Smart Environments for Occupancy Sensing and Services

Susanna Pirttikangas, Yoshito Tobe, and Niwat Thepvilojanapong

1 Overview

The term smart environment refers to a physical space enriched with sensors and computational entities that are seamlessly and invisibly interwoven. A challenge in smart environments is to identify the location of users and physical objects. A smart environment provides location-dependent services by utilizing obtained locations. In many cases, estimating location depends on received signal strength or the relative location of other sensors in the environment. Although devices employed for location detection are evolving, identification of location is still not accurate. Therefore, in addition to devices or utilized physical phenomena, algorithms that enhance the accuracy of location are important. Furthermore, other aspects of utilizing location information need to be considered: who is going to name important places and how are the name ontologies used.

This chapter introduces detecting devices, algorithms that enhance accuracy, and some prototypes of smart environments. Many interesting and open research topics can be identified within the smart environment framework.

2 Detecting Devices

Devices that detect location utilize some kind of physical measurement.The means of measurement range from wireless radio to vision and pressure.

Susanna Pirttikangas
University of Oulu, Oulu, Finland, e-mail: msp@ee.oulu.fi

Yoshito Tobe
Tokyo Denki University, Tokyo, Japan, e-mail: yoshito_tobe@osoite.jp

Niwat Thepvilojanapong
Tokyo Denki University, Tokyo, Japan, e-mail: wat@osoite.jp

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Fig. 1 ActiveBadge (from http://www.cl.cam.ac.uk/research/dtg/attarchive/thebadge.html).

2.1 Infrared

Infrared communications cannot always be used in many environments; they span very short distances and cannot penetrate walls or other obstructions and work only in a direct "line of sight." However, if these shortcomings are not obstacles, they can be used for localization.

An infrared indoor location system was developed by AT&T Cambridge (Fig. 1) [59]. It consists of a cellular proximity system that uses diffuse infrared technology. Each person the system can locate wears a small infrared badge. A central server collects badge data from fixed infrared sensors around the building. As with any diffuse infrared system, Active Badges work poorly in locations with fluorescent lighting or direct sunlight because of the spurious infrared emissions these light sources generate. Diffused infrared radiation has an effective range of several meters, which limits cell sizes to small- or medium-sized rooms.

2.2 Ultrasonic Sound

Ultrasonic sound is in the range 20-100kHz and can be used for localization. Several localization systems have used ultrasonic sound.

2.2.1 Active Bat

AT&T's researchers have developed the Active Bat location system (Fig. 2) [61, 60, 19, 2], which uses an ultrasound time-of-flight lateration technique to provide more accurate physical positioning than Active Badges. The Active Bat system is based on the principle of trilateration – position finding by measurement of distances (the better-known principle of triangulation refers to position finding by measurement of angles). A short pulse of ultrasound is emitted from a transmitter (a Bat) attached

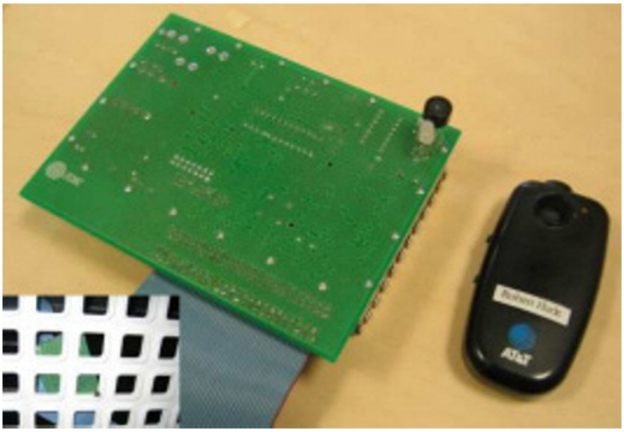

Fig. 2 A ceiling receiver (left) and a Bat (right). Inset: An installed receiver (from [18])

to the object to be located, and the times-of-flight of the pulse to receivers mounted at known points on the ceiling are measured. The speed of sound in air is known, so the distances from the Bat to each receiver can be calculated – given three or more such distances, the 3D position of the Bat can be determined (and hence that of the object on which it is mounted). By finding the relative positions of two or more Bats attached to an object, its orientation can be calculated. Furthermore, some information about the direction in which a person is facing can be deduced, even if they carry only a single Bat, by analysing the pattern of receivers that detected ultrasonic signals from that transmitter and the strength of the signal they detected.

Figure 2 shows a ceiling receiver and a Bat , which may be attached to objects or carried by personnel. Bats measure 7.5cm $\times$ 3.5cm $\times$ 1.5 cm, and are powered by a single 3.6V Lithium Thionyl Chloride cell, which has a lifetime of around fifteen months. Each Bat has a unique 48-bit code and is linked to the fixed location system infrastructure by a bidirectional 433MHz radio link. Bats have two buttons, two LEDs, and a piezo speaker, allowing them to be used as ubiquitous input and output devices, and a voltage monitor that allows their battery status to be interrogated remotely.

2.2.2 Cricket

Complementing the Active Bat system, the Cricket Location Support System [52, 45, 46] uses ultrasound emitters to create the infrastructure and embeds receivers in the object being located. This approach forces the objects to perform all their own triangulation computations. Cricket uses a combination of RF and ultrasound technologies to provide location information to attached host devices. Wall- and ceiling-mounted beacons placed throughout a building publish information on an RF channel. With each RF advertisement, the beacon transmits a concurrent ultrasonic

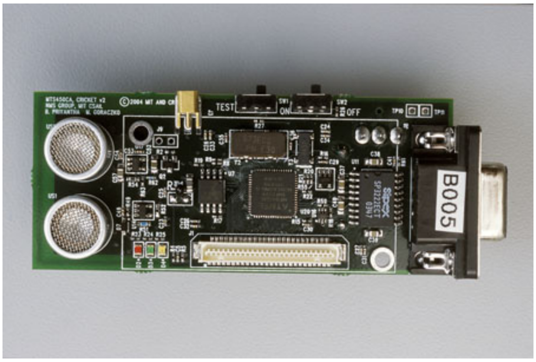

Fig. 3 A cricket device (from http://cricket.csail.mit.edu/)

pulse. Listeners attached to devices and mobiles listen for RF signals, and upon receipt of the first few bits, listen for the corresponding ultrasonic pulse. When this pulse arrives, the listener obtains a distance estimate for the corresponding beacon by taking advantage of the difference in propagation speeds between RF (speed of light) and ultrasound (speed of sound). The listener runs algorithms that correlate RF and ultrasound samples (the latter are simple pulses with no data encoded on them) and pick the best correlation. Even in the presence of several competing beacon transmissions, Cricket achieves good precision and accuracy quickly. In addition to determining spaces and estimating position coordinates, Cricket provides an indoor orientation capability via the Cricket compass.

A Cricket listener connects to the host device via an RS232 serial connection. The Cricket beacon and listener are identical hardware devices (see Figure 3). A Cricket unit can function as either a beacon or a listener, or it can be used in a "mixed" mode in a symmetric location architecture (which may be appropriate in some sensor computing scenarios), all under software control. A variety of sensors can be attached to a Cricket device via the 51-pin connector on the Cricket. There are prototypes of Crickets with a Compact Flash (CF) interface, which may be a more convenient way to attach to handhelds and laptops than the RS232 interface.

2.2.3 DOLPHIN

Inherently, a trilateration-based positioning system such as the Active Bat and Cricket systems requires precisely positioned references. Since an ultrasonic signal usually can propagate less than five meters and does not penetrate obstacles, a large number of references are required to locate objects in an actual indoor environment. To overcome the configuration cost of an indoor location system, Minami et al. [36] designed and implemented a fully distributed indoor ultrasonic positioning system called DOLPHIN (Distributed Object Localization System for Physical-space Internetworking) that locates various indoor objects based on a distributed positioning algorithm similar to iterative multilateration.

In the positioning algorithm, the nodes in the system play three different roles in a sequence: there is one master node, one transmitter node, and the rest are receiver nodes. A node that has determined its position can become a master node or a transmitter node. In every positioning cycle, the master node sends a message via an RF transceiver for time synchronization of all nodes. When a transmitter node receives the message, it sends an ultrasonic pulse. At the same time, each receiver node starts its internal counter and stops it as soon the ultrasonic pulse arrives. The receiver nodes that received the ultrasonic pulse then compute the distance to the transmitter node. If a receiver node measures a sufficient number of distances, it computes its position based on multilateration.

2.3 FM Radio

Frequency Modulation (FM) radio can also be utilized for localization. The motivation for this method comes from a new class of smart personal objects that receive digital data encoded in regular FM radio broadcasts. Krumm et al. [30] propose RightSPOT, a simple algorithm for computing the location of a device based on signal strengths from FM radio stations. RightSPOT uses a vector of radio signal strengths taken from different frequencies to identify location. Each time a location is to be inferred, the device scans through a set of FM frequencies and records the signal strength of each one. The Bayesian classification algorithm does not use absolute signal strengths, but instead uses a ranking of signal strengths to help ensure robustness across devices and other variables. This classification is motivated by the assumption that different locations will show different relative signal strengths.

2.4 WiFi

In general [21], [13], location estimation using radio frequency (RF) is done by building a radio map that tabulates signal strength values sent by access points in the environment. In order to provide accurate results, this tabulation needs to be done with a very high density - every few square meters. With this map, a statistical or deterministic prediction model for the area of interest is built [63]. Location can then be estimated by utilizing Euclidean distance to calculate the similarity of two radio scans [4]. [32] provides an excellent reference list to the subject.

Another problem is locating small devices in a sensor network using reference-sensors that have a predetermined location. Then, location of the devices needs to be obtained recursively.

2.5 Ultra-Wideband

Ultra-wideband (UWB) radio is a relatively new technology [16, 51] that utilizes electromagnetic pulses of very short duration (sub-nanosecond) and a wide bandwidth (several gigahertz). A transmitter emits such a pulse, and receivers accurately measure the local time-of-arrival of the pulse with high resolution and accuracy in real-time using a microwave hardware design. Such resolution and accuracy are needed for positioning at indoor (sub-meter) scales since radio pulses propagate at very close to the speed of light. To date, UWB positioning systems have typically employed one of two architectures: (i) a set of stationary receivers that are tightly synchronized by wire estimate the local time-differences-of-arrival of a pulse emitted by a mobile tag; or (ii) pairs of wireless nodes (such as those in an ad hoc sensor network) measure the round-trip times-of-flight of UWB pulses to estimate inter-node ranges. These time-differences-of-arrival or ranges are then fed into an appropriate location algorithm (such as multi-lateration using nonlinear regression, or a Kalman filter) to produce a location estimate for the mobile tag or sensor nodes. In open environments without obstructions that significantly attenuate or reflect the UWB pulses, accuracies of several tens of centimeters are easily achievable.

UWB positioning pulses can propagate through internal building walls without much attenuation, and UWB receivers can incorporate an array design to additionally estimate the angle-of-arrival (azimuth and elevation) of the incoming pulse. As a result, a much lower sensor density may be required to get an accurate positioning result, compared with other similarly fine-grained positioning technologies. However, this accuracy may not satisfy all applications (such as those involving real-time user interfaces or augmented/virtual reality), and multipath fading remains a challenge, particularly for indoor home, office and industrial environments [33].

2.6 Vision

A person can be tracked by cameras. As presented in [9], a person is tracked in crowded and/or unknown environments using multi-modal integration. This combines stereo, color, and face detection modules into a single robust system. Dense, real-time stereo processing is used to isolate users from other objects and people in the background. Skin-hue classification identifies and tracks likely body parts within the silhouette of a user. Face pattern detection differentiates and localizes the face within the identified body parts. Faces and bodies of users are tracked over several temporal scales: short-term (user stays within the field of view), medium-term (user exits/reenters within minutes), and long-term (user returns after hours or days).

2.7 Pressure

Smart floor techniques provide location estimation by utilizing embedded pressure sensors that capture footsteps. These systems use the data for position tracking, distinguishing between robots, animals and humans, recognizing gender, classifying the correctness of sport activity, evaluating different gait-related injuries in medical studies, and pedestrian biometric identification. The main advantage of these systems is that the user does not need to carry or wear a device or tags. However, installation of the floor is time-consuming and expensive.

In addition to the Active Badge system, the same researchers developed the Active Floor [1]. This was one of the first smart floor systems and it was built from load cells composed of L168 aluminum alloy. The compressive load on the cell is measured by a 350 Ω full bridge strain gauge and the measured quantity is called the ground reaction force (GRF). The prototype of the active floor consisted of a 4x4 array of load cells. The active floor was constructed over normal flooring. Similar floor cells were utilized in [41]. In these experiments, Hidden Markov models and nearest neighborhood classification were used to identify and track persons on the active floor. A recent study that utilizes the GRF sensor is presented in [47]. In this study, support vector machines are the main technique for analyzing the data the floor produces.

The EMFi floor is a pressure-sensitive floor that has been installed under the normal flooring of the University of Oulu's robotics research laboratory. The material, Electro-Mechanical Film [42] (EMFi), is a thin, flexible, low-price electret material that consists of cellular, oriented polypropylene film coated with metal electrodes. In the EMFi's manufacturing process, a special voided internal structure is created in the polypropylene layer, which makes it possible to store a large permanent charge in the film with a corona method using electric fields that exceed the EMFi's dielectric strength. An external force affecting the EMFi surface causes a change in the film's thickness, resulting in a change in the charge between the conductive metal layers. This charge can then be detected as a voltage.

The EMFi- floor in the laboratory is constructed of 30 vertical and 34 horizontal EMFi- sensor stripes, 30 cm wide each, which are placed under the laboratory's normal flooring (see Figure 4). So the stripes form a 30x34 matrix with a cell size of 30x30 cm. Each stripe out of a total of 64 produces a continuous signal that is sampled at a rate of 100Hz and streamed into a PC, where the data can be analyzed in order to detect and recognize the pressure events, such as footsteps, affecting the floor. This floor has been utilized to identify persons, distinguish between a robot and a human, detect abnormal events on the floor, and track people walking on the floor [57], [28].

Simple ON/OFF switch sensors have been used in [64]. This Ubifloor recognizes users with a multilayer perceptron. The sizes of the installations range from small constellations comprised of a few cells to big rooms equipped with sensors [56], [38]. Markov chains, support vector machines, and combined classifiers have been utilized in different tasks that are mentioned in the beginning of this section. In many

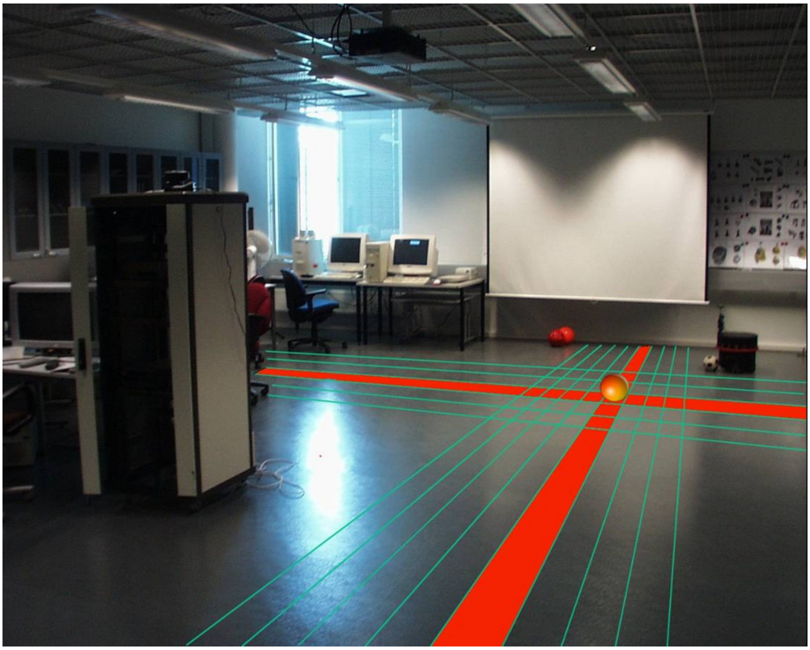

Fig. 4 Setup of EMFi- sensor stripes under the University of Oulu laboratory's normal flooring.

cases, not only one footstep, but consecutive footsteps need to taken into account in making the final decision on the identity or location of the person.

3 Estimation Algorithms

Pervasive computing systems seek to maintain current information about the status of users/objects/environments or relevant data about the situation. Occupancy sensing is aiming at providing abstract information about the users places, rather than locations as coordinates. Furthermore, one must consider whether he is interested in determining the movement of a person/object, the static position of a person/object, or the relative distance between two objects - all depending on the application.

3.1 Location Estimation

The location-awareness of Ubicomp-applications is a key element in providing calm and smart services for users. Actually, location information is the most intuitively and easily exploitable of all the context variables one could think of. Naturally, exploitation starts by creating a locating system by providing the environment and the users with sensors and developing algorithms for estimating the location of different actuators in the environment.

When location is measured, the measurement needs to be processed to remove any artifacts and noise, whatever the sensing apparatus is. This removal can be called smoothing or averaging the location estimates. While simple averaging (geometric mean) of measurements in a certain time window might be a good solution for some cases, there is a constant need for multi-sensor fusion and more sophisticated techniques in pervasive computing.

Unfortunately, in the real world, things are under constant change. Therefore, the algorithms we utilize need to be dynamic in nature or the system will need to be modified and calibrated frequently. For example, when trying to locate a user who is using a wireless LAN, one needs to take into account the fact that the signals are prone to environmental variations and the terminals might not work optimally in terms of battery life or local resources of the device. The signal strength is not the same in different locations, even at the same distance from the access points, due to blocks or reflections in the environment.

3.2 WiFi Locationing

Three techniques and different metrics for evaluating the characteristics of 802.11 location estimation are described in Table 3.2 (freely modified from [32]).

3.3 GSM cells and GPS

In the previous sections we described location estimation using WiFi. A second considerable method for locating is utilizes GSM cell-network information. According to [20] the most popular algorithm for estimating location from GSM cells is a particle filter variation utilizing point estimation that places the estimate to the latest measurement. A good comparison on algorithms for location estimation with cellular network data in different settings is presented in [8].

Locating with the NAVSTAR Global Positioning System (GPS) presents very advanced technology and is utilized in many applications, the most natural being vehicle navigation. The technique was developed for the U.S. military [15]. To get an accurate location, one needs to have visibility to at least four satellites, and the basic algorithm determines the position of a GPS receiver by utilizing Euclidean distances [37]. The satellites send signals and the positioning is done on the receiver devices. It is possible, with different techniques, to specify the location of a receiver with an accuracy of a few millimeters [55].

There are drawbacks in using GPS, as it requires a clear view to at least four satellites at all times for the GPS receiver to estimate the position. This kind of

Technology	802.11 signal-strength fingerprinting	802.11 signal-strength modeling	802.11 proximity
Accuracy	2D coordinates with 1-3 m median accuracy	2D coordinates with 10-20m median accuracy	Location accuracy dependent on AP density
Coverage	Building to campus scale. Requires 802.11 coverage and radio map. Best accuracy achieved when 3+ APs are visible.	Areas with 802.11. coverage and radio map. Best accuracy achieved when 3+ APs visible.	Anywhere with 802.11 coverage and an AP location map.
Infrastructure cost	No Additional infrastructure needed beyond 802.11 APs. Creating a radio map is time-intensive and new/removed APs require remapping.	No additional infrastructure is needed beyond 802.11 APs. Creating radio maps is less work than for fingerprinting.	No additional infrastructure is needed beyond 802.11 APs.
Per-client cost	Software-only solution for devices with 802.11 NICs.	Software-only solution for devices with 802.11 NICs.	Software-only solution for devices with 802.11 NICs.
Privacy	Very good when localization is performed on the client, but poor when localization is performed in the infrastructure.	Very good when localization is performed on the client, but poor when localization is performed in the infrastructure.	Very good when localization is performed on the client, but poor when localization is performed in the infrastructure.
Well-matched use cases	Asset and personnel tracking in indoor environments, indoor mapping/navigation/tour guides.	Social networking, tour guides, indoor/outdoor navigation/tour guides, fitness/activity tracking.	Outdoor tour guides, nearby resource advertisement, activity tracking.

Table 1 Metrics for evaluating three different WiFi location estimation methods (from [32]).

system preserves privacy, as the individual receiver makes the location estimation and it also assures worldwide coverage for all users. A side effect is that the GPS signal sent from the satellites does not penetrate walls, soil, nor water, and therefore, it cannot be used indoors, underground, or under water. In cities, tall buildings affect coverage.

3.4 Bayes Filtering

To fuse the location measurements from various sources and remove measurement noise, the most widely applied methods are Bayesian filters. Bayesian filters use noisy measurements to estimate a system's state in a probabilistic way. Usually the angle and distance between the observed object and the observer, are estimated. A good overview of Bayesian techniques for location estimation can be found in [14].

3.4.1 Kalman Filtering

The Kalman filter is an efficient and easily implementable algorithm for estimating and predicting the system's state $S(n+1)$. The system's state is estimated by measurements $z(n)$, according to a measurement and state model.

The Kalman filter is especially suitable for tracking [26], [6], [44], [53].

In addition, the Extended Kalman Filter (EKF) is also used to solve the tracking problem. There are three dynamical EKF models [65] in tracking based on the amount of internal states that the target estimates: Position (P) model, Position-Velocity (PV) model, and Position-Velocity-Acceleration (PVA) model. As one would expect, the PVA model achieves the best tracking results.

3.5 Particle Filtering

A special form of Bayesian filters, that is, particle filters, estimate the location of a user at time t by utilizing a collection of weighted particles p_t^i,w_t^i, $(i = 1,\ldots,n)$. The user's position is assumed to be represented by each p_t^i and the weight w_t^i is a likelihood that the user is in the location that the particle presents.

Particle filters have been used in robotics [17], as a very nice property of particle filters is that you can fuse many different kinds of sensor measurements to your locating system. Furthermore, [20] show that the particle filter approach is as accurate as deterministic algorithms and is practical to implement and utilize on small devices.

4 From Measurements to Meaning and Services

In this section we present different location-aware services in pervasive computing research. Location awareness is a term used for something, a system, device or object, that is aware of its or the wearers' current location.

4.1 Location-Aware Reminders

In pervasive computing, the first applications presented that utilized location information were context-aware reminders. However, utilization of these applications has not reached the larger community, yet, because the locating systems have been restricted to certain areas, such as campuses or office buildings.

One of the first reminders was Commotion [35]. Commotion utilizes GPS to locate a mobile device and people could set reminders into specific locations. Users were given reminders whenever they approached the location (within a certain user-set time limit).

The authors [11] developed Cybreminder, where location information was not the only trigger for a reminder. In their research, the main importance was to develop a toolkit [10] and a framework for easy development of context-aware applications.

A distributed location beacon system feeds MemoClip, which is a location-based wearable reminder appliance [5]. Another wearable reminder application is the Sulawesi system, where the user is located by GPS and infrared signals [39].

Stick-e Notes [7] and Place-Its [54] are designed to resemble post-its, and they are located in the environment using GPS-enabled PDA's (stick-e) or Symbian Series 60 mobile phones (Place-Its). Place-Its advantage over Stick-e is the ability to locate the device with GSM cell tower information in addition to GPS.

4.2 A Scenario on Routine Learning

After having measured and estimated a location that is satisfiable in some sense (e.g. in accuracy, speed or computational complexity, or cost) we can utilize the information to infer a higher level context. In a smart environment, it is not enough that the system reacts to the user's behavior, it is necessary to learn from the past and predict the next move. With the right algorithms, locations evolve into a significant place, and from significant places one can find traces and paths and then predict the user's next moves.

The scenario might be as follows (from [43]).

Marie buys a new mobile device. She is not very familiar with all the services the device has to offer, so it is mainly used as a phone. Marie has an electronic calendar, also. She takes the phone everywhere she goes.

Fig. 5 A scenario of utilizing the user's routines and significant places. (from [43])

After a week, the device asks Marie if she wants to get familiar with all the possibilities the device has to offer. If Marie would help the device place her important locations on the map, she could start to use the location-sensitive services, for example. From her friends, Marie has heard that these services are really convenient and wants to try them. The phone presents the places Marie has frequently visited on a map and asks her to name these places. Marie names the places and for some time she plays with the new navigation service, which is activated by clicking the names of the places in the calendar. The device shows a route from her current location to the clicked place.

Marie cannot believe her eyes when the device asks whether she would like the device to go automatically into a silent mode when she enters her office's meeting room. This is something she has been waiting for! Marie has a meeting in half an hour at her office, and she is still at home. The device reminds her that now it is time to go. Marie goes to the meeting at the office. The device is silent.

4.2.1 The Significant Place

Typically, algorithms will need a certain amount of data to learn the routines of a user. First, the significant location is recognized and then one can start making assumptions about traces, paths or sequences of places from the data. In section 4.2.3, we describe different experiments and collected data.

An interesting fact is that in the beginning of this research the significant place was not actually recognized from the measurements, but from the *lack* of measurement. Marmasse [35] and Ashbrook [3] both utilize the GPS signal, which is lost when the user goes indoors. They estimate the time that the signal is out of reach and also the distance between the spot where it disappeared and came up again (to identify cases when the GPS is being shut down instead of going into a building).

An important requirement that a place recognition algorithm needs to fulfill is that it needs to be able to handle the transition phase between two important places. If one utilizes a simple clustering algorithm, like k-means (or a modification like in [3]) or the Gaussian Mixture Model [24], the clusters that are formed include the coordinates from the transition places. Therefore, the algorithm should filter unimportant coordinates by dropping clusters where a smaller amount of time is being spent, like in [25]. Their algorithm reforms a new cluster whenever the stream of coordinates moves away from the current cluster. This approach also bypasses the limitation of traditional clustering algorithms, that the number of clusters needs to be determined beforehand.

Besides locating information, one can use sensors like accelerometers or magnetic sensors [58] or bus schedules and stop locations [34] as additional information to determine important locations. The latest developments have been automatic identification of meaningful places from GPS data [40]. In their framework, a Bayesian approach that is fully automatic and does not require any parameter tuning is presented.

The above algorithms utilize GPS signals for locationing, but [31] have used GSM-network cell information and developed their own algorithm to recognize important locations and routes. The problem with utilizing GSM cells is that the cells are large and a single cell may contain several significant locations. They state that their algorithms would work better with WiFi instead of cell-networks.

BeaconPrint is a framework and a technical foundation for recognizing and labeling significant places from both GPS and 802.11 radio [22]. In their algorithms, they emphasize the importance of recognizing places that are visited infrequently or for short durations.

4.2.2 The Routine

After the important locations have been identified, the user needs to name them or the system needs to *geocode* them. In a small-scale environment, such as an office, the infrared or ultrasound beacons can include the location name listing in the system, but this will become too hard in larger-scale environments that utilize GSM cells or GPS. Usually, manual labeling needs to be performed in these systems (see Fig. 6) . Naming the places is a difficult problem, as the naming conventions are personal and multi-dimensional.

When the places have been learned, the path can be predicted and the user's routines can be found from the data. A typical algorithm for user path prediction is the Markov model and its variations [12], [3], [35]. For example, in [3], significant locations were clustered from GPS data and they formed a Markov model for each location with transactions to every other location. Each node in the Markov model was a location, and a transition is the probability that the user is traveling between the locations.

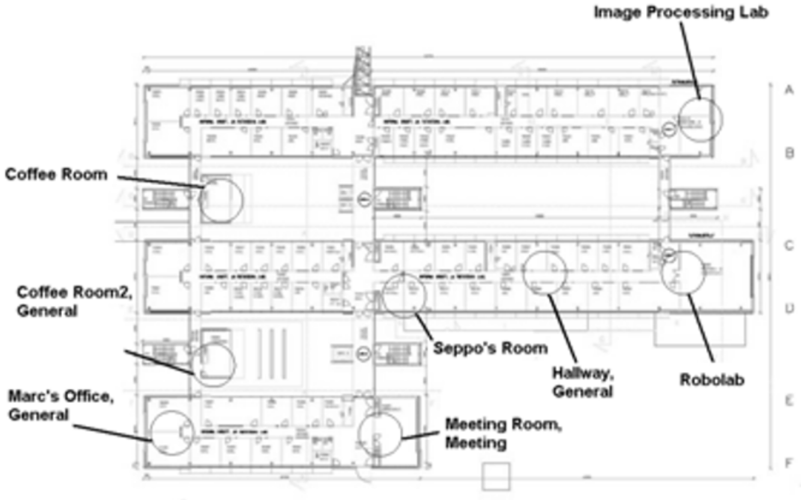

Fig. 6 Office space where the important locations have been recognized from WiFi data and the places have been prompted from the user. (from [43])

An effort has also been made to recognize relative position with respect to other people in [12]. They utilized a standard Bluetooth-enabled mobile phone and recognized social patterns in daily user activity, inferring relationships, identifying socially significant locations, and modeling organizational rhythms.

4.2.3 Data Collection tasks

Data-collection must be long enough to capture the routines and the typical behavior of the users. In this section, we discuss the different data sets collected during place recognition experiments.

In [3], they collected four months of data from a single user and it resulted in hundreds of thousands of GPS coordinates to be classified into significant locations. Also, single user data sets were collected in [40]. Here the period was one year instead of one month. The researcher was living normally in the city of Encschede and recorded daily situations with a Nokia 6680 mobile phone and an external Bluetooth GPS receiver, resulting in 700 distinct location measurements (duplicates filtered)).

They also had a second dataset collected in Innsbruck during Ubicomp 2007 for recognizing work and tourism-related location traces.

To develop BeaconPrint [22], one month of multi-sensor data (802.11 and GSM radios) were collected from three persons. GSM cellular data were collected from three users covering the period of six months, in [31].

The data collection periods are long-lasting but usually only a few persons have participated. This is because the equipment has not been available in, for example, ordinary mobile phones. The situation is changing rapidly and many mobile devices have the capability to measure location in different ways, and therefore more statistically meaningful results can be achieved in future field tests. It is very expensive to start field testing in which people need to be given new devices and instructions for performing the tests, and to follow through the experiment and analyze the results. However, the authors' view is that bringing technology to people is the only way to learn and improve systems and make technologies main-stream.

5 Platforms of smart environments

This section introduces some platforms of smart environments that were actually built.

5.1 EasyLiving

The EasyLiving system [29] is a smart environment that utilizes computer vision developed at Microsoft Research. It focuses on tracking a person and visual interaction between the system and people (Figure 7). For example, if a user has a desktop (interactive computing session) open and is using one set of devices and then moves to another suitably equipped location, the desktop moves to those devices. Additionally, the lights come on and off based on the user's location, and an appropriate set of audio speakers can be selected using knowledge of the location of the speakers and the user.

EasyLiving has 4 different sensors that measure location and identity: cameras, pressure mats, a thumbprint reader, and a keyboard login system. 3-D stereo cameras measure the location of foreground people-shaped blobs and reports position measurements as a 3-coordinate tuple. The pressure mats periodically report their binary state, i.e., whether a person is sitting or standing on them. The thumbprint reader and the login system report once whenever someone uses them to identify themselves.

The person-tracking module combines past person-tracking history, knowledge about where people are likely to appear in the room, pressure-mat measurements, and the most recent camera measurements to produce a database of continually updated estimates of where particular people are located. Since the camera sen-

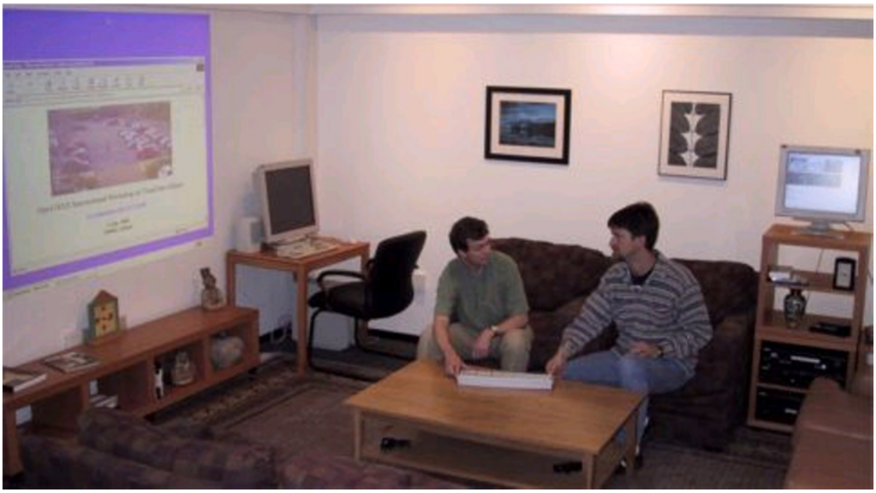

Fig. 7 EasyLiving (from http://research.microsoft.com/easyliving/).

Fig. 8 AwareHome (from http://awarehome.imtc.gatech.edu/).

sors cannot determine identity, but rather can only keep track of the identity of a blob once it is assigned, this layer combines measurements from the login sensors with the person tracking information. Knowing where the keyboard and thumbprint reader are located, when a person-identification event occurs, the person track can be assigned a unique identity (The person tracking system need never know the actual identity of the person it is tracking; all it knows is an ID number, which it assigns when the person arrives). The output of the person-tracking module is a list of locations of people in the 2D plane.

5.2 Aware Home

The Georgia Institute of Technology has developed a platform called Aware Home for a home domain [27]. The research focuses on evaluating user experiences of domestic technologies with the background of health, education, entertainment, and usable security. The location of the user is detected with the following techniques.

- **RFID floor mat system**. This system gives room-level information about people. Floor-mat-antennas are placed at known locations in the home and each has unique information about location. The inhabitants have to wear a passive RFID tag below their knees, usually in their shoes, as the floor mat antenna identifies the person during walks.

- **Computer vision techniques**. Sometimes room-level information is not enough and more information is required, like where somebody is in the room. computer vision techniques are used in Aware Home to get the whereabouts of people in the home automatically. This technique does not identify people, it gives information about the location and orientation of moving objects. In this system cameras are installed in the ceiling, four cameras in the kitchen, four cameras in the living room and six cameras in the hallway.
- **Audio techniques**. Voice techniques can be used to identify a person as each individual has their own unique voice. The system has two modes, 'training mode' and 'test mode'. In the training mode, first the user's voice is recorded and various characteristic parameters of the voice are extracted and then stored in a feature vector. In the test mode, a person is recognized by his voice; the voice is first recorded and then its characteristic parameters are extracted and compared with the feature vector. The closest match is the current speaker in the system.
- **Finger print detection**. Fingerprint techniques are also used to identify people. Scanners are installed at door locks, with each scanner having a unique location in the home. Scanners scan the fingerprints and identify the person.

5.3 PlaceLab House_n

PlaceLab House_n, developed by Massachusetts Institute of Technology and TIAX LLC, is a residential condominium consisting of smart components [23]. Hundreds of sensing components installed in the home are used to monitor activity in the environment. Each of the interior components contains a micro controller and a network of 25 to 30 sensors.

Small, wired and wireless sensors are located on the objects that people touch and use, including cabinet doors and drawers, controls, furniture, passage doors, windows, kitchen containers, etc. They detect on-off, open-closed, and object movement events. Radio frequency devices permit identification and approximate position detection of people within the PlaceLab. Nine infrared cameras, nine color cameras, and 18 microphones are distributed throughout the apartment in cabinet components and above working surfaces, such as the office desk and kitchen counters. Eighteen computers use image-processing algorithms to select the four video streams and one audio stream that may best capture an occupant's behavior, based on motion and the camera layout in the environment. They also study the positioning accuracy of a GSM beacon-based locating system in the environment.

Fig. 9 Place Lab House_n (from http://architecture.mit.edu/house_n/placelab.html).

5.4 Robotic Room

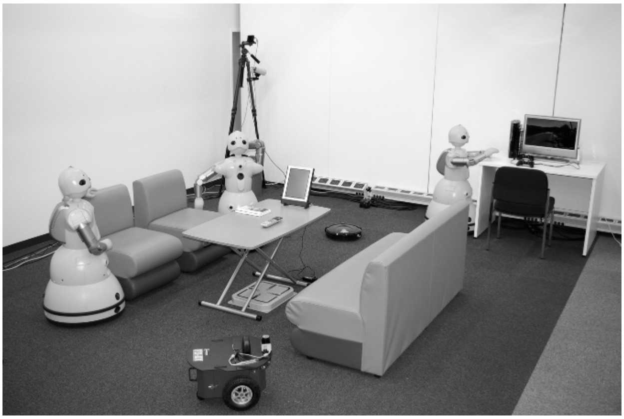

Fig. 10 Robotic Room (from http://www.ics.t.u-tokyo.ac.jp/index-j.html).

A group from the University of Tokyo has created a Robotic Room to identify a person's activity in order to support human living [48, 49, 50]. Functions of monitoring human respiration by TV camera on the ceiling or pressure sensors on the surface of the bed were realized. A human motion tracking system is based on a full body model and a bed fitted with pressure sensors. The full body model consists of a skeleton and a surface model. The bed has 210 pressure sensors under the mattress. It can measure the pressure distribution image of a lying person. The lying person's motion is tracked by considering potential energy, momentum, and the difference between the measured pressure distribution image and a pressure distribution image calculated from the full body model.

6 Conclusion

In this chapter we have different devices, techniques, and prototypes for detecting a person occupying a smart environment. The locating devices and algorithms most widely utilized in pervasive computing were listed. Tables were presented in which the different approaches are compared to each other. Occupancy sensing was widely examined in this chapter, and references to state-of-tha-art technology were given.

One cannot say which is the perfect locating method or device in different situations. The accuracy of the system is one of the main driving forces. Also privacy issues need to be considered. In many countries the law states that a person's location information cannot be utilized without permission. Furthermore, people do not want to be located everywhere and all the time. Fortunately, with the current technologies, the users can perform locating themselves on the client side. Different solutions have been presented for anonymous locating [32], but still real privacy needs to be sought for, as it is important that the users can feel safe in using the services available.

An obvious matter that one needs to remember is that location is not free. For example, setting up a WiFi locating system requires installation of several access points and also, manual calibration of the map of the area and the corresponding signal strengths. Not to mention the costs of satellite locating systems. Administration of the systems also costs money.

The services that one can offer by utilizing occupancy sensing are vast, from navigation and memory aids, automatic lifeblogging, and shopping aids to military applications, gaming, etc. The next phase is when the systems can really accurately predict the users' next moves. Efforts have been made in this kind of behavioral analysis, but we still rely on current information rather than utilizing history and future data. How to accurately classify what is happening now, where, why, and next is still an open research problem.

It can be noted that pervasive systems are getting more and more complex. The authors' opinion is that combining many locating algorithms will provide a better solution than utilizing only one single technique. When location can be obtained from anywhere, anytime, and by anyone, the new sensor fusion techniques can be seen as the winning party. One promising effort has been made in [62], where a map of a building, a wearable acceleration sensor, and WiFi (particle filter locating) were utilized to locate pedestrians. The systems are more expensive now, but as they become more common and when proper software libraries for a wide variety of locating sensors have been made, increased accuracy and ease of use can be expected.

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