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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 state 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 the application of smart environments research to health monitoring and assistance, followed by ongoing challenges for continued research.

Keywords: Smart environments; Artificial intelligence; Sensor networks; Health monitoring

1. Introduction

Designing smart environments is a goal that appeals to researchers in a variety of disciplines, including pervasive and mobile computing, sensor networks, artificial intelligence, robotics, multimedia computing, middleware and agent-based software. 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

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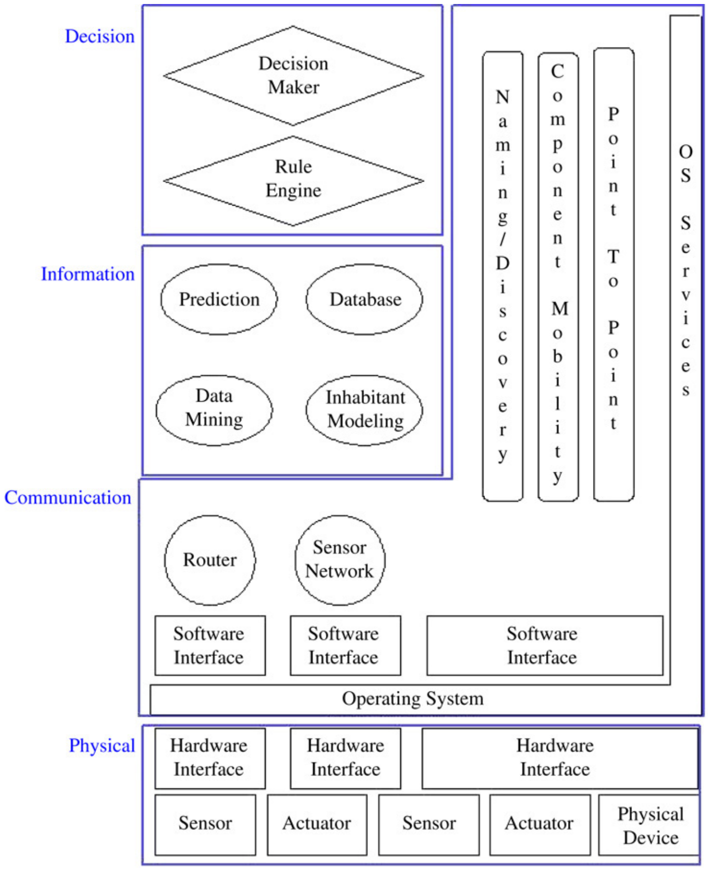

Fig. 1. The components of a smart environment.

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* [98]. Typical components of a smart environment are shown in Fig. 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

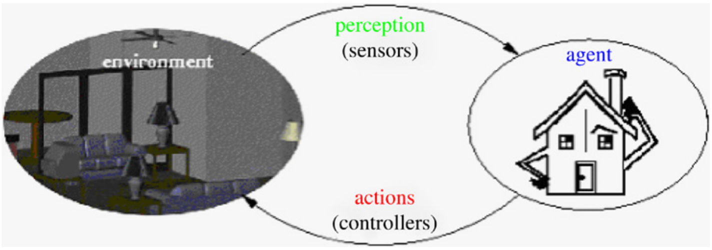

Fig. 2. Smart environment as an intelligent agent.

to the services layers (information and communication) which record the action and communicate 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.

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 an 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. Role of physical components in smart environments

Because smart environment research is being conducted in real-world, physical environments, the design and effective use of physical components such as sensors, controllers, and smart devices is vital. This is because sensors enable us to observe, monitor and interact with the physical world in real time, and also allow us to take appropriate actions. The design and modeling of a smart environment can be abstracted to an intelligent agent paradigm as shown in Fig. 2, wherein 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 limited or no practical use.

Like all intelligent agents, a smart environment relies on sensory data from the real world. As Fig. 2 shows, the environment perceives the environment using these sensors. Using this information, the agent reasons about the environment and selects an action that can be taken to change the state of the environment which can be conveyed through actuators. Table 1 lists some of the properties of the environment that need to be captured and how they can be measured.

The information required by smart environments is measured by sensors and collected and shared with the help of (wireless) sensor networks consisting of a large number of distributed sensor nodes that collaborate and coordinate to accomplish a task. Different from conventional networks with an ultimate goal of point to point (or point to multiple points) data forwarding, wireless sensor networks are often deployed to sense, collect,

Table 1
Sensors for smart environments (adapted from [49])

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, RFID or personal ID

process, and disseminate information of the targeted physical environments, such as temperature, humidity, motion, sound, and the like.

The importance of sensor networks as a research area unto itself is indicated by the increasing number of related workshops [38] and recent efforts that have been initiated by funding agencies such as DARPA [20] and NSF [64]. Indeed, wireless sensor networks have attracted a plethora of research efforts due to their vast potential applications, such as smart buildings, environment or habitat monitoring, utility plants, industry process control, homes, ships, telemedicine, crisis management, transportation systems, and so on [4,15,51].

Among desirable features, sensor/actuator networks need to be fast, easy to install and maintain, robust and self-organizing to create a ubiquitous/pervasive computing platform. However, such networks are characterized by a high degree of uncertainty in every aspect of the system, including extremely limited resources on sensor nodes such as energy, communication, computation and storage. This leads to uncertainty in the sensed data, the sensing range, localization and synchronization results, wireless channel fluctuation and transmission, topology control and routing behavior, security, and mobility [51]. Thus the success of a sensor network is determined by how effectively it can surpass these infiltrated uncertainties and provide desired confidence in the performance of various system components. Additionally, due to the deployment of large numbers of sensor nodes and hence a potentially immense amount of data, it is often impractical to gather all the sensory data from each individual sensor, in particular from the perspective of energy conservation. Therefore, in-network processing (e.g., data fusion or aggregation) is often employed as a key strategy to curtail the network load and hence reduce energy consumption [5,56]. Aggregation itself may amplify the uncertainty in sensed data coupled with resource limitations.

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 [37]. 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 [28]. 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 such applications [49]. Berkely Motes sensors and the TinyOS operating system [19] are popular platforms for working with embedded networked sensors.

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 receive 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) [87] 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 [25]. 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. The ZigBee Alliance [101] is also developing wireless monitoring and control products with low power requirements.

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. [50] propose a tool called BeanWatcher to manage 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. The use of radio frequency identification (RFID) tags to collect sensor-derived data has been described by Want [93]; Philipose et al. [72] 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. Profiles of environment inhabitants, based solely upon temperature control behavior, have been built by Vastamake [92].

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. For example, the smart sofa at Trinity College [47] 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 foreseeably customize

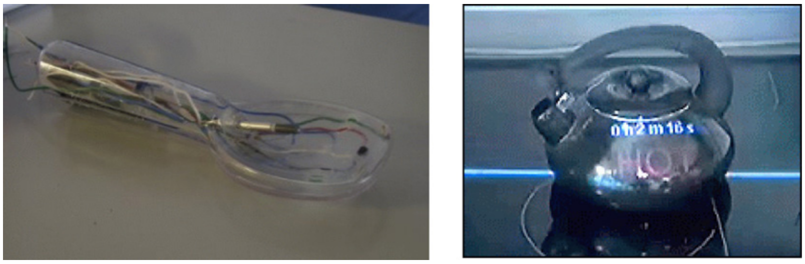

Fig. 3. The MIT intelligent spoon and interactive tea kettle [59].

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 [89]. The 200ConnectIo device [31] refrigerates food until commanded to cook it by phone, computer, or personal digital assistant (PDA).

The MIT Things That Think [59] 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 Fig. 3). The Philips interactive tablecloth [73] 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 pointed out by Rode [78], they also rarely consider difficulties encountered in cultures and markets other than the one for which they are designed. Indeed, these devices would be much more useful if they could adapt themselves to new environments and uses.

Other intelligent devices have been designed for the purpose of remotely controlling an inhabitant's environment. Examples of these physical components include smart phones [66,76], wearable computers and head-mounted displays [42,65], and a unique gesture pendant [86] which uses wearable jewelry to recognize gestures for executing control tasks. The smart jewelry created by Kikin-Gil [43] differs from other intelligent devices 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

Rapid 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 context- or situation-aware computing, pervasive computing aims at providing a *where you want, when you want, what you want and how you want* approach to the services layers shown in Fig. 1 that connect users to applications and devices.

In fact, models of 21st century ubiquitous computing scenarios [94] 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 [35] or context-aware computing.

Major challenges in pervasive computing include invisibility or (user/device) unawareness, service discovery, interoperability and heterogeneity, proactivity, mobility, privacy, security and trust [83]. In such environments, hardware and software entities are expected to function autonomously, continually and correctly. Thus, 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 the survey collected by Kumar and Das [44].

Traditionally, agents have been employed to work on behalf of users, devices and applications [9]. 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 [45].

Pervasive or smart computing systems need to efficiently support resource and service discovery — the process of discovering software processes/agents, hardware devices and services. Service discovery provides situation-awareness to devices and device-awareness to the environment. Although resource/service provisioning and discovery in mobile environments has been well addressed in the literature, not much has been reported in the context of pervasive computing. Among existing service discovery mechanisms, JINI and Salutation as well as the International Naming System (INS) [2] are used. For a comprehensive treatment of different mobile middleware architectures and systems and associated issues, refer to the work of Bellavista and Corradi [8].

3.1. Location-aware services

As mentioned above, a smart environment comprises numerous invisible devices, users, and ubiquitous services. The development of effective middleware tools to mask the effects on heterogeneous wireless devices and networks as well as mobility is a major challenge. Provisioning uniform services regardless of location is also vital. This leads to adaptive location-aware services, that are most appropriate to the location as well as to the situation under consideration.

Clearly, “Context (e.g., location and activity) awareness” is a key to building 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 the 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 [70] capture inhabitants’ footfalls, and the smart home uses these data for position tracking and pedestrian recognition.

The Neural Network House [61], the Intelligent Home [48], the House_n [36] and the MavHome [21,100] 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, for automating activities, for optimizing control of devices and tasks within the environment, and for identifying anomalies. The benefits of the approach are a reduction in the cost of maintaining the environment, a reduction in resource consumption, and provision of special health benefits for elderly and people with disabilities [22,32,34].

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 [18]. 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 [11] for optimally tracking (estimating and predicting) the location of mobile users in wireless cellular networks.

This compression-based framework [11] was later adopted to design optimal algorithm for location (activity) tracking in a smart environment [79]. This novel scheme is based on compressed dictionary management and on-line 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 makes 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 on each other. Therefore, the learning and prediction (decision-making) paradigm needs to consider the joint (simultaneous) entropy for location tracking of multiple inhabitants [81]. In the following, we consider single inhabitant and multiple inhabitant mobility tracking cases separately.

3.1.1. Single inhabitant mobility tracking

The learning and prediction based paradigm, based on information theory and text compression, manages the inhabitant's uncertainty in mobility and activity profiles in daily life. The underlying idea is to build a 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 [22,80].

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 proven [11]: It is impossible to optimally track mobility with less information exchange between the smart environment and the device (detecting the inhabitant's mobility) than the entropy rate of the stochastic mobility process. Specifically, given the past observations of the 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 the entropy rate) in an adaptive manner. To this end, based on the information-theoretic framework, an optimal on-line adaptive location management algorithm, called LeZi-update, was proposed [11]. Rather than assuming a finite mobility model, LeZi-update learns an inhabitant's movement history stored in a Lempel-Ziv type of compressed dictionary [52], builds a universal model by minimizing the 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 the 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 [61,80]. 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 allows application of universal data compression algorithms [16,52], which make very basic and broad assumptions, and yet minimize the source entropy for stationary ergodic stochastic processes [77]. 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 [16,22]. Through learning, this approach allows us to build a higher order mobility model rather than assuming a finite model, and thus minimizes the 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) [79], resource provisioning [22,80], and anomaly detection. The route prediction exploits the asymptotic equi-partition property in information theory [18], which implies that 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).

3.2. Multiple inhabitant mobility tracking

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 the entropy [18]. Recently, it was proven [81] that optimal (i.e., attaining a lower bound on the joint entropy) location tracking of multiple inhabitants is an NP-hard problem.

Assuming a cooperative environment, a cooperative game theory based learning policy was proposed [82] for location-aware resource management in multi-inhabitant smart homes. 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 the 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 the authors to investigate the multi-inhabitant location tracking problem from the perspective of stochastic (non-cooperative) game theory [81], 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 proposed model and entropy learning scheme were also validated through a simulation study and real data.

4. 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. The desktop metaphor that is generally employed for computer applications is inappropriate for a smart environment. As pointed out [1], explicit input must now be replaced with more human-life communication capabilities and with implicit actions. Designers of interfaces for smart environments need to consider issues such as the usability of the interface, the extent to which the interface is end-user friendly, and the adaptiveness of the interface.

Instead of requiring a device that is foreign to many elderly adults and other groups who can benefit from smart environments, the focus of research in this area is on *natural interfaces*. The maturing of technologies including motion tracking, gesture recognition (such as demonstrated in Fig. 4), and speech processing facilitate natural interactions with smart environments. The Classroom 2000 project [1] provides human–computer interfaces through devices such as an interactive whiteboard that stores content in a database. The

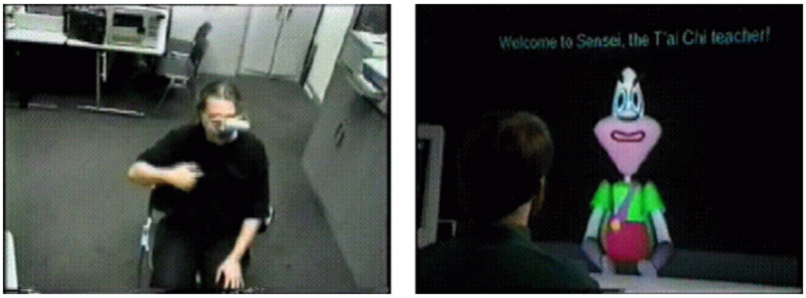

Fig. 4. Real-time recognition of forty-word American Sign Language vocabulary [71].

smart classroom [84] also uses an interactive whiteboard, and allows lecturers to write 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 [29] employs 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 to ensure that the full meaning of a discussion between co-workers is obtained through the integration of captured speech and captured writing on a whiteboard. The Monica project [46] identifies gestures and activities in order to retrieve and project needed information in a workplace environment. Xie et al. [95] also process images of human hands and use this information as a virtual mouse. Similarly, the Interactive Room (iRoom) project at Stanford [27] 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 [88]. 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 [12]. 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 [57] adapts light and sound on a performance stage automatically in response to performers' positions and movements. The driver's intent

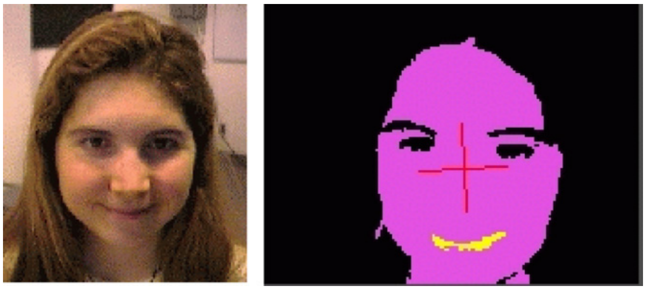

Fig. 5. Facial expression recognition [71].

project at MIT [71] recognizes driver's upcoming actions such as passing, turning, stopping, car following, and lane changing by monitoring hand and leg motions. The accuracy of classified actions reaches 97% within 0.5 s of the beginning of the driver's action. Facial expression recognition systems, such as the one shown in Fig. 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.

5. Inhabitant modeling

One feature that separates *smart* environments from environments that are user controllable is the ability to model inhabitant behavior. Inhabitant modeling is a key software component found in the information layer of a smart environment architecture (see Fig. 1). 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: (i) The data that are used to build the model; (ii) The type of model that is built; and (iii) The nature of the model-building algorithm (supervised, unsupervised).

The most common data source for model building is low-level sensor information. These data are 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 [96], 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 these data, then uses the patterns to build a hierarchical model of inhabitant behavior. The approach by Loke [53] also relies upon these 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 [24] focuses on automating a living environment. However, instead of a Markov model, they model inhabitant behavior by learning fuzzy rules that map the 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 [55] 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. The approach in [13] relies on speech detection to automatically model interacting groups in a smart environment, whereas Moncrieff [60] also employs audio data for generating inhabitant models. However, such data are 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 are available, then supervised learning approaches can be used to build a model of inhabitant activity. This approach is combined by Muehlenbrock et al. [62] with a naive Bayes learner to identify an individual's activity and current availability based on data such as PC/PDA usage. A naive Bayes learner is also employed by Tapia et al. [90] to identify inhabitant activity from among a set of 35 possible classes, based on collected sensor data.

6. 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. These technologies complete the bottom three layers of our smart environment architecture, shown in Fig. 1. However, building a fully automated environment on top of these foundations requires the decision-making component in the top layer of the architecture, and this is still a rarity. Automated decision-making and control techniques are available for this task. In the work of Simpson et al. [85], the authors discuss how AI planning systems could be employed not only to remind inhabitants of their next activity but also to complete a task if needed. Temporal reasoning combined with a rule-based system is used [23] to identify hazardous situations and return the environment to a safe state while contacting the inhabitant.

Few fully-implemented applications of decision-making technologies have been reported. One of the first is the Adaptive Home [61], 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. [99] also use a reinforcement learner to automate actual physical environments, the MavPad apartment and the MavLab workplace (shown in Fig. 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 [97]. The iDorm project [30] 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

Fig. 6. MavPad (left) and MavLab (right) automated environments.

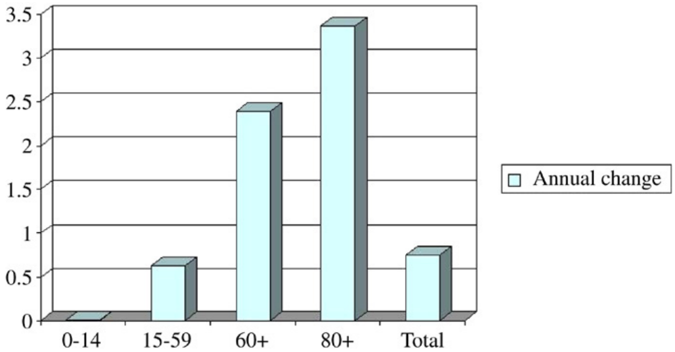

Fig. 7. Annual rate of change by age range.

rules can be added to, 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.

7. 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, and customize our shopping 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 the emergence of companies with initiatives to bring smart elder care technologies into the home [32,68]. 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

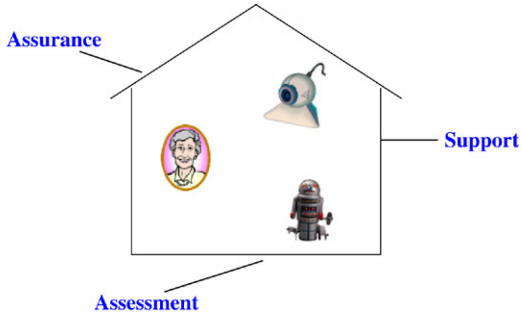

Fig. 8. Goals of environmental assistive technology.

is resulting in population aging [91]. The resulting impact on age distribution is shown in Fig. 7. Not only is the number of individuals aged 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 [75] categorizes such assistive technologies based on 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) (Fig. 8). We summarize the technologies in each of these areas.

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. In one such project [69], sensors are used to detect movement, use of appliances, and presence in a room, and from this information researchers were able to analyze the behavior patterns of two elderly ladies living alone. Nambu et al. [63] found that analyzing TV watching patterns alone was effective at identifying and analyzing behavior patterns, without the need for additional customized sensors. At the University of Virginia's MARC project [7], these sensors were able to actually categorize an 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. For example, MavHome activity data were collected [17] from an apartment dweller and used to determine increasing, decreasing, and cyclic trends in patterns. Once a baseline is established, this can be used to identify sudden changes. The approach of learning intertransaction association rules [55] can also be helpful in identifying emerging and abnormal activities, and the emotive computing work [60] 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 [54]. Mihailidis et al. [58] 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. The benefits of robotic assistants in nursing homes are demonstrated [74], while the Gator Tech Smart Home [33] provides 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. [41] show that assistance is not limited to a single environment. Using an 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. Such an assessment based on the ability of individuals to efficiently complete kitchen tasks is demonstrated by Carter and Rosen [14]. A similar type of assessment is provided [40] by monitoring individuals while they are playing computer games. Assessment in this case is based on factors such as game difficulty, player performance, and time to complete the game.

8. 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 this problem is addressed from a limited perspective [81], modeling not only multiple independent inhabitants but also 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 [10]. 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 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. [26] 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. Reported work [6,67,39] has 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 Fig. 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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References

[1] G.D. Abowd, E.D. Mynatt, Designing for the human experience in smart environments, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004, pp. 153–174.

[2] W. Adjie-Winoto, E. Schwartz, H. Balakrishnan, J. Lilley, The design and implementation of an intentional naming system, in: Proceedings of the Seventeenth ACM Symposium on Operating Systems Principles, 1999, pp. 186–201.

[3] A. Adler, R. Davis, Speech and sketching for multimodal design, in: Proceedings of the 9th International Conference on Intelligent User Interfaces, 2004, pp. 214–216.

[4] I. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, A survey on sensor networks, IEEE Communications Magazine 40 (8) (2002) 102–114.

[5] B. Krishnamachari, D. Estrin, S. Wicker, Impact of data aggregation in wireless sensor networks, in: Proceedings of the IEEE International Conference on Distributed Computing Systems, 2002, pp. 575–578.

[6] P.G. Argyroudis, D. O'Mahony, Securing communications in the smart home, in: L. Jang, M. Guo, G. Gao, N. Jha (Eds.), Proceedings of 2004 International Conference on Embedded and Ubiquitous Computing, EUC'04, Aizu-Wakamatsu, Japan, in: Lecture Notes in Computer Science, vol. 3207, Springer-Verlag, August 2004, pp. 891–902.

[7] T.S. Barger, D.E. Brown, M. Alwan, Health status monitoring through analysis of behavioral patterns, IEEE Transactions on Systems, Man, and Cybernetics, Part A 35 (1) (2005) 22–27.

[8] P. Bellavista, A. Corradi, Mobile Middleware, CRC Press, 2006.

[9] P. Bellavista, A. Corradi, C. Stefanelli, A mobile agent infrastructure for the mobility support, in: Proceedings of the 2000 ACM symposium on Applied computing, 2000, pp. 239–245.

[10] K. Belson, Your hotel room knows just what you like, November 16, 2005.

[11] A. Bhattacharya, S.K. Das, Lezi-update: An information-theoretic approach for personal mobility tracking in pcs networks, Wireless Networks 8 (2002) 121–135.
[12] A.F. Bobick, S.S. Intille, J.W. Davis, F. Baird, C.S. Pinhanez, L.W. Campbell, Y.A. Ivanov, A. Schuette, A. Wilson, The kidsroom: A perceptually-based interactive and immersive story environment, Presence 8 (4) (1999) 369–393.
[13] O. Brdiczka, J. Maisonnasse, P. Reignier, Automatic detection of interaction groups, in: Proceedings of the International Conference on Multimodal Interfaces, 2005.
[14] J. Carter, M. Rosen, Unobtrusive sensing of activities of daily living: A preliminary report, in: Proceedings of the 1st Joint BMES/EMBS Conference, 1999, p. 678.
[15] C. Chong, S. Kumar, Sensor networks: Evolution, opportunities, and challenges, Proceedings of the IEEE 91 (8) (2003) 1247–1256.
[16] J.G. Cleary, I.H. Witten, Data compression using adaptive coding and partial string matching, IEEE Transactions on Communications 32 (4) (1984) 396–402.
[17] D.J. Cook, G.M. Youngblood, G. Jain, Algorithms for smart spaces, in: Technology for Aging, Disability and Independence: Computer and Engineering for Design and Applications, Wiley, 2006.
[18] T.M. Cover, J.A. Thomas, Elements of Information Theory, Wiley, 1991.
[19] D. Culler, TinyOS: Operating system design for wireless sensor networks, Sensors (2006).
[20] Darpa Sensit, http://www.sainc.com/sensit/, 2006.
[21] S.K. Das, D.J. Cook, A. Bhattacharya, E.O. Heierman, T.-Y. Lin, The role of prediction algorithms in the mavhome smart home architecture, IEEE Wireless Communications 9 (6) (2002) 77–84.
[22] S.K. Das, C. Rose, Coping with uncertainty in wireless mobile networks, in: Proceedings of the IEEE Personal, Indoor and Mobile Radio Communications, 2004.
[23] R.L. de Mántaras, L. Saitta (Eds.), The Use of Temporal Reasoning and Management of Complex Events in Smart Homes, IOS Press, 2004.
[24] F. Doctor, H. Hagras, V. Callaghan, A fuzzy embedded agent-based approach for realizing ambient intelligence in intelligent inhabited environments, IEEE Transactions on Systems, Man, and Cybernetics, Part A 35 (1) (2005) 55–65.
[25] Echelon, http://www.echelon.com/, 2006.
[26] K. Eng, R.J. Douglas, P.F.M.J. Verschure, An interactive space that learns to influence human behavior, IEEE Transactions on Systems, Man, and Cybernetics, Part A 35 (1) (2005) 66–77.
[27] A. Fox, B. Johanson, P. Hanrahan, T. Winograd, Integrating information appliances into an interactive space, IEEE Computer Graphics and Applications 20 (3) (2000) 54–65.
[28] R. Frank, Understanding Smart Sensors, Artech House, 2000.
[29] D. Franklin, Cooperating with people: The intelligent classroom, in: Proceedings of the National Conference on Artificial Intelligence, 1998, pp. 555–560.
[30] H. Hagras, V. Callaghan, M. Colley, G. Clarke, A. Pounds-Cornish, H. Duman, Creating an ambient-intelligence environment using embedded agents, IEEE Intelligent Systems 19 (6) (2004) 12–20.
[31] L. Hales, Intelligent appliances are wave of the future, January 22, 2006.
[32] I.P. Health, http://www.intel.com/research/prohealth/cs-aging_in_place.htm, 2006.
[33] A. Helal, W. Mann, H. El-Zabadani, J. King, Y. Kaddoura, E. Jansen, The gator tech smart house: A programmable pervasive space, IEEE Computer 38 (3) (2005) 50–60.
[34] S. Helal, B. Winkler, C. Lee, Y. Kaddourah, L. Ran, C. Giraldo, W. Mann, Enabling location-aware pervasive computing applications for the elderly, in: Proceedings of the First IEEE Pervasive Computing Conference, 2003.
[35] A. Hopper, Sentient Computing, 1999.
[36] House_n. House_n Living Laboratory Introduction, 2006.
[37] IEEE 1451. A standard smart transducer interface, 2001.
[38] Information Processing in Sensor Networks (IPSN), http://www.ece.wisc.edu/ipsn05/, 2005.
[39] Amigo, Ambient intelligence for the networked home environment, http://www.hitech-projects.com/euprojects/amigo/, 2006.
[40] H.B. Jimison, M. Pavel, J. Pavel, Adaptive interfaces for home health, in: Proceedings of the International Workshop on Ubiquitous Computing for Pervasive Healthcare, 2003.
[41] H. Kautz, L. Arnstein, G. Borriello, O. Etzioni, D. Fox, An overview of the assisted cognition project, in: Proceedings of the AAAI Worskhop on Automation as Caregiver: The Role of Intelligent Technology in Elder Care, 2002, pp. 60–65.

[42] T. Keaton, S.M. Dominguez, A.H. Sayed, Browsing the environment with the SNAP & TELL wearable computer system, Personal and Ubiquitous Computing 9 (6) (2005) 343–355.
[43] R. Kikin-Gil, Buddybeads: Techno-jewelry for non-verbal communication within teenager girls groups, Personal and Ubiquitous Computing 10 (2–3) (2005) 106–109.
[44] M. Kumar, S.K. Das, Pervasive computing: Enabling technologies and challenges, in: A. Zomaya (Ed.), Handbook of Nature-Inspired and Innovative Computing: Integrating Classical Models with Emerging Technologies, Springer, 2006.
[45] M. Kumar, B. Shirazi, S.K. Das, M. Singhal, B. Sung, D. Levine, Pervasive information communities organization (PICO): A middleware framework for pervasive computing, IEEE Pervasive Computing 2 (3) (2003) 72–79.
[46] C. Le Gal, Smart offices, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004.
[47] J. Legon, 'Smart sofa' aimed at couch potatoes, 2003.
[48] V. Lesser, M. Atighetchi, B. Benyo, B. Horling, A. Raja, R. Vincent, T. Wagner, X. Ping, S.X. Zhang, The intelligent home testbed, in: Proceedings of the Autonomy Control Software Workshop, 1999.
[49] F.L. Lewis, Wireless sensor networks, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004.
[50] A. Lins, E.F. Nakamura, A.A.F. Loureiro, J. Claudionor, J.N. Coelho, Beanwatcher: A tool to generate multimedia monitoring applications for wireless sensor networks, in: A. Marshall, N. Agoulmine (Eds.), Management of Multimedia Networks and Services, Springer-Verlag, 2003, pp. 128–141.
[51] Y. Liu, S.K. Das, Information intensive wireless sensor networks: Potentials and challenges, IEEE Communications Magazine 44 (11) (2006) 142–147.
[52] J. Liv, A. Lempel, Compression of individual sequences via variable rate coding, IEEE Transactions on Information Theory 24 (5) (1978) 530–536.
[53] S.W. Loke, Representing and reasoning with situations for context-aware pervasive computing: A logic programming perspective, The Knowledge Engineering Review 19 (3) (2005) 213–233.
[54] E.F. LoPresti, A. Mihailidis, N. Kirsch, Assistive technology for cognitive rehabilitation: State of the art, Neuropsychological Rehabilitation 14 (1–2) (2004) 5–39.
[55] S. Luhr, Recognition of emergent human behaviour in a smart home: A data mining approach, in: Design and Use of Smart Environments, Journal of Pervasive and Mobile Computing (2007) (special issue).
[56] H. Luo, Y. Liu, S.K. Das, Routing correlated data with fusion cost in wireless sensor networks, IEEE Transactions on Mobile Computing 5 (11) (2006) 1620–1632.
[57] E. Mendelowitz, J. Burke, Kolo and Nebesko: A distributed media control framework for the arts, in: Proceedings of the International Conference on Distributed Frameworks for Multimedia Applications, 2005.
[58] A. Mihailidis, J.C. Barbenel, G. Fernie, The efficacy of an intelligent cognitive orthosis to facilitate handwashing by persons with moderate-to-severe dementia, Neuropsychological Rehabilitation 14 (1–2) (2004) 135–171.
[59] MIT, Things that think, 2006.
[60] S. Moncrieff, Multi-modal emotive computing in a smart house environment, in: Design and Use of Smart Environments, Journal of Pervasive and Mobile Computing (2007) (special issue).
[61] M.C. Mozer, Lessons from an adaptive home, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004, pp. 273–298.
[62] M. Muehlenbrock, O. Brdiczka, D. Snowdon, J. Meunier, Learning to detect user activity and availability from a variety of sensor data, in: Proceedings of the IEEE International Conference on Pervasive Computing and Communications, 2004.
[63] M. Nambu, K. Nakajima, M. Noshira, T. Tamura, An algorithm for the automatic detection of health conditions, IEEE Engineering Medicine Biology Magazine 24 (4) (2005) 38–42.
[64] National Science Foundation Sensors and Sensor Networks, http://www.nsf.gov/pubs/2005/nsf05526/nsf05526.htm, 2005.
[65] M. Nilsson, M. Drugge, U. Liljedahl, K. Synnes, P. Parnes, A study on users' preference on interruption when using wearable computers and head mounted displays, in: Proceedings of the IEEE International Conference on Pervasive Computing and Communications, 2005.

[66] A. Nischelwitzer, A. Holzinger, M. Meisenberger, Usability and user-centered development (UCD) for smart phones — the mobile learning engine (MLE) a user centered development approach for a rich content application, in: Proceedings of Human Computer Interaction International, 2005.
[67] P. Nixon, W. Wagealla, C. English, S. Terzis, Security, privacy and trust issues in smart environments, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004.
[68] Oatfield Estates, 2006.
[69] M. Ogawa, R. Suzuki, S. Otake, T. Izutsu, T. Iwaya, T. Togawa, Long term remote behavioral monitoring of elderly by using sensors installed in ordering houses, in: Proceedings IEEE-EMBS Special Topic Conference on Microtechnologies in Medicine and Biology, 2002, pp. 322–335.
[70] R.J. Orr, G.D. Abowd, The smart floor: A mechanism for natural user identification and tracking, in: Proceedings of the ACM Conference on Human Factors in Computing Systems, 2000.
[71] A. Pentland, Perceptual environments, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004.
[72] M. Philipose, K.P. Fishkin, M. Perkowitz, D.J. Patterson, D. Hahnel, D. Fox, H. Kautz, Inferring ADLs from interactions with objects, IEEE Pervasive Computing (2005).
[73] Philips, Interactive tablecloth, 2006.
[74] J. Pineau, M. Montemerlo, M. Pollack, N. Roy, S. Thrun, Towards robotic assistants in nursing homes: Challenges and results, Robotics and Autonomous Systems 42 (3–4) (2003).
[75] M.E. Pollack, Intelligent technology for an aging population: The use of AI to assist elders with cognitive impairment, AI Magazine 26 (2) (2005) 9–24.
[76] N. Ravi, P. Stern, N. Desai, L. Iftode, Accessing ubiquitous services using smart phones, in: Proceedings of the IEEE International Conference on Pervasive Computing and Communications, 2005.
[77] J. Rissanen, Stochastic Complexity in Statistical Inquiry, World Scientific Publishing Company, 1989.
[78] J.A. Rode, Appliances for whom? considering place, Personal and Ubiquitous Computing 10 (2–3) (2005) 90–94.
[79] A. Roy, S. Bhaumik, A. Bhattacharya, K. Basu, D.J. Cook, S.K. Das, Location aware resource management in smart homes, in: Proceedings of the Conference on Pervasive Computing, 2003, pp. 521–524.
[80] A. Roy, S.K. Das, A. Misra, Exploiting information theory for adaptive mobility and resource management in future wireless cellular networks, IEEE Wireless Communications 11 (8) (2004) 59–64.
[81] N. Roy, A. Roy, S.K. Das, Context-aware resource management in multi-inhabitant smart homes: A Nash h-learning based approach, in: The IEEE Conference on Pervasive Computing and Communications, Journal of Pervasive and Mobile Computing (2006) (special issue).
[82] N. Roy, A. Roy, K. Basu, S.K. Das, A cooperative learning framework for mobility-aware resource management in multi-inhabitant smart homes, in: Proceedings of the IEEE Conference on Mobile and Ubiquitous Systems: Networking and Services, MobiQuitous, 2005, pp. 393–403.
[83] M. Satyanarayanan, Pervasive computing: Vision and challenges, IEEE Personal Computing 8 (4) (2001) 10–17.
[84] Y. Shi, W. Xie, G. Xu, R. Shi, E. Chen, Y. Mao, F. Liu, The smart classroom: Merging technologies for seamless tele-education, IEEE Pervasive Computing 2 (2003).
[85] R. Simpson, D. Schreckenghost, E.F. LoPresti, N. Kirsch, Plans and planning in smart homes, in: J. Augusto, C. Nugent (Eds.), AI and Smart Homes, Springer Verlag, 2006.
[86] T. Starner, J. Auxier, D. Ashbrook, M. Gandy, The gesture pendant: A self-illuminating, wearable, infrared computer vision system for home automation control and medical monitoring, in: Proceedings of the IEEE International Symposium on Wearable Computing, 2000, pp. 87–94.
[87] H.B. Stauffer, The smart house system: A technical overview, The Computer Applications Journal 31 (1993) 14–23.
[88] P. Steurer, M.B. Srivastava, System design of smart table, in: Proceedings of the IEEE International Conference on Pervasive Computing and Communications, 2003.
[89] K. Swisher, “Intelligent” appliances will soon invade homes, 2006.
[90] E.M. Tapia, S.S. Intille, K. Larson, Activity recognition in the home using simple and ubiquitous sensors, in: Proceedings of Pervasive, 2004, pp. 158–175.
[91] United Nations Department of Economic and Social Affairs, http://www.un.org/esa/population/unpop.htm, 2006.

[92] R. Vastamaki, I. Sinkkonen, C. Leinonen, A behavioural model of temperature controller usage and energy saving, Personal and Ubiquitous Computing 9 (4) (2005) 250–259.
[93] R. Want, Enabling ubiquitous sensing with RFID, Computer 37 (4) (2004) 84–86.
[94] M. Weiser, The computer for the 21st century, Scientific American 265 (3) (1991) 94–104.
[95] W. Xie, E.K. Teoh, R. Venkateswarlu, X. Chen, Hand as natural man–machine interface in smart environments, in: Proceedings of the IASTED International Conference on Signal Processing, Pattern Recognition, and Applications, 2006, pp. 117–122.
[96] G.M. Youngblood, Automating inhabitant interactions in home and workplace environments through data-driven generation of hierarchical partially-observable Markov decision processes, Ph.D. Thesis, The University of Texas at Arlington, 2005.
[97] G.M. Youngblood, D.J. Cook, Data mining for hierarchical model creation, IEEE Transactions on Systems, Man, and Cybernetics, Part C (2007).
[98] G.M. Youngblood, D.J. Cook, L.B. Holder, E.O. Heierman, Automation intelligence for the smart environment, in: Proceedings of the International Joint Conference on Artificial Intelligence, 2005.
[99] G.M. Youngblood, L.B. Holder, D.J. Cook, Managing adaptive versatile environments, Journal of Pervasive and Mobile Computing 1 (4) (2005) 373–403.
[100] M. Youngblood, D.J. Cook, L.B. Holder, Managing adaptive versatile environments, in: Proceedings of the IEEE International Conference on Pervasive Computing and Communications, 2005, pp. 351–360.
[101] Zigbee Alliance, http://www.zigbee.org/, 2006.

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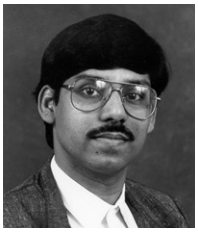

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