising popularity of the topic and a growing desire for successful projects in the marketplace, we offer an updated look at the state of the art in smart environments.

We define a smart environment as *one that is able to acquire and apply knowledge about the environment and its inhabitants in order to improve their experience in that environment* [88]. The components of a smart environment are shown in Figure 1.

Automation in a smart environment can be viewed as a cycle of perceiving the state of the environment, reasoning about the state together with task goals and outcomes of possible actions, and acting upon the environment to change the state. Perception of the environment is a bottom-up process. Sensors monitor the environment using physical components and make information available through the communication layer. The database stores this information while other information components process the raw information into more useful knowledge (e.g., action models, patterns). New information is presented to the decision making algorithms (top layer) upon request or by prior arrangement. Action execution flows top-down. The decision action is communicated to the services layers (information and communication) which record the action and communicates it to the physical components. The physical layer performs the action with the help of actuators or device controllers, thus changing the state of the world and triggering a new perception.

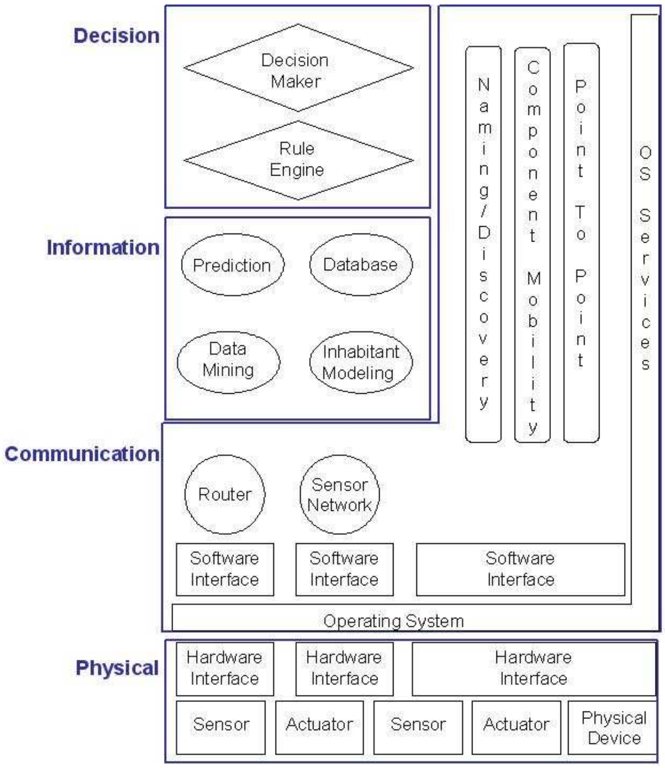

Figure 1: The components of a smart environment.

In the remainder of this paper we take a closer look at the state of the art in smart environments by providing a summary of current research in these component areas. We also summarize the fundamental challenges and solutions in modeling inhabitant's mobility and activity in smart environments. This is followed by a discussion on the application of smart environment research to health monitoring and assistance. Finally, we introduce challenges for continued research.

2 The Role of Physical Components in Smart Environments

Because smart environment research is being conducted in real-world, physical environments, design and effective use of physical components such as sensors, controllers, and smart devices is vital. In our intelligent agent design, the physical components are what allow the agent to sense and act upon the environment. Without these physical components, we end up with theoretical algorithms that have no practical use.

Like all intelligent agents, a smart environment relies on sensory data from the real world. As Figure 2 shows, the environment perceives the environment using these sensors and uses this information to reason about the environment and the action that can be taken to change the state of the environment. Table 1 lists some of the properties of the environment that need to be captured and how they can be measured.

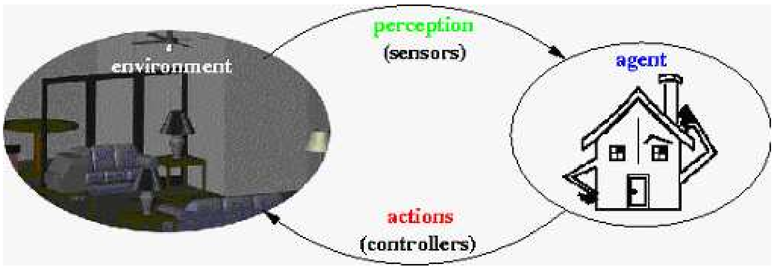

Figure 2: Smart environment as an intelligent agent.

Properties	Measurand
Physical properties	pressure, temperature, humidity, flow
Motion properties	position, velocity, angular velocity, acceleration
Contact properties	strain, force, torque, slip, vibration
Presence	tactile/contact, proximity, distance/range, motion
Biochemical	biochemical agents
Identification	personal features, personal ID

Table 1: Sensors for smart environments (adapted from [44]).

The information required by smart environments is measured by sensors and collected using sensor networks. The importance of sensor networks as a research area unto itself is indicated by the number of related workshops [34] and recent efforts that have been initiated by funding agencies such as DARPA [16] and NSF [57]. These sensor networks are responsible for acquiring and distributing data needed by smart buildings, utilities, industries, homes, ships, and transportation systems. Sensor networks need to be fast, easy to install and maintain, and self-organizing.

To assist manufacturers in creating sensors that can be interfaced to such networks, the IEEE and NIST (National Institute of Standards and Technologies) created the IEEE 1451 standard for Smart Sensor Networks [33]. The IEEE 1451 studies formalized the notion of a smart sensor as one that provides additional functions beyond the sensed quantity such as signal condition or processing, decision-making functions, or alarm functions [24]. The result is a device that takes on some of the burden of intelligent reasoning, reducing the amount of reasoning needed at the agent level. A number of companies have commercialized sensors that are suitable for wireless network applications [44].

After the intelligent agent builds a representation of the current state of the environment from perceived information, it can reason about the environment and use this information to select an action. The agent executes the action using a controller, which causes a change in the state of the environment.

Although customized controllers can be designed, an effective mechanism for controlling many devices is using power line communication (PLC). PLC provides networking and controller services using electrical wiring already deployed in most environments. X-10 technology is one of the oldest PLC protocols and is typically used to control lamps and appliances.

X-10 controllers send signals over the power line to receives and facilitate automated control from a computer as well as logging of inhabitant manual interactions with these devices. X-10 interfaces have the advantage of inexpensive pricing and ready availability, but they are often hampered by noisy signals and long delays. The Smart House Applications Language (SHAL) [79] provides a more comprehensive set of message types for specific sensing and control functions, but requires dedicated multiconductor wiring.

Reliable data transmission over electrical wiring is difficult to achieve. The HomePlug protocol specifications address this problem in the American market using error correction coding and decoding techniques together with automatic request techniques. A peer-to-peer communication protocol is available in the LonWorks protocol developed by Echelon [21]. LonWorks networks can be implemented over a wide range of medium including power lines, twisted pair, radio frequency (RF), infrared (IR), coaxial cable and fiber optics.

Much of the research in the area of physical component design is performed independently of smart environment applications. However, some efforts have focused primarily upon the design or use of these technologies to support smart environment tasks. For example, Lins, et al. [45] have created a tool called BeanWatcher that manages wireless sensor network applications for mobile devices. This tool is designed primarily for monitoring and managing multimedia data streams in the intelligent environments, and is being investigated as a management technique for intrusion detection applications in closed environments. Want [85] describes how radio frequency identification (RFID) tags can be used to collect sensor-derived data, and Philipose, et al. [65] adopt a similar approach by tagging objects in the environment and using sensed interactions to build representations of inhabitant activities as sequences of such interactions. Vastamake, et al. [84] also build profiles of environment inhabitants, based solely upon temperature control behavior.

In the same way that smart sensors move some of the reasoning work down to the physical level, so researchers have also developed a number of intelligent devices. These devices are not intended to solve the entire intelligent environment design problem, but they do provide intelligent functionality within the confines of a single object and task. The smart sofa at Trinity College [42], for example, contains programmable sensors on the couch legs that identifies the individual sitting on the couch based on their weight distribution. The couch can thus greet the individual and could forseeably customize the immediate surroundings for that person. A number of intelligent and networked kitchen appliances have been designed by companies such as GE and Whirlpool that add multimedia interfaces and status reporting capabilities to the kitchen [81]. The 200ConnectIo device [27] refrigerates food until commanded to cook it by phone, computer, or personal digital assistant (PDA).

The MIT Things That Think [52] group has developed intelligent devices such as smart hotpads that determine whether a pan is too hot to touch, a spoon that provides feedback about the temperature and viscosity of food, and a kettle that says how much longer you have to wait for tea (see Figure 3). The Philips interactive tablecloth [66] weaves a power circuit into a washable linen tablecloth, so that devices can be charged when they are placed anywhere on the tablecloth. While these devices are novel and useful for limited tasks, they typically do not consider the bigger picture of interacting with the rest of the environment. As Rode points out [71], they also rarely consider difficulties encountered in cultures and markets other than the one for which they are designed. Rode observes that these devices would be much more useful if they could adapt themselves to new environments and uses.

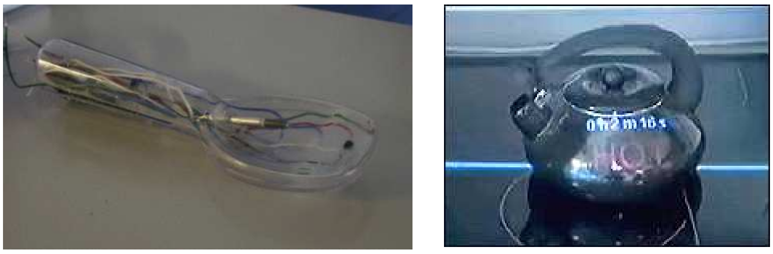

Figure 3: The MIT intelligent spoon and interactive tea kettle [52].

Other devices have been designed for the purpose of remotely controlling an inhabitant's environment. Examples of these physical components include smart phones [59, 69], wearable computers and head-mounted displays [38, 58], and a unique gesture pendant [78] which uses wearable jewelry to recognize gestures for executing control tasks. Kikin-Gil has also created a type of smart jewelry [39]. This intelligent device differs from the others in this class because it allows teenagers to communicate with each other using predefined codes emitted from their wearable jewelry, the Buddy Beads.

3 Pervasive Computing and Middleware Issues

Recent advances in smart technologies (e.g., sensors, devices and appliances, wireless networking), software agents, and middleware technologies have led to the emergence of *pervasive* or *ubiquitous computing* as perhaps the most exciting area of computing in recent times. Empowered by wireless mobile communications and computing as well as situation-aware computing, pervasive computing aims at providing *where you want, when you want, what you want and how you want* types of services to users, applications and devices. Major challenges in pervasive computing include invisibility or (user/device) unawareness, service discovery, interoperability and heterogeneity, proactivity, mobility, privacy, security and trust. In such environments, hardware and software entities are expected to function autonomously, continually and correctly. From these perspectives, pervasive communications and computing offer a suitable platform for realization of smart environments that link computers to everyday settings and commonplace tasks, and also acquire and apply knowledge effectively in our surroundings. For an overview of enabling technologies and challenges in pervasive computing, refer to [40].

Traditionally, agents have been employed to work on behalf of users, devices and applications [6]. In addition, agents can be effectively used to provide transparent interfaces between disparate entities in the environment, thus enhancing invisibility. Agent interaction and collaboration is an integral part of pervasive (intelligent) environments, as agents can overcome the limitations of hundreds and thousands of resource limited devices.

Service discovery is described as the process of discovering software processes/agents, hardware devices and services. The role of service discovery in pervasive computing is to provide environment-awareness to devices and device-awareness to the environment. Service provisioning, advertisement and service discovery are the important components of this module. Although service discovery in mobile environments has been addressed in existing work, service discovery in pervasive computing are still at its infancy. Existing service discovery mechanisms include JINI and Salutation as well as the International Naming System (INS) [2].

Several new embedded devices and sensors are being developed in the industry and research laboratories. The architecture of the Berkeley sensor motes and the TinyOS operating system [15] are very good examples of devices and technologies developed for use with embedded networked sensors. The challenge here is to design devices that are tiny (disappear into the environment), consume little or no power (perhaps powered by ambient pressure, light, or temperature); communicate seamlessly with other devices, humans, and services through a simple all-purpose communication protocol.

As mentioned above, a pervasive (or smart) environment comprises numerous invisible devices, anonymous users, and ubiquitous services. Development of effective middleware tools to mask the heterogeneous wireless networks and mobility effects is a major challenge. Provisioning uniform services regardless of location is also vital. The challenge here is to provide location-aware services in an adaptive fashion, in a form that is most appropriate to the location as well as to the situation under consideration.

4 Location-Awareness and Mobility Tracking in Smart Environments

Models of 21st century ubiquitous computing scenarios [86] depend not just on the development of capability-rich mobile devices (such as web-phones or wearable computers), but also on the development of automated machine-to-machine computing technologies, whereby devices interact with their peers and the networking infrastructure, often without explicit operator control. To emphasize the fact that devices must be imbued with an inherent consciousness about their current location and surrounding environment, this computing paradigm is also called sentient [31] or context-aware computing.

"Context (e.g., location and activity) awareness" is a key to build a smart environment and associated applications. If devices can exploit emerging technologies to infer the current activity state of the user (e.g., whether the user is walking or driving, whether he/she is at office, at home or in a public environment) and the characteristics of their environment (e.g., the nearest Spanish-speaking ATM), they can then intelligently manage both the information content and the means of information distribution. For example, the embedded pressure sensors in the Aware Home [63] capture inhabitants' footfalls, and the smart home uses these data for position tracking and pedestrian recognition.

The Neural Network House [54], the Intelligent Home [43], the House_n [32] and the MavHome [17, 90] projects focus on the development of adaptive control of home environments by also anticipating the location, routes and activities of the inhabitants. This section summarizes a novel, information theoretic paradigm for context learning and prediction that can be used for predicting with high degree of accuracy the inhabitant's future locations and activities, automating activities, optimizing control of devices and tasks within the environment, and identifying anomalies. This to reduce cost of maintaining the environment and resource consumption, and provide special health benefits for elderly and people with disabilities [18, 28, 30].

From an information theoretic viewpoint, an inhabitant's mobility and activity create an *uncertainty* of their locations and hence subsequent activities. In order to be cognizant of their contexts, the smart environment needs to minimize this uncertainty as captured by Shannon's entropy measure [14]. An analysis of the inhabitant's daily routine and life style reveals that there exist some well-defined patterns. Although these patterns may change over time, they are not too frequent or random, and can thus be learned. This simple observation may lead us to assume that the inhabitant's mobility or activity follows a piece-wise stationary, stochastic, ergodic process with an associated uncertainty (entropy), as originally proposed by Bhattacharya and Das [8] for optimally tracking (estimating and predicting) location of mobile users in wireless cellular networks.

The framework from Bhattacharya and Das was used to design an optimal algorithm for location (activity) tracking in a smart environment [72], based on compressed dictionary management and online learning of the inhabitant's mobility profile, followed by a predictive resource management (energy consumption) scheme for a single inhabitant smart space. However, the presence of multiple inhabitants with dynamically varying profiles and preferences make such tracking much more challenging. This is due mainly to the fact that the relevant contexts of multiple inhabitants in the same environment are often inherently correlated and thus inter-dependent with each other. Therefore, the learning and prediction (decision making) paradigm needs to consider the joint (simultaneous) entropy for location tracking of multiple inhabitants [74]. In the following, we consider single inhabitant and multiple inhabitant mobility tracking cases separately.

4.1 Single Inhabitant Case

The learning and prediction based paradigm, based on information theory and text compression, manage the inhabitant's uncertainty in mobility and activity profiles in daily lives. The underlying idea is to build compressed (intelligent) dictionary of such profiles collected from sensor data, learn from this information, and predict future mobility and actions. This prediction helps device automation and efficient resource management, thus optimizing the goals of the smart environment. At a conceptual level, prediction involves some form of statistical inference, where some sample of the inhabitant's movement profile (history) is used to provide intelligent estimates of future location, thereby reducing the location uncertainty associated with the prediction [18, 73].

Hypothesizing that the inhabitant's mobility has repetitive patterns that can be learned, and assuming the mobility as a stochastic random process, the following lower bound result was proved by Bhattacharya and Das [8]: It is impossible to optimally track mobility with less information exchange between the smart environment and the device (detecting inhabitant's mobility) than the entropy rate of the stochastic mobility process. Specifically, given the past observations of inhabitant's position and the best possible predictors of future position, some uncertainty in the position will always exist unless the device and the system exchange location information. The actual method by which this exchange takes place is irrelevant to this bound. All that matters is that the exchange exceeds the entropy rate of the mobility process. Therefore, a key issue in establishing bounds is to characterize the mobility process (and hence entropy rate) in an adaptive manner. To this end, based on the information-theoretic framework, Bhattacharya and Das [8] proposed an optimal on-line adaptive location management algorithm, called LeZi-update. Rather than assuming a finite mobility model, LeZi-update learns an inhabitant's movement history stored in a Lempel-Ziv type of compressed dictionary [46], builds a universal model by minimizing entropy, and predicts future locations with high accuracy. In other words, LeZi-update offers a model-independent solution to manage mobility related uncertainty.

The LeZi-update framework uses a symbolic space to represent each sensing zone of the smart environment as an alphabetic symbol and thus captures inhabitant's movement history as a string of symbols. That is, while the geographic location data are often useful in obtaining precise location coordinates, the symbolic information removes the burden of frequent coordinate translation and is capable of achieving universality across different smart spaces [54, 73]. The blessing of symbolic representation also facilitates hierarchical abstraction of the smart environment infrastructure into different levels of granularity. This approach assumes that the inhabitants' itineraries are inherently compressible and allow application of universal data compression algorithms [12, 46], which make very basic and broad assumptions, and yet minimize the source entropy for stationary Ergodic stochastic processes [70]. The LeZi-update scheme endows the prediction process, by which the system finds nodes whose position is uncertain, with sufficient information regarding the node mobility profile. So overall, the application of information-theoretic methods to location prediction allowed quantification of minimum information exchanges to maintain accurate location information, provided an on-line method by which to characterize mobility, and in addition, endowed an optimal prediction sequence [12, 18]. Through learning, this approach allows us to build a higher order mobility model rather than assuming a finite model, and thus minimizes entropy and leads to optimal performance.

Not only does the Lezi-update scheme optimally predict the inhabitant's current location from past movement patterns, this framework can also be extended to effectively predict other contexts such as activity, the most likely future routes (or trajectories) [72], resource provisioning [18, 73], and anomaly detection. The route prediction exploits the asymptotic equi-partition property in information theory [14], which implies the algorithm predicts a relatively small set (called the *typical set*) of routes that the user is likely to take. A smart environment can then act on this information by efficiently activating resources (e.g., turning on the lights lying only on these routes).

4.2 Multiple Inhabitant Case

As mentioned earlier, the multiple inhabitant case is more challenging. The mobility tracking strategy described above is optimal for single inhabitant environments only. It treats each inhabitant independently and fails to exploit the correlation between the activities and hence the mobility patterns of multiple inhabitants within the same environment. Intuitively, independent application of the above scheme for each individual actually increases the overall joint location uncertainty. Mathematically, this can be observed from the fact that conditioning reduces entropy [14]. In fact, Roy, et al. [74] proved that optimal (that attains lower bound on joint entropy) location tracking of multiple inhabitants is an NP-hard problem.

Assuming a cooperative environment, they proposed [75] a cooperative game theory based learning policy for location-aware resource management in multi-inhabitant smart homes.

Figure 4: Real-time recognition of forty-word American Sign Language vocabulary [64].

This approach adapts to the uncertainty of multiple inhabitants' locations and most likely routes, by varying the learning rate parameters and minimizing the Mahalanobis distance. However, the complexity of multi-inhabitant location tracking problem was not characterized in that work.

Hypothesizing that each inhabitant in a smart environment behaves selfishly to fulfill his own preferences or objectives and to maximize his utility, the residence of multiple inhabitants with varying preferences might lead to conflicting goals. Under this circumstance, a smart environment must be intelligent enough to strike a balance between multiple preferences, eventually attaining an equilibrium state. If each inhabitant is aware of the situation facing all others, Nash equilibrium is a combination of deterministic or randomized choices, one for each inhabitant, from which no inhabitant has an incentive to unilaterally move away. This motivated Roy, et al. [74] to investigate the multi-inhabitant location tracking problem from the perspective of stochastic (non-cooperative) game theory, where the inhabitants are the players and their activities are the strategies of the game. The goal is to achieve a Nash Equilibrium so that the smart environment is able to probabilistically predict the inhabitants' locations and activities with sufficient accuracy in spite of possible correlations or conflicts. The authors validated their model and entropy learning scheme through simulation study and real data.

5 Natural Interfaces for Smart Environments

Although designers of smart environments are encouraged by the progress that has been made in the field over the last few years, much of this progress will go unused if the technologies are difficult or unnatural for inhabitants. Abowd and Mynatt [1] points out that explicit input must now be replaced with more human-life communication capabilities and with implicit actions. The maturing of technologies including motion tracking, gesture recognition (such as demonstrated by the Pentland's project in Figure 4), and speech processing facilitate natural interactions with smart environments.

In their Classroom 2000 project, Abowd provide human-computer interfaces through devices such as an interactive whiteboard that stores content in a database. The smart classroom of Shi, et al. [76] also uses an interactive whiteboard, and allows lecturers to write or notes directly on the board with a digital pen. This classroom experience is further enhanced by video and microphones that recognize a set of gestures, motions, and speech that can be used to bring up information or focus attention in the room on appropriate displays and material. The intelligent classroom at Northwestern University [25] employs

Figure 5: Facial expression recognition [64].

many of these same devices, and also uses the captured information to infer speaker intent. From the inferred intent the room can control light settings, play videos, and display slides. In none of these cases is explicit programming of the smart environment necessary – natural actions of the inhabitants elicit appropriate responses from the environment.

Such ease of interaction is particularly important in an office environment, where workers want to focus on the project at hand without being tripped up by technology. The AIRE project [3], for example, has designed intelligent workspaces, conference rooms, and kiosks that use a variety of mechanisms such as gaze-aware interfaces and multi-modal sketching that the full meaning of a discussion between co-workers through the integration of captured speech and captured writing on a whiteboard. The Monica project [41] identifies gestures and activities in order to retrieve and project needed information in a workplace environment. Similarly, the Interactive Room (iRoom) project at Stanford [23] enables easy retrieval and display of useful information. Users can display URLs on a selected surface by simply dragging the URL onto the appropriate PDA icon.

Targeting early childhood education, a Smart Table was designed as part of the Smart Kindergarten project at UCLA [80]. By automatically monitoring kids' interaction with blocks on a table surface, the Smart Table enables teachers to observe learning progress for children in the class. Children respond particularly well to such natural interfaces, as in the case of the KidsRoom at MIT [9]. The room immerses children in a fantasy adventure in which the kids must work together to explore the story. KidsRoom presents children with an interactive fantasy adventure. Only through teamwork actions such as rowing a virtual boat and yelling a magic word will the story advance, and these activities are captured through cameras and microphones placed around the room.

Work on natural interfaces for smart environments extends well beyond simple rooms. UCLA's HyperMedia Studio project [50] adapts light and sound on a performance stage automatically in response to performers' positions and movements. The driver's intent project at MIT [64] recognizes driver's upcoming actions such as passing, turning, stopping, car following, and lane changing by monitoring hand and leg motions. Accuracy of classified actions reaches 97% within 0.5 seconds of the beginning of the driver's action. Facial expression recognition systems, such as the one shown in Figure 5, can enhance smart cars by recognizing when the driver is sleepy, or change the classroom interaction when detecting that the students are bored or confused.

6 Inhabitant Modeling

One feature that separates *smart* environments from environments that are user controllable is the ability to model inhabitant behavior. If such a model can be built, the model can be used to customize the environment to achieve goals such as automation, security, or energy efficiency. If the model results in an accurate enough baseline, the baseline can provide a basis for detecting anomalies and changes in inhabitant patterns. If the model has the ability to refine itself, the environment can then potentially adapt itself to these changing patterns.

In this overview we characterize inhabitant modeling approaches based on three characteristics.

1. The data that is used to build the model.

2. The type of model that is built.

3. The nature of the model-building algorithm (supervised, unsupervised).

The most common data source for model building is low-level sensor information. This data is easy to collect and process. However, one challenge in using such low-level data is the voluminous nature of the data collection. In the MavHome project [87], for example, collected motion and lighting information alone results in an average of 10,310 events each day. In this project, a data mining pre-processor identifies common sequential patterns in this data, then uses the patterns to build a hierarchical model of inhabitant behavior. Loke [47] also relies upon this sensor data to determine the inhabitant action and device state, then pulls information from similar situations to provide a context-aware environment. Like the MavHome project, the iDorm research conducted by Doctor, et al. [20] focuses on automating a living environment. However, instead of a Markov model, they model inhabitant behavior by learning fuzzy rules that map sensor state to actuator readings representing inhabitant actions.

The amount of data created by sensors can create a computational challenge for modeling algorithms. However, the challenge is even greater for researchers who incorporate audio and visual data into the inhabitant model. Luhr [49] uses video data to find intertransaction (sequential) association rules in inhabitant actions. These rules then form the basis for identifying emerging and abnormal behaviors in a smart environment. Brdiczka, et al. [10] rely on speech detection to automatically model interacting groups in a smart environment. Moncrieff [53] also employs audio data for generating inhabitant models. However, such data is combined with sensor data and recorded time offsets, then used to sense dangerous situations in a smart environment by maintaining an environment anxiety level.

The modeling techniques described so far can be characterized as unsupervised learning approaches. However, if prelabeled inhabitant activity data is available, then supervised learning approaches can be used to build a model of inhabitant activity. Muehlenbrock, et al. [55] combine this approach with a naive Bayes learner to identify an individual's activity and current availability based on data such as PC/PDA usage. Tapia, et al. [82] also employ a naive Bayes learner to identify inhabitant activity from among a set of 35 possible classes, based on collected sensor data.

Figure 6: MavPad (left) and MavLab (right) automated environments.

7 Decision Making

Over the last few years, supporting technologies for smart environments, as described in the earlier sections of this paper, have emerged, matured, and flourished. Building a fully automated environment on top of these foundations is still a bit of a rarity. Automated decision making and control techniques are available for this task. Simpson, et al. [77] discuss how AI planning systems could be employed to not only remind inhabitants of their next activity but also to complete a task if needed. Augusto and Nugent [19] describe the use of temporal reasoning with a rule-based system to identify hazardous situations and return the environment to a safe state while contacting the inhabitant.

Few fully-implemented applications decision making technologies have been implemented. One of the first is Mozer's Adaptive Home [54], which uses a neural network and a reinforcement learner to determine ideal settings for lights and fans in the home. This is implemented in a home setting and has been evaluated based on an individual living in the Adaptive Home. Youngblood, et al. [89] also use a reinforcement learner to automate actual physical environments, the MavPad apartment and the MavLab workplace (shown in Figure 6).

The policy is learned based on a hierarchical hidden Markov model constructed through mining of observed inhabitant actions. Like the Adaptive Home, this approach has been implemented and tested on volunteers in a living environment. The iDorm project of Hagras, et al. [26] is another of these notable projects that has realized a fully-implemented automated living environment. In this case, the setting is a campus dorm environment. The environment is automated using fuzzy rules learned through observation of inhabitant behavior. These rules can be added, modified, and deleted as necessary, which allows the environment to adapt to changing behavior. However, unlike the reinforcement learner approaches, automation is based on imitating inhabitant behavior and therefore is more difficult to employ for alternative goals such as energy efficiency.

8 Health Monitoring and Assistance

There are many potential uses for a smart environment. Indeed, we anticipate that features of smart environments would pervade our entire lives. They will automate our living environment, increase the productivity of our work environment, customize our shopping

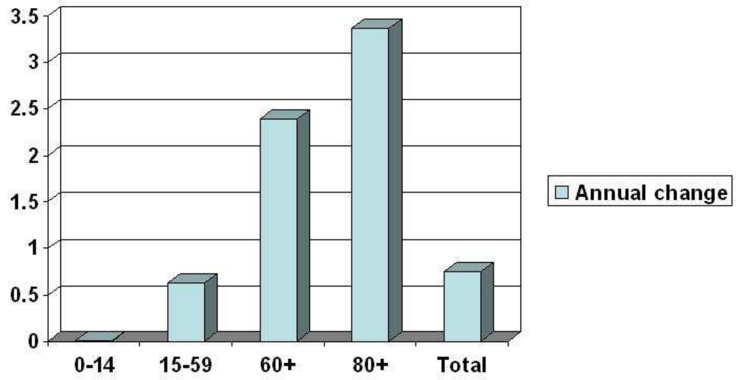

Figure 7: Annual rate of change by age range.

experiences, and accomplishing all of these tasks will also improve the use of resources such as water and electricity. In this section we focus on one class of applications for smart environments: health monitoring and assistance.

One reason for singling out this topic is the amount of research activity found here, as well as emergence of companies with initiatives to bring smart elder care technologies into the home [28, 61]. Another reason is the tremendous need for smart environment research to support the quality of life for individuals with disabilities and to promote aging in place. The need for technology in this area is obvious from looking at our current and project future demographics. Fertility decline combined with increases in life expectancy is resulting in population aging [83]. The resulting impact on age distribution is shown in Figure 7. Not only is the number of individuals age 60 and over expected to triple by 2050, but the United Nations reports that in most countries, more of these elderly people are living alone. To many people, home is a sanctuary. Individuals would rather stay at home, even at increased risk to their health and safety.

With the maturing of smart environment technologies, at-home automated assistance can allow people with mental and physical challenges to lead independent lives in their own homes. Pollack [68] categorizes such assistive technology as meeting the goals of assurance (making sure the individual is safe and performing routine activities), support (helping individual compensate for impairment), and assessment (determining physical or cognitive status). We summarize technologies in each of these area.

In the same fashion as researchers have developed technology for building models of inhabitant behavior, so similar approaches can be taken to monitor individuals to determine health status. Ogawa, et al. [62] used sensors to detect movement, use of appliances, and presence in a room and from this information were able to analyze behavior patterns of two elderly ladies living alone. Nambu, et al. [56] found that analyzing TV watching patterns alone was effective at identifying and analyzing behavior patterns, without the need for additional customized sensors. At University of Virginia's MARC project [5], these sensors were able to actually categorize individual's days into vacation (at home) and work days.

The next step in analyzing behavioral patterns is to detect changes in patterns and anomalies. Work by Cook, et al. [13] collected activity data from an apartment dweller and

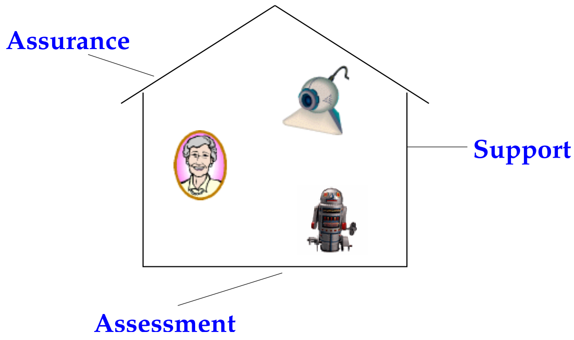

Figure 8: Goals of environmental assistive technology.

used this to determine increasing, decreasing, and cyclic trends in patterns. Once a baseline is established, this can be used to identify sudden changes. Luhr's approach [49] of learning intertransaction association rules can also be helpful in identifying emerging and abnormal activities, and Moncrieff's emotive computing work [53] actually records the anxiety of the environment based upon deviation from normal behavior. When tied with health-critical data and events, the environment may decide that information from these algorithms is important enough to alert the inhabitant and/or caregiver.

Support for individuals living at home with special challenges is found in many varied forms. If a model has been constructed of normal behavior, then the model can be used to provide reminders of normal tasks [48]. Mihailidis, et al. [51] provide this type of prompting for the specific task of handwashing, one of the more stressful tasks for caregivers. By recognizing where the individual is in the process and reminding them of the next step, the tested subjects completed the task 25% more times than without the device. Customized devices can prove useful for these individuals, as well. Pineau, et al. [67] demonstrate the benefits of robotic assistants in nursing homes, while Helal, et al. [29] provide a visitor-identifying front door, inhabitant-tracking floor and a smart mailbox to volunteer seniors living in the Gator Tech Smart Home. Kautz, et al. [37] show that assistance is not limited to a single environment. Using their activity compass, the location of an individual can be tracked, and a person who may have wandered off can be assisted back to their goal (or a safe) location.

Finally, smart environments can be used to actually determine the cognitive impairment of the inhabitants. Carter and Rosen [11] demonstrate such an assessment based on the ability of individuals to efficiently complete kitchen tasks. Jimison, et al. [36] also provide such an assessment. In their case, individuals are monitored while playing computer games, and assessment is based on factors such as game difficulty, player performance, and time to complete the game.

9 Conclusions and Ongoing Challenges

How smart are our environments? Research in the last few years has certainly matured smart environment technology to the point of deployment in experimental situations. This overview article also highlights the fact that there is active research not only in the supporting technologies areas such as physical components and middleware, but also in the modeling and decision making capabilities of entire automated environments. These highlights indicate that environments are increasing in intelligence.

However, there are many ongoing challenges that researchers in this area continue to face. The first is the ability to handle multiple inhabitants in a single environment. While Roy, et al. [74] address this problem from a limited perspective, the modeling not only of multiple independent inhabitants but also the accounting for inhabitant interactions and conflicting goals is a very difficult task, and one that must be addressed in order to make smart environment technologies viable for the general population.

Similarly, we would like to see the notion of "environment" extend from a single setting to encompass all of an inhabitant's spheres of influence. Many projects target a single environment such as a home, an office, a car, or more recently, a hotel [7]. However, by merging evidence and features from multiple settings, these environments should be able to work together in order to customize all of an individual's interactions with the outside world to that particular individual. As an example, how can we generalize intelligent automation and decision making capabilities to encompass heterogeneous smart spaces such as smart homes, vehicles, roads, offices, airports, shopping malls, or hospitals, through which an inhabitant may pass through in daily life?

An interesting direction that researchers in the future may consider is not only the ability to adjust an environment to fit an individual's preferences, but to use the environment as a mechanism for influencing change in the individual. Eng, et al. [22] have discovered that visitors may actually visit areas of a museum normally avoided through carefully-selected cues given by a robot. Similarly, environmental influences can affect an individual's activity patterns, an individual's mood, and ultimately the individual's state of health and mind.

While all of these issues are interesting from a research perspective, they also raise concerns about the security and privacy of individuals utilizing smart environment technologies. Researchers such as Argyroudis and O'Mahony [4], Nixon, et al. [60], and the Amigo group [35], have identified some of these issues and introduced possible mechanisms for ensuring privacy and security of collected data. However, much more work remains to ensure that collected data and automated environments do not jeopardize the privacy or well-being of their inhabitants.

Finally, a useful goal for the smart environment research community is to define evaluation mechanisms. While performance measures can be defined for each technology within the architecture hierarchy shown in Figure 1, performance measures for entire smart environments still need to be established. This can form the basis of comparative assessments and identify areas that need further investigation. The technology in this field is advancing rapidly. By addressing these issues we can ensure that the result is an environment with reliable functionality that improves the quality of life for its inhabitants and for our communities.

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