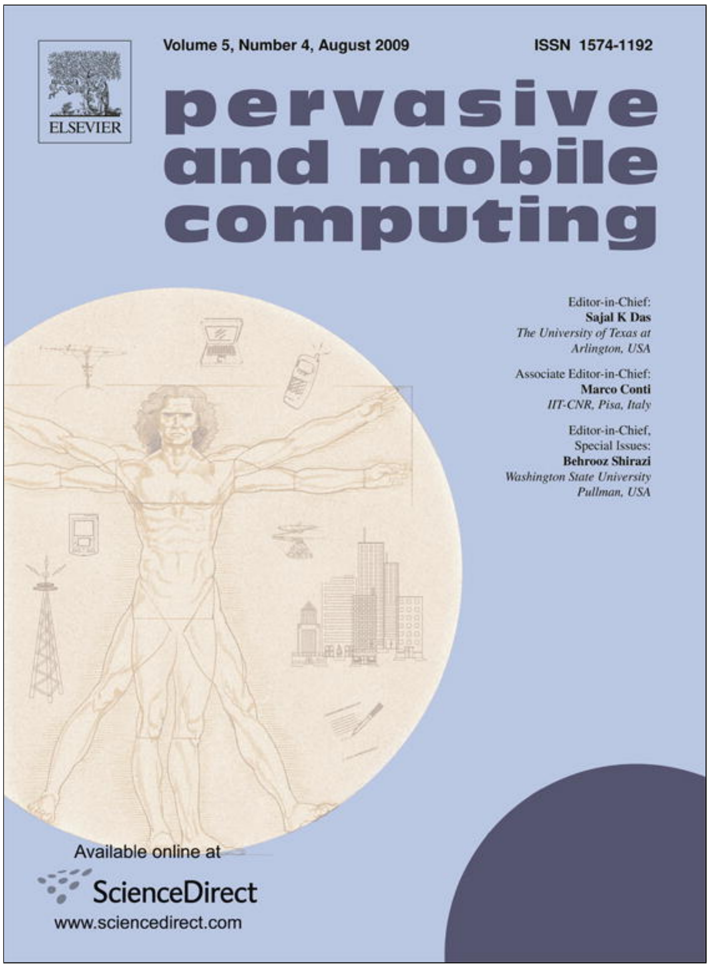
Volume 5, Number 4, August 2009
ISSN 1574-1192
ELSEVIER
pervasive and mobile computing
Editor-in-Chief:
Sajal K Das
The University of Texas at Arlington, USA
Associate Editor-in-Chief:
Marco Conti
IIT-CNR, Pisa, Italy
Editor-in-Chief, Special Issues:
Behrooz Shirazi
Washington State University
Pullman, USA
Available online at
ScienceDirect
www.sciencedirect.com

Pervasive and Mobile Computing 5 (2009) 277–298

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

journal homepage: www.elsevier.com/locate/pmc

Review

Ambient intelligence: Technologies, applications, and opportunities

Diane J. Cook [a], Juan C. Augusto [b,∗], Vikramaditya R. Jakkula [a]

[a] *School of Electrical Engineering and Computer Science, Washington State University, Pullman, WA, USA*
[b] *School of Computing and Mathematics, University of Ulster, UK*

ARTICLE INFO

Article history:
Received 15 December 2008
Accepted 1 April 2009
Available online 15 April 2009

Keywords:
Ambient intelligence
Artificial intelligence
Sensors
Decision making
Context awareness
Privacy

ABSTRACT

Ambient intelligence is an emerging discipline that brings intelligence to our everyday environments and makes those environments sensitive to us. Ambient intelligence (AmI) research builds upon advances in sensors and sensor networks, pervasive computing, and artificial intelligence. Because these contributing fields have experienced tremendous growth in the last few years, AmI research has strengthened and expanded. Because AmI research is maturing, the resulting technologies promise to revolutionarize daily human life by making people's surroundings flexible and adaptive.

In this paper, we provide a survey of the technologies that comprise ambient intelligence and of the applications that are dramatically affected by it. In particular, we specifically focus on the research that makes AmI technologies "intelligent". We also highlight challenges and opportunities that AmI researchers will face in the coming years.

1. Introduction

Computer science is a relatively new branch of science and as such it has gone through rapid and yet important transformations during the first decades of its existence. Those transformations have produced a very interesting mix of available experiences, and expectations which are making possible the creation and deployment of technology to ultimately improve the way our environments help us. This technical possibility is being explored in an area called Ambient Intelligence. Here we survey the field of Ambient Intelligence. Specifically, we review the technologies that led to and that support research in AmI. We also provide an overview of current uses of AmI in practical settings, and present opportunities for continued AmI research.

1.1. Emergence of AmI

The European Commission first charted a path for AmI research in 2001 [1]. A significant factor in this birth of the field of AmI is the evolution of technology. Computers were initially very expensive as well as difficult to understand and use. Each computer was a rare and precious resource. A single computer would typically be used by many individuals (see Fig. 1). In the next evolutionary step, many users no longer needed to take turns to use a computer as many were able to access it simultaneously. The PC revolution in the 80s changed the ratio to one user per computer. As industry progressed and costs dropped, one user often was able to access more than one computer. The type of computational resources that we have at our disposal today is dramatically more varied than a few decades ago.

Today, access to multiple computers does not necessarily just mean owning both a PC and a laptop. Since the miniaturization of microprocessors, computing power is embedded in familiar objects such as home appliances (e.g., washing

∗ Corresponding author.
E-mail addresses: cook@eecs.wsu.edu (D.J. Cook), jc.augusto@ulster.ac.uk (J.C. Augusto), vjakkula@eecs.wsu.edu (V.R. Jakkula).

1574-1192/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.pmcj.2009.04.001

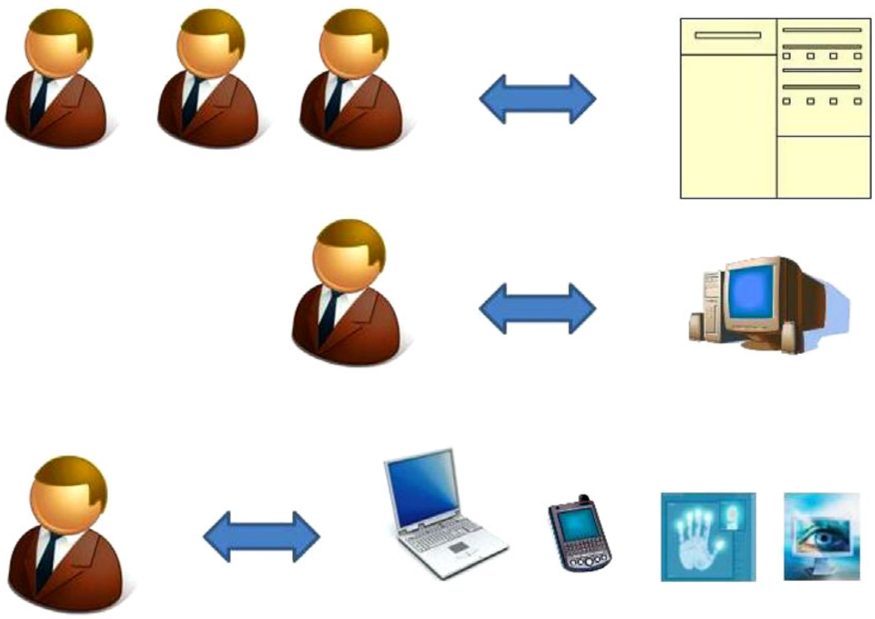

Fig. 1. A shift in people-computing power ratio.

machines, refrigerators, and microwave ovens), they travel with us outside the home (e.g., mobile phones and PDAs), and they help guide us to and from our home (e.g., cars and GPS navigation). Computers that perform faster computation with reduced power and tailor the computation to accomplish very specific tasks are gradually spreading through almost every level of our society. This widespread availability of resources sparked the realization of Ambient Intelligence.

Possessing the necessary supporting technology is not enough for an area of science to flourish. User's experiences with computers over recent decades have created an interesting context where expectations of these systems are growing and people's fear of using them has decreased. Concomitantly with this difference in the way society perceives technology there is also a change in the way services are handled. An important example of this is the decentralization of health care and development of health and social care assistive technologies. Because governments and health professionals are departing from the hospital-centric health care system, the way is paved for AmI systems to support caring for patients closer to home, within their communities. Developments, competencies and drivers are converging at the same time in history and all of the necessary components are in place: the need to distribute technology around us, the will to change the way our society interacts with technology, the available technological knowledge and all the elements to satisfy the demand.

The idea of Ambient Intelligence is not new, but what is new is that we can now seriously think about it as a reality and as a discipline with a unique set of contributions. Most of us have come across science fiction movies where doors opened when someone approached or computers were able to identify the interlocutor without their name being explicitly mentioned. Some of those features were far fetched for the technology available at the time, but gradually some features that indicate sensible autonomy on behalf of the system were targeted by industry, and AmI was born.

Technically, many of us today live in homes that were considered "smart" by 1960s standards, and for a very reasonable cost. Thermostats and movement sensors that control lighting are commonplace. Now the bar has moved much higher: even the ability to link movement sensors to a security alarm for detecting intruders will not impress a society which regularly interacts with such facilities.

Recent computational and electronic advances have increased the level of autonomous semi-intelligent behavior exhibited by systems like smart homes so much that new terms like *Ambient Intelligence* started to emerge [2,1,3]. The basic idea behind Ambient Intelligence (AmI) is that by enriching an environment with technology (e.g., sensors and devices interconnected through a network), a system can be built such that acts as an "electronic butler", which senses features of the users and their environment, then reasons about the accumulated data, and finally selects actions to take that will benefit the users in the environment.

1.2. What is AmI?

Ambient Intelligence has been characterized by researchers in different ways. These definitions, summarized in Table 1, highlight the features that are expected in AmI technologies: sensitive, responsive, adaptive, transparent, ubiquitous, and intelligent.

From these definitions, and the features that we are using (summarized in Table 1) to characterize Ambient Intelligence, we can see how the discipline compares and contrasts with fields such as pervasive computing, ubiquitous computing, and artificial intelligence. The fact that AmI systems must be *sensitive*, *responsive*, and *adaptive* highlights the dependence that AmI research has on context-aware computing.

Table 1
Features of Ambient Intelligence captured by AmI definitions. Features include Sensitive (S), Responsive (R), Adaptive (A), Transparent (T), Ubiquitous (U), and Intelligent (I).

Definition	S	R	A	T	U	I
A developing technology that will increasingly make our everyday environment sensitive and responsive to our presence [4].	√	√				
A potential future in which we will be surrounded by intelligent objects and in which the environment will recognize the presence of persons and will respond to it in an undetectable manner [1].	√	√		√	√	
"Ambient Intelligence" implies intelligence that is all around us [5].					√	√
The presence of a digital environment that is sensitive, adaptive, and responsive to the presence of people [6].	√	√	√			
A vision of future daily life ...contains the assumption that intelligent technology should disappear into our environment to bring humans an easy and entertaining life [7].		√		√	√	
A new research area for distributed, non-intrusive, and intelligent software systems [8]				√		√
In an AmI environment people are surrounded with networks of embedded intelligent devices that can sense their state, anticipate, and perhaps adapt to their needs [9].	√		√	√	√	√
A digital environment that supports people in their daily lives in a nonintrusive way (Raffler) [10].				√	√	

Similarly, the AmI feature of *transparency* is certainly aligned with the concept of the *disappearing computer*. This methodological trend was envisioned by Weiser [11], who stated:

> *"The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it".*

A recent description of the state of the art in this area of research is provided by Streitz and Nixon [12].

The notion of a disappearing computer is directly linked to the notion of "Ubiquitous Computing" [13], or "Pervasive Computing" as IBM later called it [14]. Some technical publications equate Ubiquitous Computing, Pervasive Computing, or Everyware Computing [15] with Ambient Intelligence. The nature of Ubiquitous or Pervasive Computing is captured in part by the Oxford Dictionary definition of ubiquitous:

> *Ubiquitous*: adj. present, appearing, or found everywhere [16]

and of pervasive:

> *Pervasive*: adj. (esp. of an unwelcome influence or physical effect) spreading widely throughout an area or a group of people [16].

Note that while Ambient Intelligence incorporates aspects of context-aware computing, disappearing computers, and pervasive/ubiquitous computing into its sphere, there is also an important aspect of *intelligence* in this field. As a result, AmI incorporates artificial intelligence research into its purview, encompassing contributions from machine learning, agent-based software, and robotics. As Maeda and Minami point out, AmI research can include work on hearing, vision, language, and knowledge, which are all related to human intelligence, and there is where AmI differs from ubiquitous computing [5]. By drawing from advances in artificial intelligence, AmI systems can be even more sensitive, responsive, adaptive, and ubiquitous. We characterize AmI technologies as those that exhibit characteristics listed in Table 1 and we summarize the above discussion by defining an Ambient Intelligence system as

> *"a digital environment that proactively, but sensibly, supports people in their daily lives"* [17].

The review that we offer in the next section of the paper summarizes advances that have been made in related areas that contribute to the goal of AmI systems that we have set forth.

2. Contributing technologies

From its definition, we can see that AmI has a decisive relationship with many areas in computer science. We organize the contributing technologies into five areas, shown in Fig. 2. A key factor in AmI research is the presence of *intelligence*. We adopt the notion of an intelligent agent as defined by Russell and Norvig [18]. As such, the AmI algorithm perceives the state of the environment and users with sensors, reasons about the data using a variety of AI techniques, and acts upon the environment using controllers in such a way that the algorithm achieves its intended goal. The process is illustrated in Fig. 3. Hence, we focus on technologies that assist with sensing, reasoning, and acting.

On the other hand, while AmI draws from the field of AI, it should not be considered synonymous with AI. The IST Advisory Group lists five key technologies that are required to make AmI a reality [1]. Two of these technologies clearly fall outside the typical scope of AI research and are addressed separately in this survey. These are human-centric computer interfaces and secure systems and devices. Next we discuss recent work in these contributing areas that enhance development of AmI.

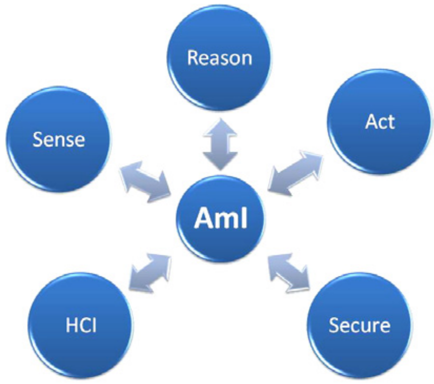

Fig. 2. Relationship between AmI and contributing technologies.

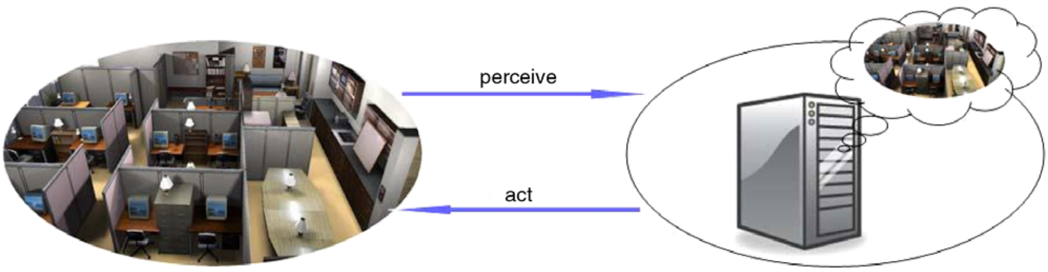

Fig. 3. Ambient intelligent agent interaction with the environment. The agent perceives the state of the environment and residents using sensors. The agent models and reasons about this information, ultimately using it to make a decision about how to act on the information. The state of the environment is changed through actions such as powerline control of devices and robotic assistance.

3. Sensing

Because Ambient Intelligence is designed for real-world, physical environments, effective use of sensors is vital. Without physical components that allow an intelligent agent to sense and act upon the environment, we end up with theoretical algorithms that have no practical use. Sensors are the key that link available computational power with physical applications.

Ambient Intelligence algorithms rely on sensory data from the real world. As Fig. 3 shows, the software algorithm perceives the environment and uses this information to reason about the environment and the action that can be taken to change the state of the environment. Perception is accomplished using a variety of sensors. Sensors have been designed for position measurement [19], for detection of chemicals and humidity sensing [20], and to determine readings for light, radiation, temperature, sound, strain, pressure, position, velocity, and direction, and physiological sensing to support health monitoring [21,22]. Sensors are typically quite small and thus can be integrated into almost any AmI application.

Tracking and identifying people in an environment is an important issue in AmI systems. If the location of a person is known, the system can serve the individual better by anticipating needs based on their preferences and delivering services based on when they are commonly required. The technology which is often used to track individuals are motion sensors. Motion sensors have been used as a backbone of security systems for decades. However, while they can detect movement they cannot provide information to distinguish who (or what) produced the movement.

As an alternative, persons and items can wear a sensor that helps to track them. An example of this technology is RFID tags that can be coupled with an RFID reader to monitor the movement of the tagged objects. This technology relies on individuals and items being tagged. In addition, the sensitivity of the tags can introduce challenges for the system. For example, if an RFID reader is positioned in a door frame to identify persons transitioning between rooms, the person can trigger the reader if they get close to the door, without necessarily moving to the next room. Such ambiguities can be resolved by integrating more than one technology. For example, motion sensors can be placed on each side of the door in combination with the RFID reader to distinguish proximity from room transitions.

Yet another technology that can be used for tracking is the I-Button. I-Buttons [23] are devices that can be as small as 16 mm. They contain a computer chip in a steel casing with a real-time clock. Each I-Button has a unique registration number and the receptor can communicate with a computer. This device can be used to identify objects or people carrying it when the i-button is placed in the appropriate reader. This has the problem that the i-button has to be physically placed over the reader to be effective which does not make it comfortable for everyday use in a house.

All these methods have limitations and cannot guarantee proper identification in all cases however they provide interesting tools and it is up to the intelligence of the system to couple them with software techniques that achieve the goal of identification and tracking. Other sensing devices that can be used to identify people are microphones (through the way of speaking and verbal explicit identification) and video cameras (through face recognition or explicit identification badges).

Table 2
Different sensing modes and their applications.

Sensing type	Common uses
Strain and pressure	Floors, doors, beds, sofas, scales
Position, direction, distance and motion	Security, locator, tracking, falls detection
Light, radiation and temperature	Security, location, tracking, health safety, energy efficiency
Solids, liquids and gases	Security and health, monitoring, pool maintenance, sprinkler efficiency
iButton	Used to identify people and objects
Sound	Security, volume control, speech recognition
Image	Security, identification, context understanding

Table 3
Contrasting characteristics of wired and wireless sensors.

Wired sensors	Wireless sensors
Cheaper sensors	More expensive
Pay for wiring	No wiring
Robust	Not as robust
Need power source	Batteries

All of these described identification technologies pose privacy concerns, which we will address later in this paper. A summary of the most common types of identification and tracking sensors is presented in Table 2.

Wireless sensor network research has become a popular area of research in recent years [24,25]. The sensor networks community has explored applications such as environmental monitoring, situational awareness, and structural safety monitoring [26–28]. A challenge that is prevalent particularly with wireless sensors and wireless sensor networks such as the popular Motes platform [29] is resource management to support long-term data collection. Most work in sensor networks has required battery power. For many applications, it is inconvenient to frequently replace batteries. Finding effective alternatives to battery power for sensor networks, however, is an ongoing research direction. A summary of these characteristics is presented in Table 3.

Making sense of sensor data is a complex task. Sensor data comes with unique features that challenge conventional data analysis techniques. They generate large volumes of multidimensional data, defying attempts to manually analyze it. If the sensors are imprecise the data can be noisy, and if a sensor fails there may be missing values. Sensor data often needs to be handled on the fly or as streaming data [30], and the data may have a spatial or temporal component to it.

When analyzing sensor data, AmI systems may employ a centralized or distributed model [31]. Sensors in the centralized model transmit data to a central server, which fuses and analyzes the data it receives. In the distributed model, each sensor has onboard processing capabilities and performs local computation before communicating partial results to other nodes in the sensor network. The choice of model will have a dramatic effect on the computational architecture and type of sensor that is used for the task [32,33]. In both cases, sensor data is collected from disparate sources and later combined to produce information that is more accurate, more complete, or more insightful than the individual pieces. Kalman filters are a common technique for performing sensor data fusion [34]. Probabilistic approaches have also been effective for modeling sensors [35,36] and combining information from disparate sources [37,38].

This processing which is focused on filtering, disambiguation and interpretation of sensed data before it is used by the higher level decision-making modules usually happens at a level of the system referred to as *middleware*. There the various elements of the distributed technology (sensors and devices interconnected through a wireless or conventional network) are integrated and the information coming from them is understood. Given the importance that this work has to maximize the understanding of the environment through the sensed data significant effort has been directed in the scientific community of this area in achieving efficient and robust middleware levels within their smart environment systems.

Ubila [39] was one of the pioneering national ubiquitous networks of projects for research and development funded by the Japanese government. The objective of the project was to develop core technologies to realize smart environments with cooperation of network, middleware and information processing technologies. UCN (Ubiquitous Computing and Networking) [40] is a nationwide Korean project in which service convergence solutions have been developed to design and manage human-centered composite services.

The European IST Amigo project [41] developed a networked home system enabling the AmI vision. Key features of the Amigo architecture are the effective integration and composing of heterogeneous devices and services from the following domains: personal computing, mobile computing, consumer electronics and home automation. One distinguishing feature of the Amigo middleware architecture is that it poses limited technology-specific restrictions: interoperability among heterogeneous services is supported through semantic-based interoperability mechanisms that are part of the Amigo architecture.

The PERSONA project (Perceptive Spaces prOmoting iNdepentent Aging) [42] aims at developing a scalable open standard technological platform for building a broad range of Ambient Assisted Living (AAL) Services. The main technical challenge is the design of a self-organizing middleware infrastructure allowing the extensibility of component/device ensembles. The communication patterns of the infrastructure are based on distributed coordination strategies for service discovery and utilization. The components of a PERSONA system interface with each other using the PERSONA middleware, which allocates a number of communication buses, each adopting specific and extendable communication strategies. Components linked with the PERSONA middleware may register to some of these communication buses; instances of middleware find each other and instances of the buses collaborate to enable interoperability among components using the middleware. Currently four types of buses have been chosen to model an AAL-space within PERSONA: the input bus, the output bus, the context bus, and the services bus. PERSONA uses a connector based approach to implement an extendible communication mechanism between distributed instances of the middleware (peers). The current prototype of the PERSONA middleware implemented on the OSGi platform uses connectors based on UPnP, Bluetooth, and R-OSGi.

4. Reasoning

Sensing and acting provide links between intelligent algorithms and the real world in which they operate. In order to make such algorithms responsive, adaptive, and beneficial to users, a number of types of reasoning must take place. These include user modeling, activity prediction and recognition, decision making, and spatial-temporal reasoning.

4.1. Modeling

One feature that separates general computing algorithms from those that are responsive to the user is the ability to model user behavior. If such a model can be built, it can be used to customize the behavior of the AmI software toward the user. If the model results in an accurate enough baseline, the baseline can provide a basis for detecting anomalies and changes in resident 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 AmI user modeling approaches based on three characteristics: (a) The data that is used to build the model, (b) The type of model that is built, and (c) 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 smart home project [43], 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 resident behavior. Loke [44] also relies upon this sensor data to determine the resident 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. [45] focuses on automating a living environment. However, instead of a Markov model, they model resident behavior by learning fuzzy rules that map sensor state to actuator readings representing resident 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 resident model. Luhr [46] uses video data to find intertransaction (sequential) association rules in resident actions. These rules then form the basis for identifying emerging and abnormal behaviors in an Intelligent Environment. Brdiczka, et al. [47] rely on speech detection to automatically model interacting groups of individuals. Moncrieff [48] also employs audio data for generating resident models. However, such data is combined with sensor data and recorded time offsets, then used to sense dangerous situations by maintaining an environment anxiety level.

Identifying social interactions has been a common theme in AmI research. In addition to the work of Brdiczka, Laibowitz, et al. [49] have also used wireless sensor networks to analyze social dynamics in large meetings. They have been able to detect key interaction characteristics such as interest and affiliation from sensor data in groups of over 100 people.

4.2. Activity prediction and recognition

A second contribution that reasoning algorithms offer is the ability to predict and recognize activities that occur in AmI environments. Much of this work has occurred in smart environments research, where the AmI application is focused on a single environment which is outfitted with sensors and designed to improve the experience of the resident in the environment [50]. Examples of such recognition tasks are listed in Table 4. Notice that each of these activity recognition tasks are fairly basic services expected from the AmI systems listed in each case, still achieving recognition of those activities to a highly satisfactorily level is a formidable challenge in each case. We will come back to these cases in future sections.

The Neural Network House [51], the Intelligent Home [52], the House_n [53] and the MavHome [54,55] projects adaptively control home environments by anticipating the location, routes and activities of the residents (i.e., a person moving within an AmI space). Prediction algorithms have been developed for both the single [56] and the multiple [57,58] resident cases. Predicting resident locations, and even resident actions, allows the AmI system to anticipate the resident's needs and assist with (or possibly automate) performing the action [59].

Activity recognition is not an untapped area of research. Because the need for activity recognition technology is great, researchers have explored a number of approaches to this problem. The approaches differ according to the type of sensor data that is used for classification and the model that is designed to learn activity definitions.

Table 4
Examples of task recognition problems in different environments.

Environment	Activity to be recognized
Smart home	Lifestyle patterns (e.g., adequate food intake and sleeping)
Hospital	Medicine intake (e.g., ensure the right medicine is taken in the right quantity)
Smart office	Use of resources (e.g., documents and meeting rooms)
Smart car	Driving behaviour (e.g., to increase safety if driver is falling asleep)
Smart classroom	Lecturer–student interaction (e.g., focus camera on a part of the whiteboard or on lecturer)
Street under surveillance	Monitoring behaviour (e.g., focus on number plate of speeding car)

4.2.1. Sensor data

Researchers have found that different types of sensor information are effective for classifying different types of activities. When trying to recognize actions that involve repetitive body motions (e.g., walking, running, sitting, standing, climbing stairs), data collected from accelerometers positioned on the body has been used [60]. In contrast, other activities are not as easily distinguishable by body position. In these cases, researchers such as Munguia-Tapia et al. [61] and Philipose et al. [68] observe the smart home residents interaction with objects of interest such as doors, windows, refrigerators, keys, and medicine containers. Munguia-Tapia et al. installed state-change sensors on key items to collect object interaction data, while Philipose et al. put RFID tags on items and asked participants to wear gloves with RFID tag readers that recorded when the individual was close to a key item. Other researchers, including Cook and Schmitter-Edgecombe [62], rely upon motion sensors as well as item sensors to recognize ADL activities that are being performed.

In addition, some researchers such as Brdiczka et al. [63] video tape smart home residents and process the video to recognize activities. While individuals have traditionally been resistant to at-home video monitoring [64], the acceptance of this technology in the home is increasing. On the other hand, processing the video is very computationally expensive and relies upon first tracking the resident before the correct video data can be captured and analyzed [65]. Because the many individuals are reluctant to allow video data or to wear sensors, researchers also consider technology that makes use only of passive sensors that could be installed in a smart environment.

4.2.2. Activity models

The number of machine learning models that have been used for activity recognition varies almost as greatly as the types of sensor data that have been tested. Nave Bayes classifiers have been use with promising results for activity recognition [63,45,66,61]. Nave Bayes classifiers identify the activity that corresponds with the greatest probability to the set of sensor values that were observed. These classifiers assume that the features are conditionally independent. However, when large amounts of sample data are provided the classifiers yield good accuracy despite this assumption. Other researchers, including Maurer et al. [60] have employed decision trees to learn logical descriptions of the activities. This approach offers the advantage of generating rules that are understandable by the user, but it is often brittle when high precision numeric data is collected. An alternative approach that has been explored by other researchers is to encode the probabilistic sequence of sensor events using Markov models, dynamic Bayes networks, and conditional random fields [62,67–69]. In our experiments we initially tested a nave Bayes classifier for activity recognition because of the model simplicity and because a large amount of sample data is available for these experiments.

4.3. Decision making

Over the last few years, supporting technologies for Ambient Intelligence have emerged, matured, and flourished. Building a fully automated AmI application 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. [70] discuss how AI planning systems could be employed to not only remind individuals of their typical next daily activity, but also to complete a task if needed. Augusto and Nugent [71] describe the use of temporal reasoning with a rule-based system to identify hazardous situations and return an environment to a safe state while contacting the resident.

Few fully-implemented applications decision making technologies have been implemented. One of the first is Mozer's Adaptive Home [51], 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. [72] also use a reinforcement learner to automate physical environments with volunteer residents, the MavPad apartment and the MavLab workplace.

The iDorm project of Hagras, et al. [73] 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 resident 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 resident behavior and therefore is more difficult to employ for alternative goals such as energy efficiency.

Amigoni, et al. [74] employs a Hierarchical Task Network (HTN) planner to generate sequences of actions and contingency plans that will achieve the goal of the AmI algorithm. For example, the AmI system may respond to a sensed health need

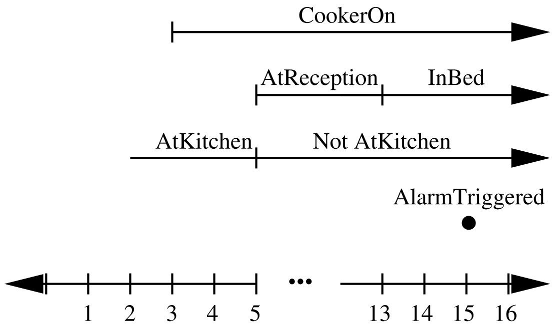

Fig. 4. Detecting hazards in the kitchen.

by calling a medical specialist and sending health vitals using any available device (cell phone, email, or fax). If there is no response from the specialist, the AmI system would phone the nearest hospital and request ambulance assistance.

4.4. Spatial and temporal reasoning

Very little can be done within an AmI system without an explicit or implicit reference to where and when the meaningful events occurred. For a system to make sensible decisions it has to be aware of where the users are and have been during some period of time. These insights, together with other information, will provide important clues on the type of activities the user is engaged in and the most adequate response.

Spatial and temporal reasoning are two well established areas of AI [75]. They have been the subject of intense research for a couple of decades and there are well known formalisms and algorithms to deal with spatial, temporal, and spatio-temporal reasoning. Gottfried et al. [76] has shown how the traditional frameworks for spatial reasoning and for temporal reasoning can be used to have a better understanding of the activities in an AmI application. In an environment such as an airport or a home, for example, such reasoning can be used to analyze trajectories of people within a room and classify them as "having a clear goal" or "being erratic" [77].

Both dimensions, space and time, are useful to understand key elements of a situation under development. For example, lets assume we are monitoring activities in order to prevent hazardous situations at home. Whenever someone turns on the cooker and leaves it unattended for more than 10 units of time, then the system has to take action (turning off the cooker automatically or warning the user, U). Consider a scenario in which the AmI environment sensed the cooker has been turned on, after which a sequence of sensor signals (e.g., movement sensors combined with RFID sensors) was captured detecting the location of U moving from the kitchen to a reception area and then into the bedroom. Finally, the bed occupancy sensor (a pressure pad) detects the person is in bed. By the point at which the person is in bed the condition that more than 10 units have left the cooker unattended is satisfied. All the conditions will be fulfilled for the warning rule to be triggered. This situation is pictured in Fig. 4.

Lets consider another situation in which the doorbell has been rung and the resident does not respond within 5 min. However, the AmI system detects that the person is at home and knows the resident is not hearing impaired. This can be identified as a potential emergency and may trigger a procedure where caregivers are notified and will try to contact the individual visually or by telephone.

Situations of arbitrary complexity can be detected by using language which allows the specifications of situations involving repetitions, sequences, frequencies and durations of activities related to the activities of entering to rooms or moving from one room to the next one [78]. In [71] such a language is used to integrate both concepts in the same formalism and to obtain spatio-temporal reasoning combined with active databases in the identification of interesting situations like those described above.

An alternative formalism for reasoning about time is based on Allen's temporal logic [80]. Allen suggested that it is more common to describe scenarios by time intervals than by time points, and defined thirteen relations that comprise a temporal logic: before, after, meets, meet-by, overlaps, overlapped-by, starts, started-by, finishes, finished-by, during, contains, and equals. Jakkula, et al. [79] found that these temporal relations play a beneficial role in prediction and anomaly detection for ambient environments. Consider, as an example, a medicine compliance tool that makes sure an elderly person consistently takes pills right after eating food. The two activities are related by the "after" relationship. When the relationship is violated, the system can respond with a reminder for the individual. The nine intervals that were used for prediction and anomaly detection in Jakkula's TempAl algorithm are shown in Fig. 5.

5. Acting

AmI systems tie reasoning to the real world through sensing and acting. Intelligent and assistive devices provide a mechanism by which AmI systems can executive actions and affect the system users. Another mechanism is through robots. Relationships between human and machines have been explored extensively in science fiction stories. However as Turkle points out [81], watching children and the elderly now commonly interact tenderly with robot pets brings "science fiction

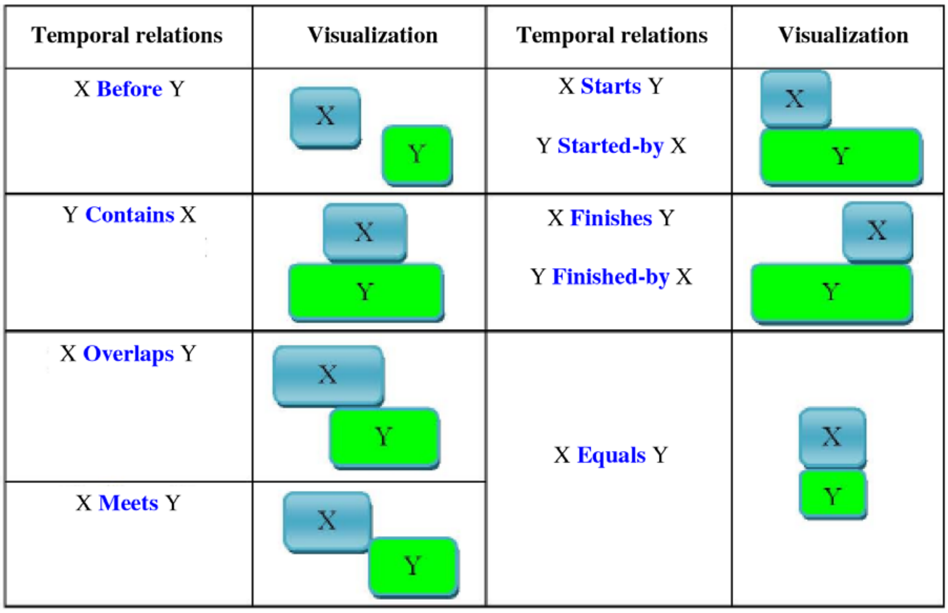

Fig. 5. Boundary conditions for nine of Allen's temporal intervals. These nine have been used for event prediction and anomaly detection [79]. Here X and Y represent the duration of activities.

into everyday life and technophilosophy down to earth". Research in robotics has progressed to the point where users need no longer wrestle with how to give them to move to a specified location, but instead can formulate requests such as "bring me the medicine on the counter". Indeed, such robot assistants are already found in nursing homes [82] and provide an outlet for nurturing contact for the elderly.

Robots are able to provide an even wider range of assistive tasks to support AmI. They can monitor the vital signs of their masters and provide conversational stimulation. Robots are now capable of exhibiting much more human-like emotions and expressions than in the past [83] and can even influence human decision. One such case is the museum traffic control project [84], where a robot generated cues that caused visitors to travel to portions of the museum that were normally avoided. Robots provide AmI systems with self-mobility and human-likeness, which facilitates human interaction and allows the influence of AmI to more greatly pervade human culture.

6. Human–computer interaction

A characteristic that the IST Advisory Group highlighted as necessary to further societal acceptance of AmI [1] is that AmI should be made easy to live with. This is further detailed as a need to define human-centric computer interfaces that are context aware and natural. Here we highlight some recent advances in these areas.

6.1. Context awareness

Models of 21st century ubiquitous computing scenarios [11] 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 [85] or context-aware computing.

"Context (e.g., location and activity) awareness" is a key to building Ambient Intelligence 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 [86] capture residents' footfalls, and the home uses these data for position tracking and pedestrian recognition.

Research in context-aware computing includes mechanisms of determine a user's context even with imperfect information [87] and designing context services as found in IBM's Context Sphere [88]. Providing this type of context-aware infrastructure makes it possible to design office spaces that smoothly move information between displays, walls, and tables [89] and learn to customize lighting and temperature based on learned resident preferences [90]. Cheverst, et al. [91] have built upon these capabilities to design a location-aware electronic tourist guide.

Context-awareness is a key feature of AmI systems and one that is dependent on the characteristics of the environment. Some elements in these environments are more more recurrent than others across different applications. For example the location as well as the time and duration of states, events and activities are usually crucial to understand the key latest developments in a specific environment. But then identifying the actors is usually also very relevant and as we discussed in an early section this may not be a trivial task, even if combining more than one sensor (e.g., movement sensor and RFID). An option is to add to the identification infrastructure, microphone and/or image processing, for example by analyzing the images taken with a video camera and matching it to other images of the expected occupants of a place. A context can mean many different things with subtle qualifications. Let us consider for example that we want the system to take specific actions (e.g., playing calming music) when "the place is noisy" or when "the occupant is sad". These contexts are hard to specify (when a noisy environment is noisy enough?) and also difficult to detect with accuracy (how to know when a person is sad?). Face recognition, facial gestures recognition, "body language" recognition can all contribute and be meaningful but are still far from being robust.

6.2. Natural interfaces

An important aspect of AmI has to do with interaction. On one side there is a motivation to reduce the human–computer interaction (HCI) [92]. The system is supposed to use its intelligence to infer situations and user needs from the recorded activities, much as a butler observes activities unfold with the expectation of helping when (and only if) needed. This is the idea of an "intelligent social user interface" [93]. On the other hand, a diversity of users may need or voluntarily seek direct interaction with the system to indicate preferences, needs, etc. HCI has been an important area of study since the inception of computers. Today, with so many gadgets incorporating computing power of some sort, HCI continues to thrive as an important area that prevents AmI technologies from becoming "ubiquitous clutter" [94].

Although designers of Ambient Intelligence systems 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 residents. Abowd and Mynatt [95] point 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 [96], facial expression recognition [97] and emotion recognition [98], speech processing [99], and even whistle processing [100] facilitate natural interactions with intelligent environments. In some cases, diverse interface mechanisms are combined to form multi-modal interfaces [101–103].

Several large projects that focus on processing disparate yet complementary types of multimedia information in order to pursue goals such as understand human–human communication, perform body tracking, and recognize gestures. Large multimedia corpora have been collected by VACE [104], ISL [105], ICSI [106], NIST [107], and MM4 [108]. An example Ambient Intelligence project that targets the goals of being unobtrusive, Ubiquitous, and adaptive is the DARPA DARPA Cognitive Agent that Learns and Organizes (CALO) project [109]. CALO's goal is to be an AI-based personal assistant. CALO acquires knowledge on its own by learning associations among sources of information the user accesses (email, human contact, web pages, appointments) and can use these discoveries to track topics, schedule tasks, and summarize information for the user. The European project COGAIN [110] uses eye-based environmental control to support home automation. User–home interaction is achieved as direct interaction. Integration between the eye tracking interfaces, or other interaction modalities, and the wide variety of equipment that may be present in an intelligent house (appliances and devices) is granted by a central module for abstraction and harmonization called House Manager. It is based on the implementation of a Domotic House Gateway that adopts technologies derived from the semantic web to abstract devices and to enable interoperability of different automation subsystems.

Work on natural interfaces for Ambient Intelligence has taken AmI applications out of single rooms and buildings to even richer settings. UCLA's HyperMedia Studio project [111] adapts light and sound on a performance stage automatically in response to performers' positions and movements. The driver's intent project at MIT [112] recognizes driver's upcoming actions such as passing, turning, stopping, car following, and lane changing by monitoring hand and leg motions. The use of facial expression recognition enhances the automobile by recognizing when the driver is sleepy, or change the classroom interaction when detecting that the students are bored or confused. New Songdo City, a "ubiquitous city" being built in South Korea, is implementing many AmI ideas on a city-wide scale [113]. Such a large-scale sharing of data facilitates easy access to city resources for residents.

Images also help assess a situation where safety can be compromised. The Wireless Sensor Networks Lab at Stanford University uses a network of video cameras to infer a sequence of body postures (Fig. 6) and hence detect possible hazards like a fall [114].

Images can be also used as in visual arts. Now more than ever, art can be "experienced". One example of the use of AmI to transform the way people relate and understand their environment is being implemented through the UNSEEN project [115]. A nature interpretation center set in eastern Québec where real-time images of native plants are examined and used by the system to present the plants and their current state of development through challenging and original perspectives.

7. Privacy and security challenges

Ambient Intelligence offers great benefits to users by customizing their environments and unobtrusively meeting their needs. As Brey points out [116], AmI potentially gives more control to humans by making their environments more

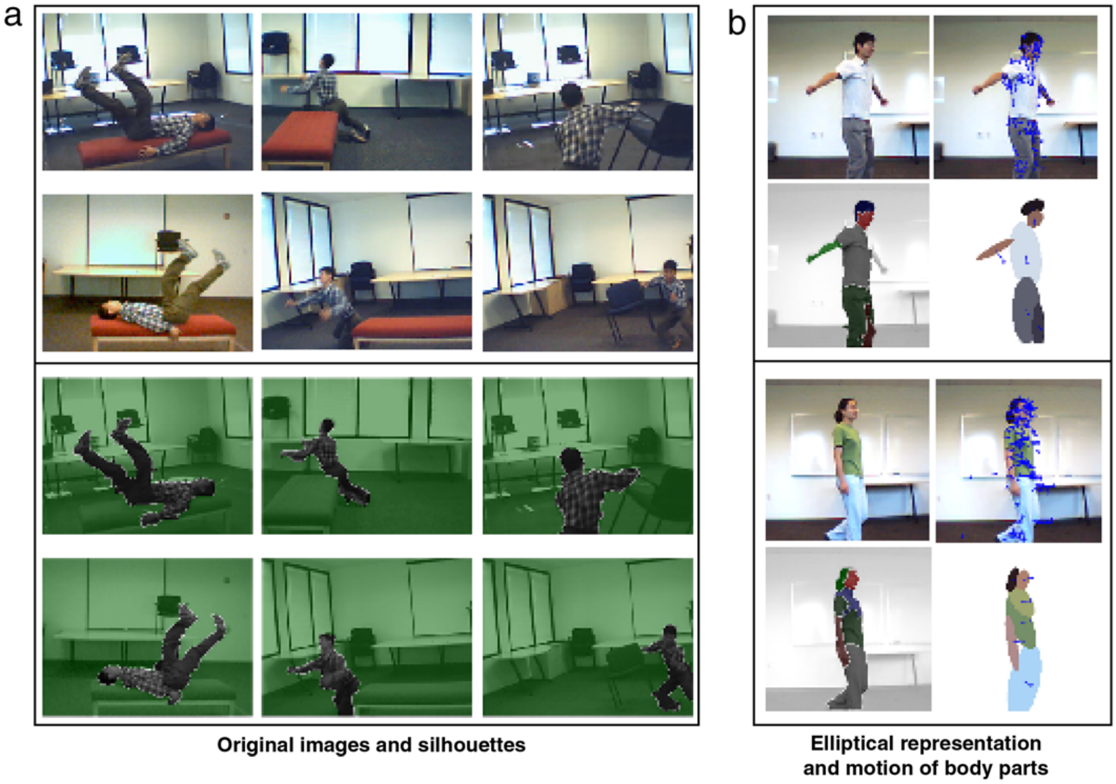

Fig. 6. (a) Sample images from two cameras showing different postures. (b) Elliptical model representations with average motion vectors for the moving body parts. Images provided by the Stanford Wireless Sensor Networks Lab.

responsive to intended actions, by supplying humans with customized information, and by reducing the cognitive or physical effort that is required to perform a task. At the same time, AmI can take away control when the environment performs the wrong action, when it forces humans to perform extra or corrective actions, when it shares information with third parties, and when it gives monitoring and data collection access to third parties.

Wright [117] argues that delivering personalized services opens up the possibility for the corresponding personal information to be stored and shared. As Bohn, et al. [118] point out, the sayings that "the walls have ears" and "if these walls could talk" have become a reality which is disturbing to many. In fact, in a 2003 survey [119], respondees indicated that privacy protection was more important to them than any potential benefits provided by technologies found in Ambient Intelligence applications. In addition, what is considered obtrusive and privacy invading differs by age group and culture [64]. For example, one reason that U-City in Korea is developing so quickly is that there is a quicker acceptance of loss of privacy by residents there [113].

The use of image processing through video cameras as a potential kind of sensor is a controversial area. Naturally the amount of information that can be collected in that way is very valuable in terms of assessing a situation. On the other hand, it raises clear issues of privacy and the "big brother" syndrome. Still there are applications where users think the benefits out weight the drawbacks and are decided to accept it as part of the system that is build to benefit them. One such example is the image processing system that recognizes hand based gestures that can be used to give orders to a system and control several different appliances in an easy way without individual remote control units [120].

Not all image processing techniques compromise privacy. For example, in [121] a system is reported which monitors the top of a cooking unit scanning with a camera capable to process images from a thermal perspective. If the cooker has been left unattended for an important length of time and the image processing unit can classify the warmth emanating from the cooker into a dangerous level it will trigger an alarm. It is important the way the image is used and the level of acceptance the user has for the successful use of this technology. On the other hand, non-camera sensors do not necessarily perform a better job of ensuring privacy. As Bohn, et al. [118] argue, individual models, even seemingly innocuous ones such as walking patterns and eating habits, can be combined to provide very detailed information on a person's identify and lifestyle.

In addition to intentional privacy violations, Ambient Intelligence technologies can raise other security issues [122]. At the sensor level, sensor reliability, handling errors, and installation errors can create security risks. To ensure security in sensor networks, the designer must consider these factors together with sensor communication channel reliability and security, and sensor data security. While encrypting collected data can address some of the data privacy issues, the challenge is to implement the required security using minimal resources.

There is a great deal of research being investigated to mitigate the privacy and security risks of Ambient Intelligence. Some of these projects focus on keeping sensed data such as location information private [123], while other projects are designing devices that can act as secure keys for providing and receiving personal information [124]. In lieu of transporting specialized devices, biometric information can be used to access sensors and collected information [125].

As Joinson, et al. [126] reveal from their survey of potential AmI users, privacy is a preference that should be customizable by users. There are situational aspects of AmI environments that trigger different privacy concerns in different people. As a result, privacy should be a decision that is influenced by context. This type of approach is advocated by Preuveneers, et al. [127], who are designing such context-driven privacy measures. Their solution is to obtain the minimal amount of personal information that is needed to achieve the user's goal. Detailed personal information can be reduced by inferring needed information from previously-processed data, and the impact of obtaining personal information on the user's goal can be analyzed to determine whether the information should be obtained.

8. AmI applications

There are many settings in which Ambient Intelligence can greatly impact our lives. Some of these applications have already been pursued by AmI researchers. In this section, we highlight current AmI applications. By summarizing existing implementations, we also draw attention to the technologies that are necessary to create the implementations and the challenges that AmI researchers still face. It is important to note that not all of the applications described in this section embody the six features of AmI systems that we listed in Table 1. However, they all reflect a subset of the AmI features. Perhaps even more importantly, the ideas presented in the applications themselves may spark the creation of future AmI solutions that do reflect all of our defined AmI characteristics.

8.1. Smart homes

An example of an environment enriched with Ambient Intelligence is a "smart home". Several artifacts and items in a house can be enriched with sensors to gather information about their use and in some cases even to act independently without human intervention. Some examples of such devices are electrodomestics (e.g., cooker and fridge), household items (e.g., taps, bed and sofa) and temperature handling devices (e.g., air conditioning and radiators). Expected benefits of this technology can be: (a) increasing safety (e.g., by monitoring lifestyle patterns or the latest activities and providing assistance when a possibly harmful situation is developing), (b) comfort (e.g., by adjusting temperature automatically), and (c) economy (e.g., by controlling the use of lights). This is a popular use of many technologies such as active badges [128] and indoor positioning systems [129].

An example of a project that addressed intelligent use of energy for the well being of a house occupants is the Europen project ALADIN—Ambient Lighting Assistance for an Ageing Population, [130]. It aimed to extend our knowledge about the impact of lighting on the wellbeing and comfort of older people and translate this into a cost-effective open solution. The adaptive lighting system consists of several components including an intelligent open-loop control, which can adapt various light parameters in response to the psycho-physiological data it receives, as well as advice and biofeedback applications. Adaptive lighting can contribute to healthy sleep (i.e., at appropriate durations, frequencies and times of the day), which are essential to preserve and enhance people's lifestyle.

In addition to investigating intelligent devices in a home, an example of Ambient Intelligence is allowing the home itself to possess intelligence and make decisions regarding its state and interactions with its residents. There are several physical smart homes that have been designed with this theme in mind. The MavHome project treats an environment as an intelligent agent, which perceives the environment using sensors and acts on the environment using powerline controllers [131].

At the core of its approach, MavHome observes resident activities as noted by the sensors. These activities are mined to identify repetitive patterns and compression-based predictors are employed to identify likely future activities. The results from these two algorithms are employed in building a hierarchical Markov model of the resident and the environment, based on which a policy can be learned for automating environmental control. Initially the approach was evaluated for its ability to predict and automate daily interactions with the environment that the resident would typically perform manually (e.g., turn on the overhead light when entering the apartment). From one month of data collected on a volunteer resident, MavHome was able to reduce the needed daily interactions by 76%, on average [132].

The Gator Tech Smart House is built from the ground up as an assistive environment to support independent living for older people and individuals with disabilities. The home is equipped with a large number of sensors and actuators, and generates a large volume of data streams [133]. Data streams are filtered through an OSGi service bundle, providing opportunity for data folding, modeling, and encryption [134].

The Gator Tech project currently uses a self-sensing service to enable remote monitoring and intervention caregivers of elderly persons living in the house. The application is a classical example that demonstrates the tension found between two noble goals: preserving privacy and providing useful smart environment benefits.

The University of Essex's intelligent dormitory (iDorm) [45] is a real AmI test-bed comprised of a large number of embedded sensors, actuators, processors and networks in the form of a two bed roomed apartment. It is a full-size domestic apartment containing the usual rooms for activities such as sleep, work, eating, washing and entertaining.

A common interface to the iDorm and its devices is implemented through Universal Plug and Play (UPnP), and any networked computer running a standard Java process can access and control the iDorm directly [73]. Fuzzy rules are learned from observing resident activities [135] and are used to control select devices in the dorm room.

The Aware Home [95] project has been developed by the Georgia Institute of Technology. This home consists of two identical but independent living spaces, each one with: two bedrooms, two bathrooms, one office, kitchen, dining room, living room and laundry room. There is also a shared basement with a home entertainment area and control room for centralized computing services. The house has been built using standard construction techniques. Some of the technology deployed in the house are human position tracking through ultrasonic sensors, RF technology and video, recognition through floor sensors and vision techniques.

One of the applications of the tracking and sensing technologies in the Aware Home is a system for finding Frequently Lost Objects such as keys, wallets, glasses, and remote controls. The system uses RF tags attached to each object the user would like to track and a long-range indoor positioning system to track these objects. The user will interact with the system via LCD touch panels. The system will guide the user to the lost object using spatialized audio cues (e.g., ''your keys are in the bedroom''). Other tracking technologies in the house can assist with the task of locating objects.

The DOMUS lab is based at the Computer Science Department of the University of Sherbrooke (Quebec, Canada) and it has been in operation since 2003. It is run by a multidisciplinary team and one of the main aims of the lab is to achieve an implementation of smart homes based on pervasive assistants which can provide mobile orthosis [136].

The three main lines of investigation within DOMUS are [137]: (a) Pervasive Cognitive Assistant: provide assistance adapted to specific cognitive deficits (memory, initiation, planning, attention,) (b) Cognitive Modeling: describe the specific behaviors of the cognitive impaired people using descriptive representations, (c) Mobile Orthose: Help people to manage their ADLs outside and allow caregivers to monitor them and collect ecological data on symptoms and medication side-effects.

Recognizing the emerging popularity of smart homes and their benefits, several industry-led projects are also developing smart homes. Siemens [138] has invested in smart homes that provide services to enhance entertainment, security and economy. Energy saving, lighting control, networked home entertainment, and safety devices for the monitoring of children are some of the features that Siemens advertises. Touch screens can be used to operate the central control unit and units can be remotely activated and controlled, for example by using the mobile phone. Areas of application for Siemen's research vary from adaptive offices and Smart Homes to intelligent cars [139].

Philips [140] has already developed smart homes for the market that highlight innovative technology on interactive displays. For several years, the company has been overseeing the HomeLab at Eindhoven (NL) [141]. Research conducted at the HomeLab has been focused on interaction and how the houses of today can increase their support to daily living from three perspectives: (a) Need to belong and share experiences, (b) Need for thrills, excitement and relaxation, and (c) Need to balance and organize our lives [142]. One important aspect of Philips research is the level of social awareness that has to be embedded in the AmI system to be adequate and acceptable to users, in particular to elderly people [143]. The company has been very active in the market [144].

Microsoft also has a laboratory devoted to the research on the interaction of humans with systems and the use of artificial intelligence to support daily life activities. Some of the topics that have been investigated are related to the availability of users and the suitability of interrupting them [145].

These by no means are the only Smart Home projects being developed throughout the world and there are significant developments in many regions of the world. There is a long list of projects being currently developed in many other countries, especially Japan and Korea. We address the readers to other sources of literature (e.g., [146–149]) for more details (Fig. 7).

8.2. Health monitoring and assistance

There are many potential uses for an Intelligent Environment. Indeed, we anticipate that features of Intelligent Environments would pervade our entire lives. They will automate aspects of our life, increase the productivity at work, 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 Ambient Intelligence: 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 intelligent elder care technologies into the home [150–152]. Another reason is the tremendous need for research on Ambient Intelligence 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. By 2040, 23% of the population will be 65+ [153] and over 11 million people will suffer from dementia related to Alzheimer's disease [154], with the long-term projected total losses to the US economy expected to be nearly 2 trillion dollars [155].

Given the costs of US nursing home care (approximately $ 40,000 a year with an additional $ 197 billion of free care being offered by family members) [156] and the importance that Americans place on wanting to remain in their current residence as long as possible [157], use of technology to enable individuals with cognitive or physical limitations to remain in their homes longer may be more cost effective and promote a better quality of life. Placement in nursing homes may sometimes be premature because of family concerns related to safety issues [158] and AARP reports [159] strongly encourage increased funding for home modifications that keep older adults independent in their own homes. The need for this technology is not limited to the United States: The Commission of the European Communities [160] indicates that early patient discharge from hospitals due to introduction of mobile health monitoring would save 1.5 billion Euros each year in Germany alone.

Fig. 7. Example smart homes: the MavHome (upper left) iDorm (upper right), Gator Tech Smart House (middle), Aware Home (lower left), and Domus Lab (lower right).

With the maturing of supporting technologies, at-home automated assistance can allow people with mental and physical challenges to lead independent lives in their own homes [161–163] and reduce the physical and emotional toll that is taken on caregivers [164]. Some of these technologies focus on assurance, or making sure our friends and loved ones are safe and healthy at home. AmI techniques for recognizing activities [165–167], monitoring diet and exercise [168,169], and detecting changes or anomalies [170] support this goal.

The next category of health technologies targets the goal of providing support to individuals with cognitive or physical impairments. AmI techniques can be used to provide reminders of normal tasks [171] or the sequence of steps that comprise these tasks [172]. Use of devices such as the activity compass [173] can actually remind individuals of the route that will get them back to a safe location if they have wandered off. For those with physical limitations, automation of their home and work environment [174] can allow them to live independent lives at home.

AmI technologies can also be used to assess the cognitive limitations of individuals. Carter and Rosen [175] demonstrate such an assessment based on the ability of individuals to efficiently complete kitchen tasks. Jimison, et al. [176] 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.

Finally, AmI can be used to enhance the quality of life for individuals who would otherwise lead solitary lives at home. Intel has created the "Proactive Health Group" which performs research and development of technologies that can increase the quality of life of older adults [177]. One important aspect of older adults related to wellbeing is their social network.

Intel has developed systems which using wireless sensors examines this particular aspect of the daily life of a person. Intel's technologies provide information to caregivers summarizing the social interactions the individual has had at home and offers advice on how to improve that aspect of a person's life.

8.3. Hospitals

While bringing health care to homes is an exciting development, hospitals are still needed for a variety of reasons. The concentration of costly equipment and specialized professionals is valuable in many situations. Applications of AmI in hospitals can vary from enhancing safety for patients and professionals to following the evolution of patients after surgical intervention. Many of the AmI technologies found in smart homes can be adapted for use in specific rooms or areas of a hospital [178].

At a different level, AmI can be used to improve the experience of hospital visitors. For example, the Lutheran General Hospital in Chicago has built the Yacktman Children's CT Pavilion where patients are entertained and helped by Ambient Intelligence during their examination sessions [179]. Patients can select a topic of preference for their visit and as they enter to the hospital their identity is read from their RFID-encoded cards. The system is then aware of their presence at the unit, and also of their preferences, being able to tailor the lighting and wall/ceiling projections when they are in a particular room. The images projected can be used to calm the anxiety of the patient but also to guide them. For example, if a child is required to hold his breath during an examination a figure in the projection will do the same. The child's fear may be reduced by letting them understand the procedure they are about to undertake. Children waiting for a scan can use a small scale toy scanner unit and scan toy animals, which are recognized by RFID sensors, and the toys will trigger the appropriate images on a display.

Ambient Intelligence can also be used to link hospital care with smart home technology. As another example, the Ulster Community Hospitals Trust of Northern Ireland [180] has set up the PathFinder project with the goal of caring for elderly and vulnerable people in their homes. By eventually equipping 3000 homes in the community with sensors and monitoring their well-being, PathFinder can increase the level of autonomy, independence and safety for these individuals, particularly if they have a medical condition which may be detrimental to their lifestyle.

Hospitals can increase the efficiency of their services by monitoring patients' health and progress through analysis of activities in their rooms. They can also increase safety by, for example, only allowing authorized personnel and patients to have access to specific areas and devices. The latest issue of Consumer Reports [181] laments the status of assisted care facilities in the US and the need in most for additional staffing. Ambient Intelligence capabilities can be used in this setting to reduce the burden of staff nurses in assisted care facilities, and to make them aware more quickly of residents' needs they arise. In addition, tracking is used to find doctors or nurses in a hospital setting when they are urgently needed. This is the most common use of many technologies such as active badges [182].

8.4. Transportation

Transport means are also valuable settings for AmI technologies. We spend a significant part of our life traveling in different ways. Train stations, buses, and cars can be equipped with technology that can provide fundamental knowledge about how the system is performing at each moment. Based on this knowledge, preventive actions can be applied and the experience of people using that transport can be increased by using the system more effectively. Public transport can benefit from AmI technology including GPS-based spatial location, vehicle identification and image processing to make transport more fluent and hence more efficient and safe. As an example we can consider the I-VAITs project [183] aiming to assist drivers by gathering important information through the way they use different elements of the car (pressure on breaks) or their movements and image processing of the driver's face expressions (as mood indicators). This can allow a system to assist the driver more effectively when is help most needed, such as while executing tricky maneuvers.

Pentland, in partnership with Nissan Cambridge Basic Research, [184] has built a system that allows the car to "observe" the driver, continuously estimating the driver's internal state and responding appropriately. An HMM model of the driver's hand and leg motions and associated actions (e.g., passing, turning, stopping, car following, lane change, or speeding up) was built. This was used to classify real driver's actions in relation to the artificial model. The system was able to accurately identify what action the driver was beginning to execute. This detection can be done as soon as the action started with high accuracy (97% within 0.5 s of the beginning an action, rising to over 99% accuracy within two seconds). This quick scenario identification allow a real-time optimization of the car's performance to suit a particular situation, and to warn the driver about possible dangers.

Microsoft also employs AmI technologies for driver assistance by providing route planners. They also generate inference about possible preferred routes and provide customized route suggestions for drivers [185,186].

8.5. Emergency services

Safety-related services like fire brigades can improve the reaction to a hazard by locating the site of an accident more efficiently and also by preparing a route to reach the place in connection with street services. This can be realized using image processing and traffic monitoring as found in the e-Road project [187]. This service can also quickly locate a place where a hazard is occurring or is likely to occur and prepare a better access to it for security personnel.

Similarly, the PRISMATICA project [188] uses cameras to monitor public transportation locations. By detecting situations such as overcrowding, the presence of people or objects that are not moving, motion in a forbidden direction, and intrusion, the environment and officials can respond quickly to ensure the safety of individuals using public transportation.

8.6. Education

Not only do students learn about technologies such as Ambient Intelligence in the classroom, but AmI can also help improve the learning experience for these students. Education-related institutions can use technology to track students' progression on their tasks and frequency of their attendance at key events. In the Georgia Tech Classroom 2000 project [189], Abowd provides human–computer interfaces through devices such as an interactive whiteboard that stores content in a database. The smart classroom of Shi, et al. [190], 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 retrieve information or focus attention on appropriate displays and material.

The intelligent classroom at Northwestern University [191] 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 Ambient Intelligence system necessary — natural actions of the inhabitants elicit appropriate responses from the environment.

In their Reconfigurable Context Sensitive Middleware (RCSM) Project at Arizona State University [192], Yau provides enhanced collaborative learning in smart classroom environments using PDAs to monitor the situation in terms of the locations of PDAs, noise, light, and mobility activity. They use the current situation to trigger communication activity among the students and the instructor for group discussion and automatic distribution of presentation materials. At San Francisco State University [193] the smart classroom project focuses not only on supporting user interactions but also visualizing the behaviors.

Targeting early childhood education, a Smart Table was designed as part of the Smart Kindergarten project at UCLA [194]. 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 [195]. 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.

8.7. Workplaces

Facilitating interaction is particularly important in a workplace environment, where workers want to focus on the project at hand without being tripped up by technology. The AIRE project [196], 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 [197] identifies gestures and activities in order to retrieve and project needed information in a workplace environment. Similarly, the Interactive Room (iRoom) project at Stanford [198] 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.

NIST Smart Space and Meeting Recognition projects are developing tools for data formats, transport, distributed processing, and metadata which aid context-aware smart meeting rooms that sense ongoing human activities and respond to them [199]. A cooperative effort from a network of Portuguese Universities [200] is developing a system which is able to support Distributed Decision Making Groups through the use of an agent-based architecture. The system is able to exhibit intelligent, and emotional-aware behavior, and supports argumentation, through interaction with individual persons or groups.

Production-centered places like factories are capable of self-organizing according to the production/demand ratio of the goods produced. This demands careful correlation between the collection of data through sensors within the different sections of the production line and the pool of demands via a diagnostic system which can advice the people in charge of the system at a decision-making level. Production environments can be also enriched with AmI technology in order to increase important aspects of the process, such as safety of the employees. The MOSES system [201] uses AmI to infer where the personnel is located and what task are performing. The system relies upon RFID technology to recognize positioning of the important elements of the environment. As workers are equipped with RFID readers, the system can track the development of activities and therefore can advise the employee what tasks remain to be done. The iShopFloor [202] provides an architecture for intelligent manufacturing process planning, scheduling, sensing, and control. The system is based on three main agents: resource agents (manufacturing devices), product/part agents (parts), and service agents (coordination of resource and parts agents).

9. Final words

Humans have learned through the millennia how to benefit from their environments. Whether it was by obtaining food or shelter we learned how different habitats can give us fundamental elements for our survival or comfort.

In search of security and predictability our modern society began to imbue their surroundings with technology in order to more easily obtain essential elements for the functioning of society and in order to make key elements of survival and comfort available to the masses. Until recently, this technology has been passive.

We have reached a point where technology allows humanity to make these technologies more active. The goal of ambient intelligence is not only to provide such active and intelligent technologies, but to weave them seamlessly into the fabric of everyday lives and settings and to tailor them to each individual's specific needs.

9.1. Ongoing challenges

The area has produced a significant volume of work [203,204], still, systems which have to interact with humans face important challenges. They differ in many ways from those that validate their usefulness only by accepting a well-delimited input, computing a solution and displaying the result. AmI systems have to interact sensibly with the user in a variety of sophisticated ways.

Crucially, AmI systems need to be aware of the users preferences, intentions, and needs. AmI systems should know when it is convenient to interrupt a user, and when to make a suggestion but also when is more convenient to refrain from making a suggestion. Sometimes acting may be essential to save a life or to prevent an accident. Too much intervention from the system can be inadequate and even can make the system useless if the user get tired of it and decides not to pay attention anymore. All that social tact that humans learn throughout life is not simple to achieve.

There are many practical challenges that need to be met in each of the contributing technological areas we have surveyed. For example, many AmI applications relying upon wireless sensors are at the mercy of the battery life for the sensors. Researchers are starting to investigate batteryless approaches to sensing [68], but much work remains to be done to make this approach robust and easy to use. In the area of user modeling and activity analysis, an ongoing challenge is to model multiple residents in an environment. While this has been investigated for location tracking in a limited context [57], solving the general problem of activity modeling, recognition, and prediction for multiple-resident settings is an open and very difficult problem.

In this paper we discussed issues related to security and privacy for AmI systems. Some steps have been taken to better understand privacy issues and to address these in AmI systems. The dependability of AmI systems has not been researched to the same extent. An ongoing challenge for AmI researchers is to design self-testing and self-repairing AmI software that can offer quantitative quality-of-service guarantees.

In addition, the IST Advisory Group has stated a goal that AmI facilitates human contact [1]. In contrast, current AmI research has actually raised fears of isolationism [118]. A new direction that can be forged for AmI researchers is to investigate mechanisms for supporting and enriching human socialization and interaction, and orient AmI toward community and cultural enhancement.

Much study and experimentation is still needed to know what sensors, in which quantity and in which particular distribution are needed to guarantee an acceptable level of service. As technology advances and provides new sensors the line will be continually moving.

9.2. Conclusions

Ambient Intelligence is fast establishing as an area where a confluence of topics can converge to help society through technology. We have summarized the flexibility of the idea, the current state of the art and current trends at research labs and companies.

There are still many challenges ahead and improvements are needed at all levels: infrastructure, algorithms and human–computer interaction for AmI systems to be widely accepted and more important of all, be useful to society. We are conscious that the realization of the aims set up for AmI are not easily reachable but the field is gaining momentum. Many important elements are advancing and we are optimistic that this will bring the synergy that is needed to materialize the goal of Ambient Intelligence.

Acknowledgment

These notes greatly benefited with the kind input of many colleagues around the world: Emile Aarts, Marc Böhlen, Vic Callaghan, Boris de Ruyter, Björn Gottfried, Hans Guesgen, Sylvain Gyroux, Sumi Helal, Eric Horvitz, Sebastian Hüebner, Helene Pigot, Maureen Schmitter-Edgecombe, Hamid Aghajan, Sajal Das, and the anonymous reviewers.

References

[1] I.A. Group, Scenarios for ambient intelligence in 2010, 2001.
[2] E. Aarts, R. Harwig, M. Schuurmans, Ambient intelligence, in: The Invisible Future: The Seamless Integration of Technology into Everyday Life, McGraw-Hill, 2002, pp. 235–250.

[3] E. Zelkha, The future of information appliances and consumer devices, Palo Alto Ventures, Palo Alto, California, 1998.
[4] E. Aarts, J. Encarnacao, True Visions: The Emergence of Ambient Intelligence, Springer, 2006.
[5] E. Maeda, Y. Minami, Steps toward ambient intelligence, NIT Technical Review 4 (1) (2006).
[6] Phillips Research, Ambient intelligence: Changing lives for the better, 2007. www.research.phillips.com/.
[7] C.K.M. Crutzen, Invisibility and the meaning of ambient intelligence, International Review of Information Ethics 6 (2006) 1–11.
[8] J. Rech, K.-D. Althoff, Artificial intelligence and software engineering: Status and future trends, Themenschwerpunkt KI & SE, KI 3 (2004) 5–11.
[9] A. Vasilakos, W. Pedrycz, Ambient Intelligence, Wireless Networking, and Ubiquitous Computing, Artech House Publishers, 2006.
[10] Phillips Research, Other perspectives on ambient intelligence, 2007.
[11] M. Weiser, The computer for the twenty-first century, Scientific American 165 (1991) 94–104.
[12] N. Streitz, P. Nixon, The disappearing computer, Communications of the ACM 48 (3) (2005) 32–35 (special issue).
[13] M. Weiser, Hot topics: Ubiquitous computing, IEEE Computer 26 (10) (1993) 71–72.
[14] P. Krill, IBM research envisions pervasive computing, InfoWorld (2000).
[15] A. Greenfield, Everyware: The Dawning Age of Ubiquitous Computing, Peachpit Press, 2006.
[16] Oxford, Oxford Dictionary and Thesaurus, Oxford University Press, 2007.
[17] J. Augusto, Ambient intelligence: The confluence of pervasive computing and artificial intelligence, in: A. Schuster (Ed.), Intelligent Computing Everywhere, Springer, 2007, pp. 213–234.
[18] S.J. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, 2nd ed., Prentice Hall, 2003.
[19] R.F. Wolffenbuttel, K.M. Mahmoud, P.L. Regtien, Compliant capacitive wrist sensor for use in industrial robots, IEEE Transactions on Instrumentation and Measurements 39 (1990) 991–997.
[20] G. Delapierre, H. Grange, B. Chambaz, L. Destannes, Polymer-based capacitive humidity sensor, Sensors and Actuators 4 (1) (1983) 97–104.
[21] M. Ermes, J. Parkka, J. Mantyjarvi, I. Korhonen, Detection of daily activities and sports with wearable sensors in controlled and uncontrolled contitions, IEEE Transactions on Information Technology in Biomedicine 12 (2008) 20–26.
[22] V. Stanford, Biosignals offer potential for direct interfaces and health monitoring, IEEE Pervasive Computing 3 (2004) 99–103.
[23] ibutton. http://www.maxim-ic.com/products/ibutton/ibuttons/.
[24] Y. Li, M.T. Thai, W. Wu, Springer, 2008.
[25] G. Pottie, W. Kaiser, Wireless sensor networks, Communications of the ACM 43 (5) (2000) 51–58.
[26] M. Gaynor, S.L. Moulton, M. Welsh, E. LaCombe, A. Rowan, J. Wynne, Integrating wireless sensor networks with the grid, IEEE Internet Computing 8 (4) (2004) 32–39.
[27] K. Martinez, J.K. Hart, R. Ong, Environmental sensor networks, Computer 37 (8) (2004) 50–56.
[28] N. Peterson, L. Anusuya-Rangappa, B.A. Shirazi, W. Song, R. Huang, D. Tran, S. Chien, R. LaHusen, Volcano monitoring: A case study in pervasive computing, in: Pervasive Computing: Innovations in Intelligent Multimedia and Applications, Springer, 2008.
[29] G. Anastasi, A. Falchi, A. Passarella, M. Conti, E. Gregori, Performance measurements of motes sensor networks, in: Proceedings of the International Workshop on Modeling Analysis and Simulation of Wireless and Mobile Systems, 2004, pp. 174–181.
[30] S. Madden, M.J. Franklin, Fjording the stream: An architecture for queries over streaming sensor data, in: Proceedings of the International Conference on Data Engineering, 2002, pp. 555–566.
[31] I.F. Akyldiz, W. Su, Y. Sankarasubramanian, E. Cayirci, A survey on sensor networks, IEEE Communications Magazine 40 (2002) 102–114.
[32] L. Benini, M. Poncino, Ambient intelligence: A computational platform perspective, in: Ambient Intelligence: Impact on Embedded System Design, Kluwer, 2003, pp. 31–50.
[33] D.N. Jayasimha, S.S. Iyengar, R.L. Kashyap, Information integration and synchronization in distributed sensor networks, IEEE Transactions on Systems, Man, and Cybernetics 21 (5) (1991) 1032–1043.
[34] K. Brammer, G. Siffling, Kalman Bucy Filters, Artech House, 1989.
[35] H.F. Durrant-Whyte, Uncertain geometry in robotics, IEEE Transactions on Robotics and Automation 4 (1) (1988) 23–31.
[36] H.R. Hashemipour, S. Roy, A.J. Laub, Decentralized structures for parallel Kalman filters, IEEE Transactions on Automatic Control 33 (1988) 88–93.
[37] J.O. Berger, Statistical Decisions, Springer-Verlag, 1985.
[38] J. Manyika, H. Durrant-Whyte, Data Fusion and Sensor Management: A Decentralized Information-Theoretic Approach, Ellis Horwood, 1994.
[39] Ubila. http://www.ubila.org/.
[40] UCN. http://ace.netmedia.gist.ac.kr/.
[41] Amigo. http://www.hitech-projects.com/euprojects/amigo/.
[42] PERSONA. http://www.aal-persona.org/.
[43] 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.
[44] 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.
[45] 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.
[46] S. Luhr, Recognition of emergent human behaviour in a smart home: A data mining approach, Journal of Pervasive and Mobile Computing 3 (2007) 95–116 (Special issue on Design and Use of Smart Environments).
[47] O. Brdiczka, J. Maisonnasse, P. Reignier, Automatic detection of interaction groups, in: Proceedings of the International Conference on Multimodal Interfaces, 2005, pp. 28–34.
[48] S. Moncrieff, Multi-modal emotive computing in a smart house environment, Journal of Pervasive and Mobile Computing 3 (2) (2007) 74–94 (Special issue on Design and Use of Smart Environments).
[49] M. Laibowitz, J. Gips, R. Aylward, A. Pentland, J.A. Paradiso, A sensor network for social dynamics, in: Proceedings of the International Conference on Information Processing in Sensor Networks, 2006, pp. 483–491.
[50] D.J. Cook, S.K. Das, How smart are our environments? An updated look at the state of the art, Journal of Pervasive and Mobile Computing 3 (2) (2007) 53–73.
[51] 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.
[52] 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.
[53] MIT, House_n Living Laboratory Introduction, 2006. architecture.mit.edu/ house_n/publications.
[54] 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.
[55] 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.
[56] K. Gopalratnam, D.J. Cook, Online sequential prediction via incremental parsing: The active lezi algorithm, IEEE Intelligent Systems 22 (2) (2007).
[57] N. Roy, A. Roy, S.K. Das, Context-aware resource management in multi-inhabitant smart homes: A nash h-learning based approach, in: Proceedings of the IEEE Conference on Pervasive Computing and Communications, 2006, pp. 148–158.
[58] N. Roy, A. Roy, S.K. Das, Context-aware resource management in multi-inhabitant smart homes: A framework based on nash *h*-learning, Journal of Pervasive and Mobile Computing 2 (4) (2006) 372–404.

[59] 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.
[60] U. Maurer, A. Smailagic, D. Siewiorek, M. Deisher, Activity recognition and monitoring using multiple sensors on different body positions, in: Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks, 2006, pp. 99–102.
[61] 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.
[62] D. Cook, M. Schmitter-Edgecombe, Assessing the quality of activities in a smart environment, Methods of Information in Medicine (2009).
[63] O. Brdiczka, P. Reignier, J. Crowley, Detecting individual activities from video in a smart home, in: Proceedings of the International Conference on Knowledge-Based and Intelligent Information and Engineering Systems, 2007, pp. 363–370.
[64] B.K. Hensel, G. Demiris, K.L. Courtney, Defining obtrusiveness in home telehealth technologies: A conceptual framework, Journal of the American Medical Informatics Association 13 (4) (2006) 428–431.
[65] C. Stauffer, E. Grimson, Learning patterns of activity using real-time tracking, IEEE Transactions on Pattern Analysis and Machine Intelligence 22 (8) (2000) 747–757.
[66] 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.
[67] I.L. Liao, D. Fox, H. Kautz, Location-based activity recognition using relational Markov networks, in: Proceedings of the International Joint Conference on Artificial Intelligence, 2005, pp. 773–778.
[68] M. Philipose, J.R. Smith, J. Bing, A. Mamishev, S. Roy, K. Sundara-Rajan, Battery-free wireless identification and sensing, IEEE Pervasive Computing 4 (1) (2005) 37–45.
[69] C. Wren, E. Munguia Tapia, Toward scalable activity recognition for sensor networks, in: Proceedings of the Workshop on Location and Context-Awareness, 2006.
[70] R. Simpson, D. Schreckenghost, E.F. LoPresti, N. Kirsch, Plans and planning in smart homes, in: J. Augusto, C. Nugent (Eds.), Designing Smart Homes: The Role of Artificial Intelligence, Springer Verlag, 2006.
[71] J. Augusto, C. Nugent, The use of temporal reasoning and management of complex events in smart homes, in: R.L. deMántaras, L. Saitta (Eds.), Proceedings of European Conference on Artificial Intelligence, ECAI 2004, August 22-27, IOS Press, Amsterdam, The Netherlands, 2004, pp. 778–782.
[72] G.M. Youngblood, L.B. Holder, D.J. Cook, Managing adaptive versatile environments, Journal of Pervasive and Mobile Computing 1 (4) (2005) 373–403.
[73] 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.
[74] F. Amigoni, N. Gatti, C. Pinciroli, M. Roveri, What planner for ambient intelligence applications? IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans 35 (1) (2005) 7–21.
[75] A. Galton, Qualitative Spatial Change, Oxford University Press, 2000.
[76] B. Gottfried, H. Guesgen, S. Hüebner, Spatiotemporal reasoning for smart homes, in: J.C. Augusto, C.D. Nugent (Eds.), Designing Smart Homes — The Role of Artificial Intelligence, in: LNCS, vol. 4008, Springer, Heidelberg, 2006, pp. 16–34.
[77] J.C. Augusto, H. Wang, J. Liu, Situation assessment during disaster management, International Journal of Computational Intelligence Systems 1 (1) (2008) 237–247.
[78] A. Galton, Eventualities, in: Fisher, Gabbay, Vila (Eds.), Handbook of Temporal Reasoning in Artificial Intelligence, Elsevier, 2005, pp. 25–28.
[79] V. Jakkula, A. Crandall, D.J. Cook, Knowledge discovery in entity based smart environment resident data using temporal relations based data mining, in: Proceedings of the ICDM Workshop on Spatial and Spatio-Temporal Data Mining, 2007.
[80] J.F. Allen, G. Ferguson, Actions and events in interval temporal logic, Journal of Logic and Computation 4 (1994) 531–579.
[81] S. Turkle, Whither psychoanalysis in a computer culture? 2002. futurepositive.synearth.net/2002/11/13.
[82] 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).
[83] C. Brezeal, B. Scassellati, A context-dependent attention system for a social robot, in: Proceedings of the International Joint Conference on Artificial Intelligence, 1999, pp. 1146–1151.
[84] 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: Systems and Humans 35 (1) (2005) 66–77.
[85] A. Hopper, Sentient Computing, 1999.
[86] 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, The Hague, Netherlands, 2000.
[87] A.K. Dey, J. Mankoff, G.D. Abowd, S. Carter, Distributed mediation of ambiguous context in aware environments, in: Proceedings of the Annual Symposium on User Interface Software and Technology, 2002, pp. 121–130.
[88] H. Lei, Context awareness: A practitioners perspective, in: Proceedings of the International Workshop on Ubiquitous Data Management, 2005, pp. 43–52.
[89] J. Rekimoto, M. Saitoh, Augmented surfaces: A spatially continuous work space for hybrid computing environments, in: Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems, 1999, pp. 378–385.
[90] S. Yoshihama, P. Chou, D. Wong, Managing behavior of intelligent environments, in: Proceedings of the IEEE International Conference on Pervasive Computing and Communications, 2003, pp. 330–337.
[91] K. Cheverst, N. Davies, K. Mitchell, A. Friday, C. Efstratiou, Developing a context-aware electronic tourist guide: Some issues and experiences, in: Proceedings of the Conference on Human Factors in Computing Systems, 2000, pp. 17–24.
[92] A. Dix, J. Finlay, G.D. Abowd, R. Beale, Human–Computer Interaction, 3rd ed., Prentice Hall, 2003.
[93] E.J. van Loenen, The ambience project, 2007. www.hitech-projects.com/euprojects/ambience/.
[94] N. Shadbolt, Ambient intelligence, IEEE Intelligent Systems 18 (4) (2003) 2–3.
[95] 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.
[96] S.S. Ge, Y. Yang, T.H. Lee, Hand gesture recognition and tracking based on distributed locally linear embedding, Image and Vision Computing 26 (12) (2008) 1607–1620.
[97] M. Pantic, Face for ambient intelligence, in: Y. Cai, J. Abascal (Eds.), Ambient Intelligence in Everyday Life, Springer, 2006, pp. 32–66.
[98] R. Nakatsu, Integration of multimedia and art for new human–computer communications, in: Proceedings of the Pacific Rim International Conference on Artificial Intelligence, 2002, pp. 19–28.
[99] R. Xu, G. Mei, Z. Ren, C. Kwan, J. Aube, C. Rochet, V. Stanford, Speaker identification and speech recognition using phased arrays, in: Y. Cai, J. Abascal (Eds.), Ambient Intelligence in Everyday Life, Springer, 2006, pp. 227–238.
[100] U. Esnaola, T. Smithers, Whistling to machines, in: Y. Cai, J. Abascal (Eds.), Ambient Intelligence in Everyday Life, Springer, 2006, pp. 198–226.
[101] H. Aghajan, J. Augusto, R.L.-C. Delgado (Eds.), Human-Centric Interfaces for Ambient Intelligence, Elsevier, 2009.
[102] H. Ailisto, A. Kotila, E. Strommer, Ubicom applications and technologies, 2007. www.vtt.fi/inf/pdf/tiedotteet/2003/T2201.pdf.
[103] R. Cantoni, Bodyarchitecture: The evolution of interface towards ambient intelligence, in: G. Riva, F. Vatalaro, F. Davide, M. Alcaniz (Eds.), Ambient Intelligence, IOS Press, 2005.
[104] L. Chen, R.T. Rose, Y. Qiao, I. Kimbara, F. Parrill, H. Welji, T.X. Han, J. Tu, Z. Huang, M. Harper, F. Quek, Y. Xiong, D. McNeill, R. Tuttle, T. Huang, Vace multimodal meeting corpus, in: Proceedings of the International Workshop on Machine Learning for Multimodal Interaction, 2006, pp. 40–51.
[105] S. Burger, V. MavLaren, H. Yu, The isl meeting corpus: The impact of meeting type on speech type, in: Proceedings of the International Conference on Spoken Language Processing, 2002.

[106] J. Garofolo, C. Laprum, M. Michel, V. Stanford, E. Tabassi, The nist meeting room pilot corpus, in: Proceedings of the Language Resource and Evaluation Conference, 2004.
[107] I. McCowan, D. Gatica-Perez, S. Bengio, G. Lathoud, M. Barnard, D. Zhang, Automatic analysis of multimodal group actions in meetings, IEEE Transactions on Pattern Analysis and Machine Intelligence 27 (2005) 305–317.
[108] T. Schultz, A. Waibel, The isl meeting room system, in: Proceedings of the Workshop on Hands-Free Speech Communication, 2001.
[109] CALO, Calo: Cognitive agent that learns and organizes. http://caloproject.sri.com (accessed July 16, 2008).
[110] COGAIN. http://www.cogain.org/.
[111] E. Mendelowitz, J. Burke, Kolo and nebesko: A distributed media control framework for the arts, in: Proceedings of the International Conference on Distributed Frame works for Multimedia Applications, 2005, pp. 113–120.
[112] A. Pentland, Perceptual environments, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004.
[113] P.L. O'Connell, Korea's high-tech utopia, where everything is observed, October 5, 2005.
[114] A. Keshavarz, A.M. Tabar, H. Aghajan, Distributed vision-based reasoning for smart home care, in: Proc. of ACM SenSys Workshop on DSC, October 2006.
[115] M. Bohlen, N. Tan, Garden variety pervasive computing, IEEE Pervasive Computing Mobile and Ubiquitous Systems 3 (1) (2004) 29–34.
[116] P. Brey, Freedom and privacy in ambient intelligence, Ethics and Information Technology 7 (3) (2005) 157–166.
[117] D. Wright, The dark side of ambient intelligence, The Journal of Policy, Regulation and Strategy for Telecommunications 7 (6) (2005) 33–51.
[118] J. Bohn, V. Coroama, M. Langheinrich, F. Mattern, M. Rohs, Social, economic and ethical implications of ambient intelligence and ubiquitous computing, in: W. Weber, J. Rabaey, E. Aarts (Eds.), Ambient Intelligence, Springer, 2005, pp. 5–29.
[119] Privacy Rights Clearinghouse, RFID position statement of consumer privacy and civil liberties organizations, 2003.
[120] J.-H. Do, S.H. Jung, H. Jang, S.-E. Yang, J.-W. Jung, Z. Bien, Gesture-based interface for home appliance control in smart home, in: C. Nugent, J.C. Augusto (Eds.), Smart Homes and Beyond - Proceedings of the 4th International Conference on Smart Homes and Health Telematics, ICOST 2006, June 2006, in: Assistive Technology Research Series, vol. 19, IOS Press, Belfast, UK, 2006, pp. 23–30.
[121] J. Halls, Ultra low resolution thermal imaging for kitchen hazard detection, in: C. Nugent, J.C. Augusto (Eds.), Smart Homes and Beyond - Proceedings of the 4th International Conference On Smart homes and health Telematics, in: Assistive Technology Research Series, vol. 19, IOS Press, Belfast, UK, 2006, pp. 231–238.
[122] J. Delsing, P. Lindgren, Sensor communication technology towards ambient intelligence, Measurement Science and Technology 16 (2005) 37–46.
[123] Y. Cho, S. Cho, D. Choi, S. Jin, K. Chung, C. Park, A location privacy protection mechanism for smart space, in: Information Security Applications, Springer, 2004, pp. 162–173.
[124] F. Zhu, M.W. Mutka, L.M. Ni, The master key: A private authentication approach for pervasive computing environments, in: Proceedings of the International Conference on Pervasive Computing, 2006.
[125] E. Vildjiounaite, S.-M. Mäkelä, M. Lindholm, R. Riihimäki, V. Kyllönen, J. Mäntyjärvi, H. Ailisto, Unobtrusive multimodal biometrics for ensuring privacy and information security with personal devices, in: Proceedings of the International Conference on Pervasive Computing, 2006.
[126] A.N. Joinson, C. Paine, U.-D. Reips, T. Buchanan, Privacy and trust: The role of situational and dispositional variables in online disclosure, in: Workshop on Privacy, Trust and Identity Issues for Ambient Intelligence, 2006.
[127] D. Preuveneers, L. Demuynck, B. Elen, K. Verslype, B.D. Decker, Y. Berbers, P. Verbaeten, Context-driven prevention of unintended identity disclosure, in: Workshop on Privacy, Trust and Identity Issues for Ambient Intelligence, 2006.
[128] A.M.R. Ward, Sensor-driven computing, Ph.D. Thesis, Cambridge University, 1998.
[129] M. Hazas, A. Hopper, Broadband ultrasonic location systems for improved indoor positioning, IEEE Transactions on Mobile Computing 5 (5) (2006) 536–547.
[130] ALADIN. http://www.ambient-lighting.eu/.
[131] G.M. Youngblood, D.J. Cook, Data mining for hierarchical model creation, IEEE Transactions on Systems, Man, and Cybernetics, Part C (2007).
[132] G.M. Youngblood, L.B. Holder, D.J. Cook, Managing adaptive versatile environments, in: Proceedings of the International Conference on Pervasive Computing, 2005, pp. 351–360.
[133] 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.
[134] M. Ali, W. Aref, R. Bose, A. Elmagarmid, A. Helal, I. Kamel, M. Mokbel, NILE-PDT: A phenomenon detection and tracking framework for data stream management systems, in: Proceedings of VLDB'05, 2005, pp. 1295–1298.
[135] H. Hagras, F. Doctor, A. Lopez, V. Callaghan, An incremental adaptive life long learning approach for type-2 fuzzy embedded agents in ambient intelligent environments, IEEE Transactions on Fuzzy Systems (2007).
[136] H. Pigot, A. Mayers, S. Giroux, B. Lefebvre, N.N.V. Rialle, Smart house for frail and cognitive impaired elders, in: First International Workshop on Ubiquitous Computing for Cognitive Aids UbiCog'02, Goteborg, Sweden, September 2002.
[137] B. Bouchard, A. Bouzouane, S. Giroux, A keyhole plan recognition model for alzheimer's patients: First results, Journal of Applied Artificial Intelligence 22 (7) (2007) 1–34.
[138] Siemens, 2006. networks.siemens.de/smarthome/en/index.htm.
[139] M. Berger, Towards ambient intelligence — An industrial view, in: J. Augusto, D. Shapiro (Eds.), Proceedings of the 1st Workshop on Artificial Intelligence Techniques for Ambient Intelligence, AITAmI'2006, Riva del Garda, Italy, 2006, p. 8.
[140] Philips, 2006. www.research.philips.com/technologies/syst_softw/ami/background.html.
[141] B. deRuyter, E. Aarts, Ambient intelligence: Visualizing the future, in: Proceedings of the Conference on Smart Objects and Ambient Intelligence, 2005, pp. 203–208.
[142] Philips, 365 days ambient intelligence research in homelab, 2003. www.research.philips.com/.
[143] B. deRuyter, Social interactions in ambient intelligent environments, in: J. Augusto, D. Shapiro (Eds.), Proceedings of the 1st Workshop on Artificial Intelligence Techniques for Ambient Intelligence, AITAmI'2006, Riva del Garda, Italy, 2006, pp. 9–10.
[144] E. Aarts, J. Encarnacao (Eds.), True Visions: Tales on the Realization of Ambient Intelligence, Springer, Berlin, 2006.
[145] E. Horvitz, P. Koch, J. Apacible, Busybody: Creating and fielding personalized models of the cost of interruption, in: Proceedings of CSCW, Conference on Computer Supported Cooperative Work, ACM Press, 2004, pp. 507–510.
[146] S. Giroux, H. Pigot (Eds.), From Smart Homes to Smart Care (Proceedings of the 3rd International Conference on Smart Homes and Health Telematic, ICOST2005), in: Assistive Technology Research, vol. 15, IOS Press, Sherbrooke, Canada, 2005.
[147] M. Mokhtari (Ed.), Independent Living for Persons with Disabilities and Elderly People (Proceedings of the 1st International Conference on Smart Homes and Health Telematic, ICOST2003), in: Assistive Technology Research, vol. 12, IOS Press, Paris, France, 2003.
[148] C.D. Nugent, J.C. Augusto (Eds.), Proceedings of the 4th International Conference on Smart Homes and Health Telematic, ICOST 2006, in: Assistive Technology Research, vol. 19, IOS Press, Belfast, UK, 2006.
[149] D. Zhang, M. Mokhtari (Eds.), Toward a Human Friendly Assistive Environment (Proceedings of the 2nd International Conference on Smart Homes and Health Telematic, ICOST2004), in: Assistive Technology Research, vol. 14, IOS Press, Singapore, 2004.
[150] Intel Proactive Health, 2006. www.intel.com/research/prohealth/cs-aging_in_place.htm.
[151] Oatfield Estates, 2006. www.elite-care.com/oatfield.html.
[152] C. Larson, In elder care, signing on becomes a way to drop by, February 4, 2007.
[153] S. Lanspery, J.J. Callahan Jr., J.R. Miller, J. Hyde, Introduction: Staying put, in: S. Lanspery, J. Hyde (Eds.), Staying Put: Adapting the Places Instead of the People, Baywood Publishing Company, 1997, pp. 1–22.
[154] L.E. Herbert, P.A. Scherr, J.L. Bienias, D.A. Bennett, D.A. Evans, Alzheimer's disease in the US population: Prevalance estimates using the 2000 census, Archives of Neurology 60 (2000) 1119–1122.

[155] R.L. Ernst, J.W. Hay, The US economic and social costs of alzheimer's disease revisited, American Journal of Public Health 84 (1994) 1261–1264.
[156] P.J. Grayons, Technology and home adaptation, in: S. lanspery, J. Hyde (Eds.), Staying Put: Adapting the Places Instead of the People, Baywood Publishing Company, 1997, pp. 55–74.
[157] J. Gross, A grass-roots effort to grow old at home, August 14, 2007.
[158] G. Smith, S. Della Sala, R.H. Logie, E.A. Maylor, Prospective and retrospective memory in normal aging and ementia: A questionnaire study, Memory 8 (2000) 311–321.
[159] AARP, These four walls…Americans 45+ talk about home and community, 2003.
[160] Commission of the European Communities, Ageing well in the information society: An i2010 initiative, 2007.
[161] 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.
[162] M. Saito, Expanding welfare concept and assistive technology, in: Proceedings of the IEEK Annual Fall Conference, 2000, pp. 156–161.
[163] D.H. Stefanov, Z. Bien, W.-C. Bang, The smart house for older persons and persons with physical disabilities: Structure, technology arrangements, and perspectives, IEEE Transactions on Neural Systems and Rehabilitation Engineering 12 (2) (2004).
[164] P. Vitaliano, D. Echeverria, J. Yi, P. Phillips, H. Young, I. Siegler, Psychophysiological mediators of caregiver stress and differential cognitive decline, Psychology and Aging 20 (3) (2005) 402–411.
[165] 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.
[166] M. Nambu, K. Nakajima, M. Noshira, T. Tamura, An algorithm for the automatic detection of health conditions, IEEE Enginering Medicine Biology Magazine 24 (4) (2005) 38–42.
[167] 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.
[168] A. Helal, M. Schmalz, D. Cook, Smart home-based health platform for behavioral monitoring and alteration of diabetes patients, Journal of Diabetes Science and Technology 3 (1) (2008) 1–8.
[169] K. hao Chang, S. yen Liu, H. hua Chu, J.Y. jen Hsu, C. Chen, T. yun Lin, C. yu Chen, P. Huang, The diet-aware dining table: Observing dietary behaviors over a tabletop surface, in: Proceedings of the International Conference on Pervasive Computing, in: Lecture Notes in Computer Science, vol. 3968, Springer Verlag, 2006, pp. 366–382.
[170] 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.
[171] E.F. LoPresti, A. Mihailidis, N. Kirsch, Assistive technology for cognitive rehabilitation: State of the art, Neuropsychological Rehabilitation 14 (1–2) (2004) 539.
[172] 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.
[173] 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.
[174] G.M. Youngblood, L.B. Holder, D.J. Cook, A learning architecture for automating the intelligent environment, in: Proceedings of the Conference on Innovative Applications of Artificial Intelligence, 2005, pp. 1576–1583.
[175] 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.
[176] 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.
[177] J. Lundell, Ubiquitous computing to support older adults and informal caregivers, in: S. Giroux, H. Pigot (Eds.), From Smart Homes to Smart Care (Proceedings of the 3rd International Conference on Smart Homes and Health Telematic, ICOST2005), in: Assistive Technology Research, vol. 15, IOS Press, Sherbrooke, Canada, 2005, pp. 11–22.
[178] D. Sanchez, M. Tentori, J. Favela, Activity recognition for the smart hospital, IEEE Intelligent Systems 23 (2008) 50–57.
[179] S. Marzano, People as a source of breakthrough innovation, Design Management Review 16 (2) (2005).
[180] Ulster Community and Hospitals Trust, Interim poicy on research governance process, 2005.
[181] Consumer Reports, Profits vs. patients: CR investigates nursing homes, August 2007.
[182] S. Mitchell, M.D. Spiteri, J. Bates, G. Coulouris, Context-aware multimedia computing in the intelligent hospital, in: Proceedings of the ACM SIGOPS European Workshop, 2000.
[183] A. Rakotonirainy, R. Tay, In-vehicle ambient intelligent transport systems (i-vaits): Towards an integrated research, in: Procedings of 7th International IEEE Conference on Intelligent Transportation Systems, ITSC 2004, Washington DC, USA, 2004, pp. 648–651.
[184] A. Pentland, Perceptual environments, in: D. Cook, S. Das (Eds.), Smart Environments: Technologies, Protocols and Applications, Wiley, 2005.
[185] J. Krumm, E. Horvitz, Predestination: Inferring destinations from partial trajectories, in: UbiComp 2006: Eighth International Conference on Ubiquitous Computing, 2006, pp. 243–260.
[186] J. Letchner, J. Krumm, E. Horvitz, Trip router with individualized preferences: Incorporating personalization into route planning, in: Eighteenth Conference on Innovative Applications of Artificial Intelligence, 2006.
[187] S. Dashtinezhad, T. Nadeem, B. Dorohonceanu, C. Borcea, P. Kang, L. Iftode, Trafficview: A driver assistant device for traffic monitoring based on car-to-car communication, in: Proceedings of the Vehicular Technology Conference, 2004, pp. 2946–2950.
[188] S.A. Velastin, B.A. Boghossian, B.P.L. Lo, J. Sun, M.A. Vicencio-Silva, PRISMATICA: Toward ambient intelligence in public transport environments, IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans 35 (1) (2005) 164–182.
[189] G.D. Abowd, Classroom 2000: An experiment with the instrumentation of a living educational environment, IBM Systems Journal 38 (4) (1999) 508–530.
[190] Y. Shi, W. Xie, G. Xu, R. Shi, E. iChen, Y. Mao, F. Liu, The smart classroom: Merging technologies for seamless tele-education, IEEE Pervasive Computing (April–June) (2003) 47–55.
[191] D. Franklin, Cooperating with people: The intelligent classroom, in: Proceedings of the National Conference on Artificial Intelligence, 1998, pp. 555–560.
[192] S.S. Yau, S. Gupta, F. Karim, S. Ahamed, Y. Wang, B. Wang, A smart classroom for enhancing collaborative learning using pervasive computing technology, in: Proceedings of the WFEO World Congress on Engineering Education, 2003.
[193] E. Lank, A. Ichnowski, S. Khatri, Zero knowledge access to a smart classroom environment, in: Proceedings of the Workshop on Ubiquitous Display Environments, 2004.
[194] P. Steurer, M.B. Srivastava, System design of smart table, in: Proceedings of the IEEE International Conference on Pervasive Computing and Communications, 2003, p. 473.
[195] A.F. Bobick, S.S. Intille, J.W. Davis, F. Baird, C.S.P. ez, 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.
[196] 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.
[197] C. Le Gal, Smart offices, in: D.J. Cook, S.K. Das (Eds.), Smart Environments: Technology, Protocols, and Applications, Wiley, 2004.
[198] 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.
[199] V. Stanford, Infrastructure for distributed and embedded systems and interfaces, in: Proceedings of the Embedded Systems, Ambient Intelligence and Smart Surroundings Conference, 2005.

[200] G. Marreiros, R. Santos, C. Ramos, J. Neves, P. Novais, J. Machado, J. Bulas-Cruz, Ambient intelligence in emotion based ubiquitous decision making, in: J.C. Augusto, D. Shapiro (Eds.), Proceedings of the Second Workshop on Artificial Intelligence Techniques for Ambient Intelligence, 2007, pp. 86–91.
[201] M. Stoettinger, Context-awareness in industrial environments, 2004. www.mobile-safety.com.
[202] W. Shen, S. Lang, L. Wang, ishopfloor: An internet-enabled agent-based intelligent shop floor, IEEE Transactions on Systems, Man, and Cybernetics, Part C 35 (3) (2005) 371–381.
[203] H. Nakashima, H. Aghajan, J. Augusto (Eds.), Handbook on Ambient Intelligence and Smart Environments, Springer Verlag, 2009.
[204] Journal on Ambient Intelligence and Smart Environments (JAISE) 1 (1) (2009) (State of the Art in Ambient Intelligence and Smart Environments - Inaugural issue).