Ann. Telecommun. (2010) 65:505–521
DOI 10.1007/s12243-010-0176-0

Health and wellness monitoring through wearable and ambient sensors: exemplars from home-based care of elderly with mild dementia

Jit Biswas · Andrei Tolstikov · Maniyeri Jayachandran · Victor Foo · Aung Aung Phyo Wai · Clifton Phua · Weimin Huang · Louis Shue · Kavitha Gopalakrishnan · Jer-En Lee · Philip Yap

Received: 18 November 2009 / Accepted: 12 April 2010 / Published online: 16 May 2010

Abstract Monitoring and timely intervention are extremely important in the continuous management of health and wellness among all segments of the population, but particularly among those with mild dementia. In relation to this, we prescribe three design principles for the construction of services and applications. These are ambient intelligence, service continuity, and micro-context. In this paper, we provide three exemplars from our research and development activities that illustrate the use of these design principles in the construction of services and applications. All the applications are drawn from the field of care for mild dementia patients in their living quarters.

Keywords Activity recognition · Context awareness · Ambient intelligence · Mild dementia · Smart homes · Health telematics

1 Introduction

The importance of continuous health and wellness monitoring [1, 2] is increasingly being emphasized these days. It is said that the management of health should progress to the management of wellness, which is beginning to assume a more holistic view of the quality of life of an individual, the emphasis being on proactive management of wellness, rather than reactive management of illness. There is widespread consensus that proactive management of wellness and independent living (i.e., elderly people living in their own homes with minimal help from caregivers) go hand in hand. But, living alone, elderly must be monitored continuously because their declining functional and cognitive abilities render them susceptible to many dangers and medical complications.

Our focus among the elderly is on those diagnosed with mild dementia. This group of elderly people need special attention since they suffer from some conditions that make them particularly vulnerable to problems while living alone (see Table 1). In order to understand how the "management of wellness" should be carried out for mild dementia patients in their living quarters, we have primarily relied on an inductive approach from an application-driven perspective. In this paper, we present applications and services for elderly with mild dementia. These applications and services have different levels of ambient intelligence and make use of wireless sensor networks and back-end systems to provide flexible services. Three design principles permeate through these applications. These are ambient intelligence, service continuity, and micro-context. *Ambient intelligence* is a core requirement in an architecture that supports human centric computing. It is based on the presupposition that sensors are available in the ambient environment in a ubiquitous manner, and sensor-acquired data are being continuously analyzed and processed, in order to provide high level summary information as well as event information. *Service continuity* is associated with mobility of one or more active agents in the system. One of the core requirements of

J. Biswas (✉) · A. Tolstikov · M. Jayachandran · V. Foo · A. A. P. Wai · C. Phua · W. Huang · L. Shue · K. Gopalakrishnan
Institute for Infocomm Research, I^{2}R,
Singapore, Republic of Singapore
e-mail: biswas@i2r.a-star.edu.sg

J.-E. Lee · P. Yap
Alexandra Hospital,
Singapore, Republic of Singapore

Table 1 Level of cognitive decline and corresponding deficits [3]

Level	Severity of dementia	Subjective and objective deficits
1	No cognitive decline	No subjective or objective deficits
2	Very mild cognitive decline	Some subjective complaints, no objective deficits
3	Mild cognitive decline	Mild working memory deficits (attention, concentration)
4	Moderate cognitive decline	Episodic memory deficits (memory of recent events)
5	Moderately severe cognitive decline	Explicit memory deficits (ability to accomplish usual tasks)
6	Severe cognitive decline	Severe memory deficits (which cause delusion)
7	Very severe cognitive decline	All verbal activities are lost

service continuity is the reliable forwarding of events and user data. Finally, *micro-context* is a collection of software and systems based on underlying sensors and sensor networks which permits the recognition and use of fragments of information about a user and the user's activity context that may be germane to a particular line of reasoning. Thus, micro-context may be regarded as a sensor-based enabling technology for ambient intelligence. Instead of going further into each of these three design principles, we discuss services and applications where they have been emphasized and exemplified.

The applications and services in our system are depicted in Fig. 1. There are six loosely coupled applications and services, namely:

I. The wearable device monitoring service (WDMS)

The first service is the *wearable device monitoring service*. It comprises the device and its associated hardware and software components that must be put in place and activated for the purpose of continuously monitoring certain physiological parameters or physical activity level of the wearer of the device.

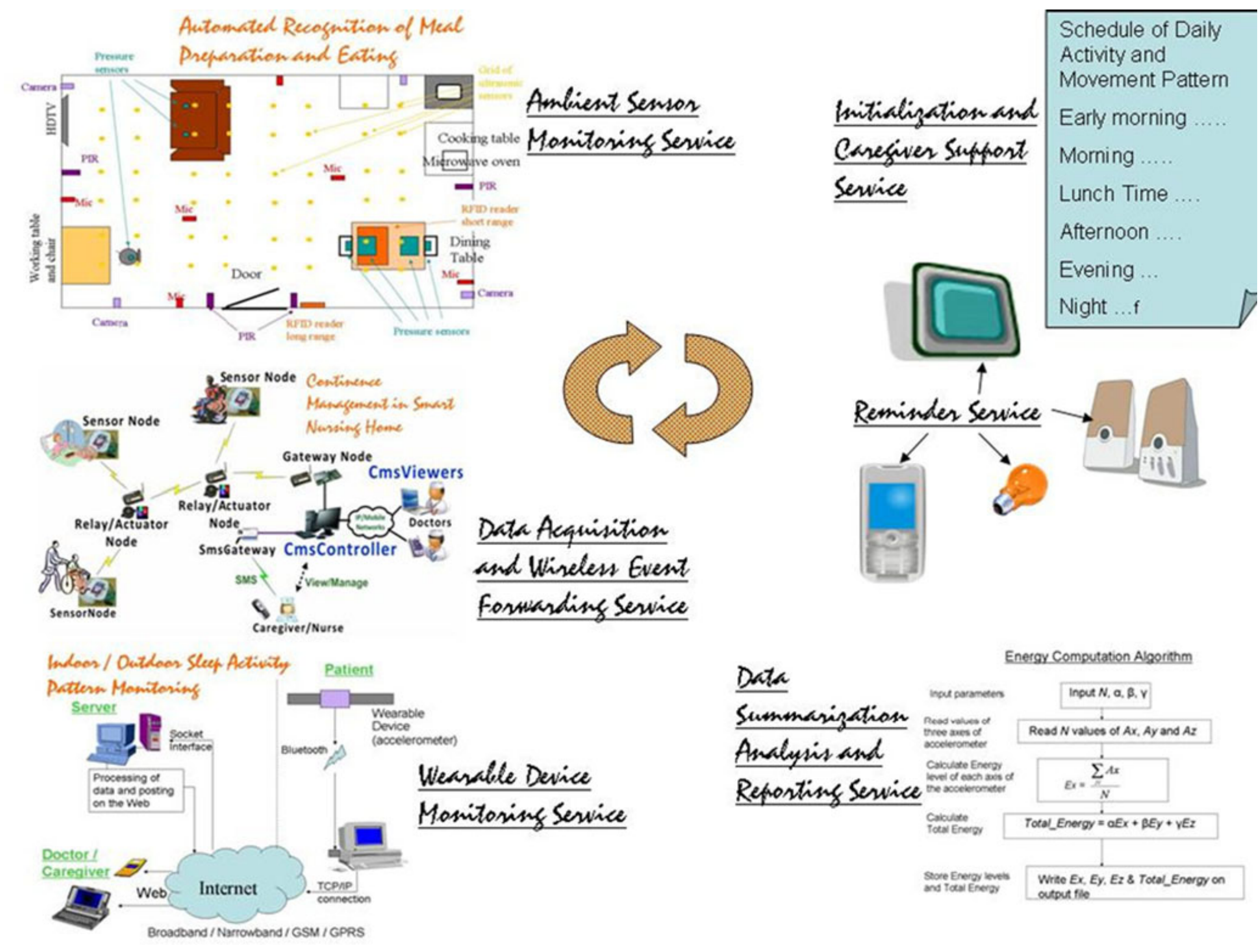


Fig. 1 Applications and services in the system

II. The Data Acquisition and Wireless Event Forwarding Service (DAWEFS)

The *Data Acquisition and Wireless Event Forwarding Service* is the second service. The emphasis of data acquisition and event forwarding is on the reliable transfer of important data and events in the system. Among the elderly, important events such as falls are sporadic and require constant surveillance. A wasteful approach is to have all the sensors active all of the time. This is wasteful since, for majority of the time, the system observes quiescent data. The challenge is to design a system that acquires the data at a rate that is just sufficient to capture reliably, the critical events in the system and forward them to the consumer, or server, without loss of critical information. Note that the sampling rate and the forwarding rate could differ and traded off, depending on cost of resources and urgency of application need.

III. The Ambient Sensor Monitoring Service (ASMS)

The third service is the *Ambient Sensor Monitoring Service*. Ambient intelligence makes use of sensors in the ambient space of smart homes and smart nursing homes to automatically recognize certain activities or conditions that occur. Indoor location and tracking systems are a part of ambient intelligence, however, the intelligence that is being discussed here is at a higher level, closer to human understanding and experience. Thus, the coveted goal of ambient intelligence is to detect not only the identities and locations of the occupant of the smart space, but also his/her detailed activities in terms of sequences of tasks achieved whether or not these tasks and sequences of tasks are in some sense "normal" or "abnormal". If this goal were to be attained, then, it would be possible to design far more appropriate and personalized interventions for persons living at home with dementia, who are in need of assistance in carrying out their activities of daily living.

IV. The data summarization analysis and reporting service (DSARS)

The *data summarization analysis and reporting service* consists of the algorithmic steps involved in analyzing the data collected from the wearable sensor and examining it for various endogenous and exogenous events. *Endogenous* events are intrinsic to the person or phenomenon being observed, whereas *exogenous* events have to do with factors that are external to the phenomenon being observed, but affect the data acquisition process. An example of endogenous event is a high rate of activity in the signal level, leading to a possible alarm condition in the health of the person being monitored. An example of an exogenous event is low level of remaining power, indicating that there may be a disruption of data acquisition soon if the power source is not replaced/replenished within a small time interval. Both endogenous and exogenous events are of importance in determining the criticality factor of the event.

V. The initialization and caregiver support service (ICSS)

The fifth service is the *initialization and caregiver support service*. According to inputs from doctors, the very basic activities of daily living (ADLs) necessary for independent living are feeding, grooming, toileting, ambulation, and bathing. The ICSS consists of a set of tools and software that enables a patient's ADL schedule to be entered in a user-friendly manner by the caregiver (non-programmer).

VI. The Reminder Service (RS)

The last service is the *Reminder Service* [7]. It assumes a means of reminding or alerting event occurrences, flagging them as critical, semi-critical, or routine. This module is an external service in the system and could be as simple as a short message service gateway provided by a third-party provider or a complete reminder subsystem developed for a particular instantiation of the system.

The first three services, i.e., services I, II, and III are depicted on the left-hand side of Fig. 1. These have to do with different complexity levels of data acquisition. The last three services, i.e., IV, V, and VI which appear on the right-hand side of Fig. 1, have to do with *analytics and complex functions*. From these loosely coupled services, applications are created. In this paper, we present three such applications, namely Indoor/Outdoor Sleep Activity Pattern Monitoring [4], Continence Management in Smart Nursing Home [5], and Automated Recognition of Meal Preparation and Eating [6]. The first two are more applied and have been incorporated into trials involving people with dementia. The last application is more upstream in nature and has several research and deployment-related issues that are still being resolved in the laboratory before a reliable prototype can be tested in a real smart home setting.

The remainder of this paper is organized as follows. In section 2, we present the notion of micro-context. In section 3, we present the Indoor/Outdoor Sleep Activity Pattern Monitoring system that illustrates the design principles of service continuity and ambient intelligence. Section 4 presents continence management in smart nursing home, an application that illustrates the importance of service continuity in event capture and forwarding. Section 5 presents the Automated Recognition of Meal Preparation and Eating, a prototype application which illustrates the importance of the use of micro-context information in the acquisition of fine granularity events in a smart home. We end in section 6 with a few observations about how we see the future directions of services and applications emerge, as these design principles are adopted widely.

2 Micro-context—a design principle for equipping smart spaces with low-level context information from sensors

In dealing with sensors and information obtained through sensors, we have found that intelligence should be kept agnostic of the sensing layer and sensing platform. Activity recognition is aided and abetted by the incorporation of micro-context, fine-grained information about a subject's (or object's) state which may become very useful in the reasoning towards monitoring or assisting the end-user. Figure 2 shows how micro-context or the aggregation of low-uncertainty information is carried out. Sensor information from a particular sensing modality is processed to obtain a set of features. The features are mapped into primitives through training algorithms, either in situ or remotely. The set of primitives, however, is most often characterized by a high degree of uncertainty due to a variety of reasons such as insufficient data, noise, or unavailability of transmission capacity. We therefore employ another level of processing (combiner stage) in order to reduce the level of uncertainty in the activity primitives. In the example presented later, in section 5, we show how, in the presence of uncertainty from two modalities, namely accelerometer (with noisy information) and Radio Frequency Identifier (RFID) (with insufficient information), we are able to classify eating activity primitives with a high degree of certainty. Such activity primitives are called *micro-context*, since they provide important information about the targeted behaviors or activities that are being analyzed.

Note that micro-context consists of partial states of the system which are in some sense intermediate states towards the creation of a final inference. These partial states may not have significance of their own; nevertheless, in our architecture, they are published as micro-context information which exists independently. Note that micro-context is more than just a piece of information from a sensor. It is either partial context or a portion of a movement or behavior which has been detected unambiguously. There is a confidence value annotating this information. In the following two sub-sections, we discuss how uncertainty is handled within micro-context and a top-down approach at recognition of behavioral patterns.

2.1 Handling of uncertainty within micro-context

As the application grows in complexity, uncertainty of micro-context has to be handled in increasingly sophisticated ways. For sleep-activity pattern monitoring, context information is inferred from time of day and level of activity from accelerometer readings. In this case, uncertainty is inherently present in the data abstracted from the sensor, and the only way to handle such uncertainty is through probabilistic modeling, which we have done with a state transition diagram and thresholds assigned to state transitions. Misclassification may occur, for example, when a particularly high level of restlessness in the middle of sleep has been classified as "awake". This is an inherent limitation of the system. For more sophisticated systems, such as eating activity detection, uncertainty is handled through the notion of entropy. The reason for this is the fact that more complex systems use more sensor modalities, and with larger pool of possible resources to use, the need for resources management arises. Unlike simple systems, where a fixed number of sensors is used all the time and uncertainty is only evaluated post-factum, the system with management has to do the selection of resources before the result is obtained. Although we may not predict the exact

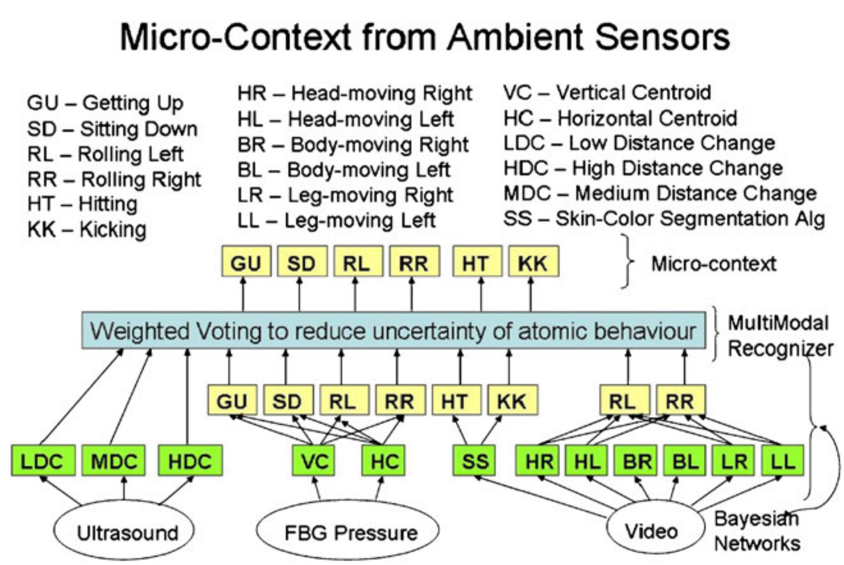


Fig. 2 Micro-context generation

result or probability distribution of result which will be obtained using selected resource, we nevertheless may estimate the probabilities of possible probability distributions of the result obtained using combination of resources. The expected entropy is a single metric describing this multiplicity of probability distributions. Since expected entropy is a very abstract metric, a mapping describing dependency between expected entropy values at different time with more common-sense oriented Information Quality metrics may be useful.

2.2 Top-down behavioral pattern recognition

Behavioral patterns are fixed when activities are simple, as in the exemplars discussed in this paper. However, for handling realistic systems such as monitoring of elderly people for extended periods of time, the system should be capable of handling complex sequences of activities and classifying them into behaviors of various kinds, flagging certain patterns that are regarded as “agitated behavior”, “erroneous behavior”, etc. We are experimenting with a grammar-based approach to deal with complex scenarios in a top-down fashion.

3 Indoor/outdoor sleep activity pattern monitoring: focusing on continuous monitoring of critical data

The application discussed herein illustrates the design principles of service continuity and ambient intelligence. It uses the WDMS and ASMS for capturing data from wearable and ambient sensors and ICSS for maintenance of schedules. It also uses DSARS for summarization and analysis of data and RS for sending appropriate reminders. Since reliable event and data forwarding is assumed, the wireless event forwarding service DAWEFS is not used by this application.

Among patients with mild dementia, sleep can be quite problematic. In an attempt to chart the circadian patterns of those with aberrant sleep behavior, we carried out an initial trial of Actigraphy using wearable accelerometers. The subjects were a group of nursing home residents with sleep problems. However, the system deployed was general enough to be used indoors or outdoors on a 24/7 basis. One of our secondary goals was to determine the effectiveness of a service-oriented approach towards continuous monitoring of patient health data. We found that sleep activity pattern monitoring with wearable accelerometers is fraught with problems and uncertainty. Robustness is a major issue when it comes to realistic deployment and use. Most of the problems with deployment and use do not show up in research prototypes which are typically carried out in research laboratories by engineers. Thus, the systems need to undergo several iterations of re-development before they can be successfully put to trial. In the following paragraphs, we target a particular problem that is encountered with the streams of data that emerge from wearable sensors.

3.1 The personal schedule

The personal schedule consists of the patient's personal profile, capturing expected daily movement and activity patterns, important pre-conditions and post-conditions of certain events (such as beginning time or ending time), and other items captured on a calendar with a granularity of day, week, and month levels. The caregiver support system captures information about the caregiver's visit patterns on a daily basis, contact particulars, and replacement caregiver or alternative person to contact in case of an alarm condition. The ICSS is used to generate templates and schemas for the WDMS to populate with data. This data are used to personalize the system further and refine the rules used to derive important events. The schedule is also represented in a simple mathematical model for representation within a computer.

Table 2 shows wearable devices that may or may not be worn during basic ADLs. In general, our algorithm may be applied to instrumental ADLs, a larger set of activities that includes cooking, using the telephone, cleaning the house, etc. Furthermore, the wearable devices may be multiple for each modality—for instance, accelerometers may be worn on both wrists and on ankles, as when studying gait patterns of the elderly. Pulse oximeters are usually worn on the fingertip, but other configurations exist (for example on the lobe of the ear). Depending on the activity, the caregiver or person close to the patient would know what the likelihood is of the device being removed prior to the activity (and hence, the likelihood of data loss arising from possible non-wearing of the device after the activity is over). In addition to the above, there are unpredictable ways in which data loss may occur. For example, in our experience, in one of our trials, the device was removed and thrown into the trash by a patient with mild dementia. Such occurrences are modeled in our system by a random activity and assigned a certain probability from empirical observation.

3.2 Critical data discontinuity avoidance algorithm

The key idea in the algorithm to avert critical data discontinuity is as follows. When an impending critical data discontinuity (CDD) event is detected, the system schedules a high-priority recovery procedure called an *intervention*, which attempts to forestall the discontinuity. This recovery procedure leads to a step of intervention by

Table 2 Wearable devices that may or may not be worn during ADLs

ADL device	Sleeping and napping	Dressing and grooming	Bathing	Feeding (eating and drinking)	Toileting	Ambulation
Accelerometer	√	√	×	√	√	√
Pulse oximeter	√	×	×	×	√	√
Two-lead ECG	√	√	×	√	√	√

√ - may be worn, × - may not be worn

the caregiver (or if possible, the patient). The rate at which interventions are carried out is called the rate of intervention (ROI). The rate at which interventions are requested is called the alarm rate. Ideally, interventions will be carried out at the same rate as alarms, however realistically speaking the alarm rate will probably be higher, since some alarms may be ignored, and others may be false.

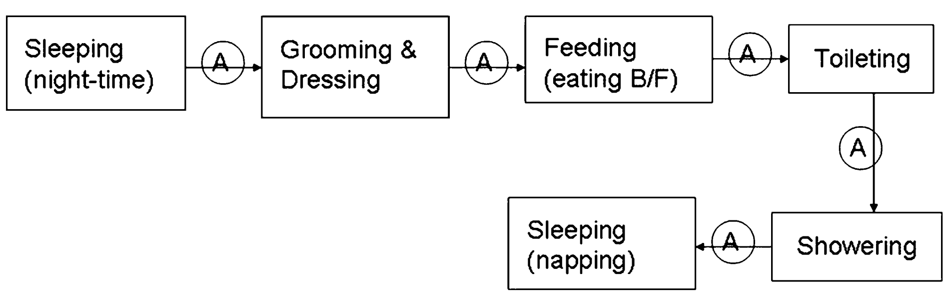
In case of a highly conservative intervention policy, requests may be sent out when not needed because of false alarms based on inaccurate sensor information or overly conservative reasoning. In this case, the alarm rate will be too high and the system may impose too much load on the caregiver and patient. On the other hand, if intervention requests are too infrequent, the system will fail to request action when intervention is really needed to avert data loss. In the worst case, the entire data collection procedure (trial) may need to be repeated, leading to rework, additional cost, and delays. It is clear that the rate of intervention must be adjusted in a manner that keeps the critical data discontinuity within acceptable bounds. We have proposed a method to contain the critical data discontinuity rate within acceptable bounds, while at the same time minimizing the ROI.

3.2.1 Step 1—temporal consistency checking of activities in the schedule

The schedule (derived from ICSS) can in general be represented as a graph, although for simplicity, we represent it herein as a simple chain of activities. Let there be two consecutive activities in a schedule A_i and A_{i+1}, which is a portion of the schedule for the day. Activities A_i and A_j may be of the same type. Each activity type has the following attributes: Temporal attributes of activities

Earliest start time	EST	Latest end time	LET
Latest start time	LST	Maximum duration	MAXD
Earliest end time	EET	Minimum duration	MIND

Consistency assertions are made regarding these times and the associated tasks. Activities must be in sequence, and simple rules are entered through the ICSS to specify the temporal consistency and ordering constraints that apply. These consistency constraints are also associated with thresholds which are entered through the ICSS. A sample set of rules is presented in Table 3.



Note 1: 'A' denotes Ambulation, which is also an Activity of Daily Living (ADL).

Note 2: A linear schedule may be unrealistic in most circumstances. We use it here to simplify the presentation and bring out the key contributions. In general a graph (directed acyclic graph representation would be more appropriate and the extension to this case is straightforward.

Note 3: In the simplified fragment shown above, context information is not depicted. However our system has access to such information as gathered by ambient intelligence in smart homes. Thus the rules for making intelligence decisions regarding sensor data acquisition and possible critical data discontinuity will incorporate ambient intelligence and accompanying knowledge to refine the conclusions.

Table 3 Temporal consistency constraints (patient)

Rule	Predicate or precondition	Action
1	(ActType=nap) ^ (EST<morning nap start threshold)	Notify caregiver "early nap"
2	(ActType=sleep) ^ [(LST+MAXD)<Wake up threshold]	Notify caregiver "late wakeup"
3	…	…

An ADL type is characterized by a basic ADL type {ambulation, grooming, dressing, toileting, feeding} and a time block indicator {dawn, morning, late morning, lunch, early afternoon, late afternoon, evening, late evening, night (pre-bedtime), night (sleeping time)}. Note these notions overlap quite a lot, and their interpretations vary from person to person. Therefore, instead of reasoning with probabilities, we use fuzzy logic for our reasoning. Meals too can be of various types—e.g., breakfast, snack before lunch (may occur a number of times), lunch, snack after lunch, afternoon tea time snack, etc.). Once again, there can be a large amount of variability in the definitions, timings, interpretations of these terms, and the best way we handle these semantic categories in this paper is through the introduction of personalization. Thus, the ICSS permits the time durations of activities to be personalized for each patient and what is considered to be normal for one patient could be quite abnormal for another.

Based on the time of day (obtained from a computer's internal clock), a software agent determines what should be the current activity of the elderly person. If there is a deviation from that activity, an error is flagged. This type of error is termed an endogenous error, since it arises from a process that is intrinsic to the phenomenon being observed. A *Tracker* is a software agent that tracks the activities of a patient, ensuring that the consistency rules are enforced at each point, and firing the actions associated with each rule as soon as an error condition or constraint violation takes place. At this point, the only form of reminder we consider is an alarm for the attention of the caregiver either through a text message alert or a computer generated alarm. It is assumed that the caregiver is always available to take the message and respond appropriately. This rather simplistic assumption may be relaxed with more sophistication added to the reminder service.

Based upon the time of day and on past history, a probability is assigned to each activity at a particular time. This is actually a continuous probability distribution but modeled as a discrete probability. Thus, P_i is the probability that the activity is A_i at a certain time t.

3.2.2 Step 2—detection of data discontinuity

In this paper, the only means for detection of data discontinuity is through the observation of the single wearable sensor data stream. However, in the smart home context, another basic organizational principle, namely micro-context [8], may easily be used in conjunction with the information from the ICSS to set up mechanisms for detection of data discontinuity.

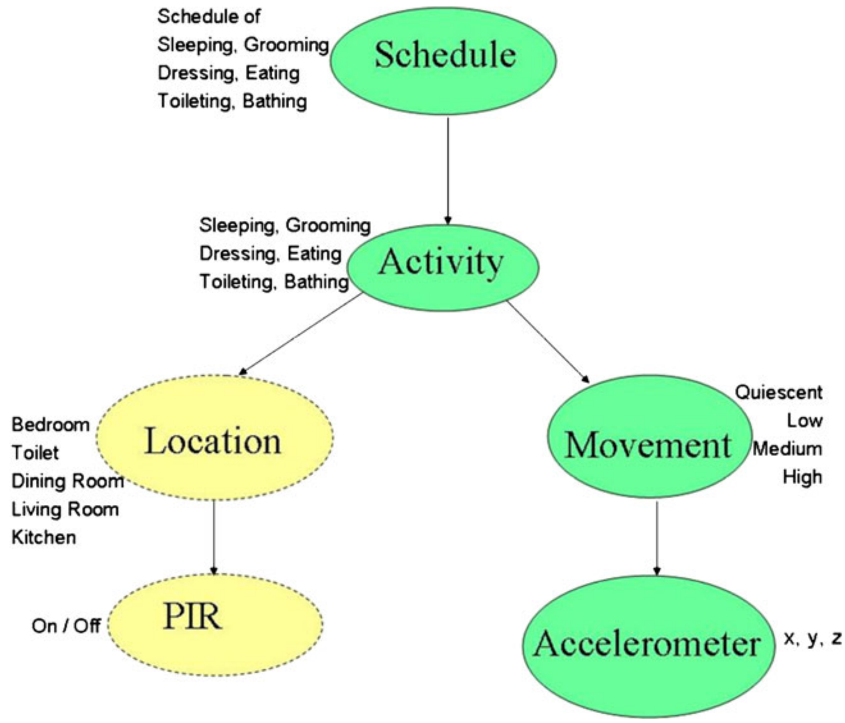
An important type of endogenous error that the tracker observes is the instance of the wearable device being not worn. Q_i is the probability of not wearing (forgetting to wear) the wearable device at the i^{th} stage of the ADL plan. The values of Q_i are collected at the data collection (or training) phase. Our prototype caters to both cases where Q_i values are consistent throughout a given population (e.g., healthy, elderly with dementia, etc.) or where the Q_i values vary from person to person within a group and therefore must be learned for each person individually. Based on the energy computation, we determine the normalized energy level of the monitored signal from the wearable device. If there are no readings coming in, there may be a power disruption or a communication failure (Fig. 3).

Based on the normalized energy level we determine if the device is currently worn or not worn. If not worn, we send a reminder via the reminder service, either to the caregiver or to the patient as deemed appropriate at the time, given the activity and the state of the patient. If the device is worn, we determine if the activity level is matching with that of the activity from Step 1. For this, we use Bayesian reasoning (Fig. 4).

In the absence of training, the conditional probabilities are entered on the basis of laboratory experimentation and trials in the homes of the researchers. During actual deployment, at runtime, the certainty level of the activity is computed dynamically based on time of day, energy level (based on actual readings), and a decision is taken whether or not to request intervention in case of anomaly detection.

Fig. 3 Three stages of data transfer: acquisition, forwarding and storage

Fig 4 Bayesian reasoning model for activity prediction based on schedule and observations. Note that, currently, we do not have location information incorporated into the prototype



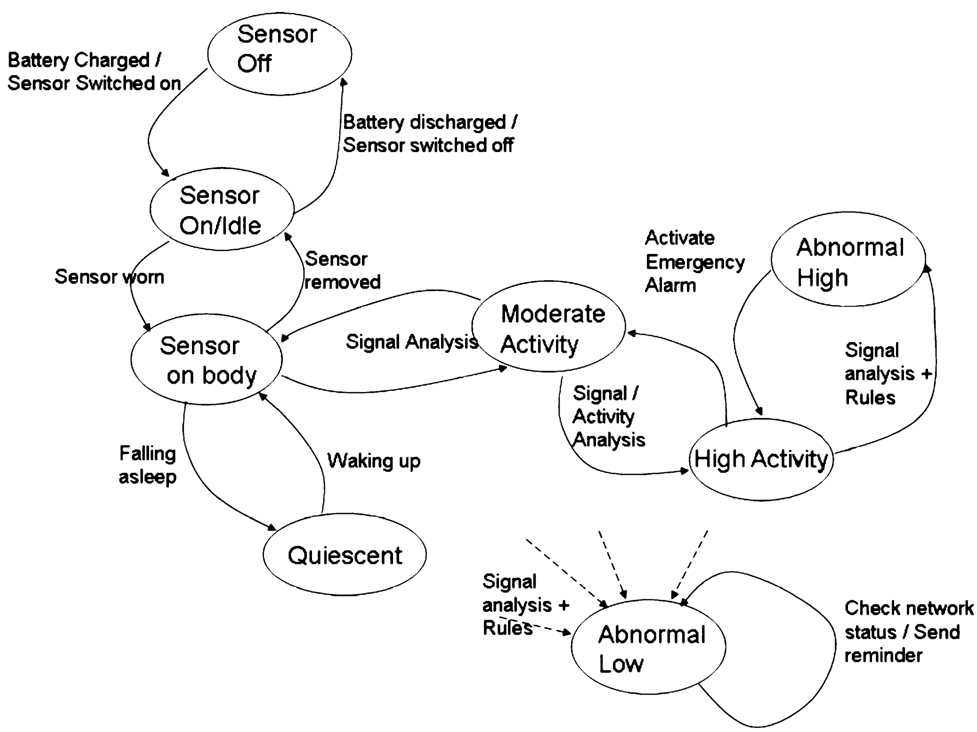
3.2.3 Step 3—the device plan—handling exogenous events

The handling of exogenous events (i.e., those arising from extrinsic factors such as battery failure, network unavailability, etc.), is discussed further in this section. Figure 5 shows the important states of a wearable sensor. The state transition diagram of the important states shown in the figure are not comprehensive but representative. In our work, we have considered only a subset of these states; however, it is conceivable that others may wish to consider the entire set of states or even a superset of these states.

3.2.4 Step 4—decision on reminder

Based on the predicted activity and the likelihood of wearing or not wearing the device, we propose an algorithm

Fig. 5 Monitoring important states of a wearable sensor



to determine what would be the optimal manner in which to send out a reminder. The key ideas in the algorithm are (a) to calculate the CDD likelihood based on certainty (or confidence) and (b) to minimize CDD likelihood and maximize certainty at the same time. In Table 4, we present the major reasons that we have observed for critical data discontinuity. It is noteworthy that even though continuous monitoring requires the continuity of critical data monitoring, there are several ways to conserve resources within the system, despite this requirement of continuous monitoring of critical events. The algorithms that are related to resource conservation are also related to the algorithms that have to do with detection of discontinuity. Thus, we can employ similar techniques to achieve two goals in one, namely resource management as well as the monitoring of critical data discontinuities.

3.3 Formalization of the management algorithm

In this section, we describe the algorithm for minimizing the duration of CDD and the rate of false alarms. Figure 6 shows the flowchart of the algorithm.

3.4 Some additional remarks

The advantage of the above application is that it may be used at the trial phase and continued into deployment, thereby providing a ready-made mechanism to monitor activity of the elderly using the wearable monitoring device. Domain knowledge can be incorporated from experts in case training is infeasible or inappropriate. The algorithm minimizes false alarm rate by maximizing the confidence level (information quality) while at the same time keeping the critical data discontinuity down to an acceptable level. The algorithm combines case based or model based reasoning along with Bayesian reasoning in a common framework and can be readily extended to incorporate other methods of knowledge acquisition (such as fuzzy reasoning).

Previously [9], we have considered a simple model for information loss as data are uploaded from a wearable sensor device to a server that is located either in a nearby location (in the case of indoor usage) or on a geographically remote server (in the case of outdoor WAN usage over 3G cellular infrastructure). We have developed an algorithm based on bounds placed on data loss probability. Using these probabilities as a regulating mechanism, we expect to guarantee the completeness of information obtained from the sensors and therefore the continuity of critical data.

There is uncertainty arising from the endogenous factors which are beyond the control of the system (user-related factors such as randomness in activity performance and technology-related factors such as packet congestion on the network). There is also uncertainty arising from exogenous factors, such as technology-related factors which are to an extent within the control of the system. For example, if the battery level is low, the system can send out a reminder for replacement or recharging of the battery. If the output buffer is getting full, the system may move to a more compute-intensive but space-efficient representation scheme. In our

Table 4 Device conditions that may lead to critical data discontinuity

No	Causes	Solution	Remarks
1	Sensor battery failure	Battery status can be retrieved from sensor data. Detect "no data" from sensor or BT connection failure	
2	BT connection failure	Same as (1)	This can also happen if the patient goes out-of-range and comes back again to range.
3	Nurse/caregiver forgot to set up the sensor for the patient.	No data (sensor OFF) or no/repetitive movements (sensor ON)	Sensor being located in the area of nurse room can be an indication (sensor is ON).
4	Patient removes the sensor and throws off.	Same as (4). No data (power OFF) or no/repetitive movements	Can the action of trying to remove the sensor be detected? Or the sequence of events that leads to this?
5	Sensor removed for shower	Same as (3)	Refer to the Vivago solution Someone inside the shower room can be detected using PIR.
6	Power supply to mobile phone or gateway switched off.	Monitor the phone battery status. No data updates, no keep alive messages from phone.	Accidentally or power failure
7	Phone hangs or program failure due to unexpected bug.	No data or keep alive received at server side.	Can a watchdog timer be implemented to report this to server?
8	3G/network connection failure	Same as (7). No data, No keep-alive received at server.	

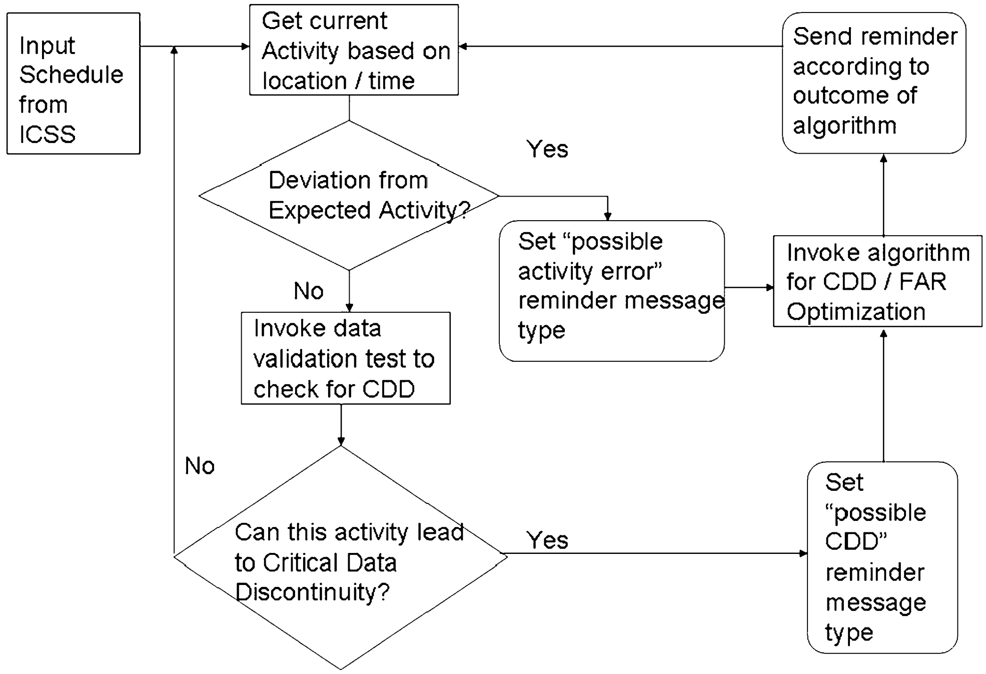


Fig. 6 Flowchart of the algorithm

related work, we have modeled the space of resource management for wireless sensor networks in the presence of arbitrary phenomena. We have studied the notion of sensor selection and optimization of resources on such networks. Herein, we use some of the results from [9] and [10] and from related work [11] that specifically concerns the modeling of data loss in wireless sensor networks and resource optimization in ambient sensing applications. It is to be noted that though our preferred embodiment has a one-hop network on the air from sensor to gateway; in theory, the link could be multi-hops and could be supported by a wireless sensor network.

4 Continence management in smart nursing home

In this section, we discuss another innovative application that makes use of loosely coupled services, namely continence management in smart nursing home. As in the previous case, this application also illustrates the design principles of service continuity and ambient intelligence. It uses the WDMS for capturing data from wearable sensors. Analytics and schedule management are very simple for this application and need not be customized or personalized. Hence, DSARS and ICSS are not used. Reliable event capture and forwarding are extremely important, and hence, DAWEFS is used over a multi-hop wireless sensor network using Zigbee nodes as relay nodes. RS is an important service for this application.

Due to decline in physical and mental abilities, those with dementia may suffer incontinence and related problems. Therefore, reliable continence assessment and good continence promotion are important to alleviate the inconveniences faced by patients as well as caregivers. Our primary goal was to develop a smart continence management system by exploiting various systems mentioned above. Based on requirements from medical professionals, both hardware and software components were developed, targeting needs from various operational perspectives. To prove the effectiveness and practicality of the system, medical and usability trials were conducted, and in fact, some of these trials are still under way, in a nursing home in Singapore. Preliminary results are promising for long-term incontinence care.

The smart continence management system was iteratively designed, taking into consideration both the needs of the patients and their caregivers. Cost was also an important factor which was inherent in decision making during the design and development stages, ruling out several "obvious" technologies such as wireless LAN. The system which was finally deployed is depicted in Fig. 7. This solution is capable of monitoring several persons simultaneously, given that they are located in the same local area for example within as in a nursing home or a similar care facility. The patient may be in bed or in a wheelchair, and events and data are forwarded reliably and continuously from all the patients. Smooth transition in terms of the person moving from the bed to the wheelchair and back again is important. For this reason, we have had to modify an earlier design which called for the caregiver to remember to physically remove the receiver unit from the bedside and mount it on the wheelchair. This called for additional work to be performed by the caregiver which was deemed to be an undesirable departure from their normal duties.

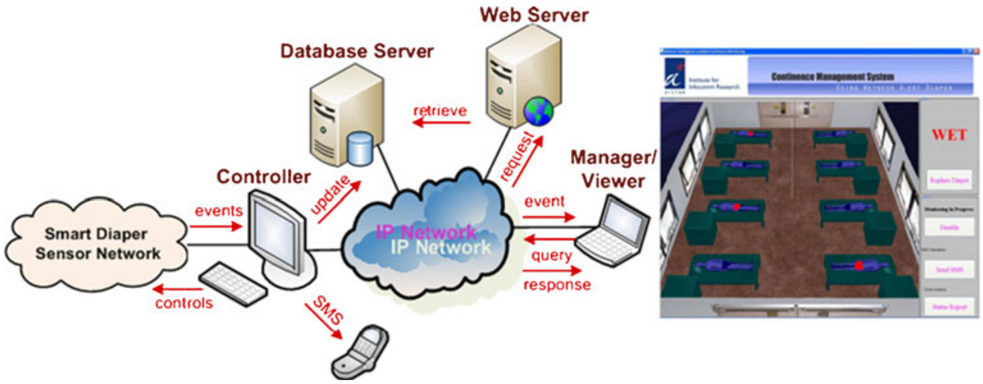


Fig. 7 Architecture and GUI of smart continence management

In the current deployment, a separate receiver unit is therefore permanently attached to the wheelchair. Given that the type of sensor we are using is of the non-disposable type, there is, at present, a requirement that it should be washed and re-used. Once again, this introduces work which is outside of the normal duties of the caregiver. For this reason (and only for the initial trials), we decided to have additional units of new sensors ready for use in case a diaper needs to be replaced. The cleaning and recycling of sensors from soiled diapers then becomes a batch operation which can be scheduled and performed offline—at a convenient time.

Figure 8 shows the various system components and the relationships among them. The first component is the *sensor unit* (Fig. 8a), which is composed of the wetness sensor and transmitter pair coupled with the wireless communication facility. Its main tasks are to detect wetness in the diaper and subsequently report the detected event. The second component (Fig. 8b), the *intelligence unit* is built by integrating the diaper receiver unit and the alert system with the sensor node, which is mounted on the micaZ mote [12] wireless sensor network platform. Its main function is to capture wetness events and to receive control events (messages), to take decisions on incontinence status, activating the integrated optional alert system as needed and managing devices and disseminating the events to other units wirelessly. The third component is the *relay unit* (Fig. 8c), which is composed of the primary alert system integrated within it. Its main functions are to relay messages between the intelligence and the service units and to activate the alert system upon receiving notification requests to notify caregivers. The final component, as shown in Fig. 8d, is the *service unit* which consists of a wireless gateway, an Short Message Service (SMS) gateway, and a server. This provides a user-friendly Graphical User Interface (GUI) to manage and provide continence care, SMS alert services, and a web-based manager and viewer applications for handling incontinence.

4.1 Details of the system

The system may be classified into two subsystems, the multi-hop relayed sensor network and the continence management subsystems. Multi-hop relayed sensor network is composed of sensor node for sensing and eventing (generation of events), relay/actuator nodes for actuating and relaying, and gateway node for intercommunication. Sensing hardware and embedded software development on wireless mote platform [12] are carried out providing the multi-hop signal relaying, event detection, alert notification, and actuation control. Continence management subsystem consists of server and/or client PCs and an SMS gateway. The software modules include the controller that supports data acquisition, alerts, intervention, and intelligence, and the viewer that provides user-friendly and simple 3D interactive user interfaces for managing incontinence episodes.

The step-by-step operation procedures from wet detection, intervention to care giving are mostly automated with

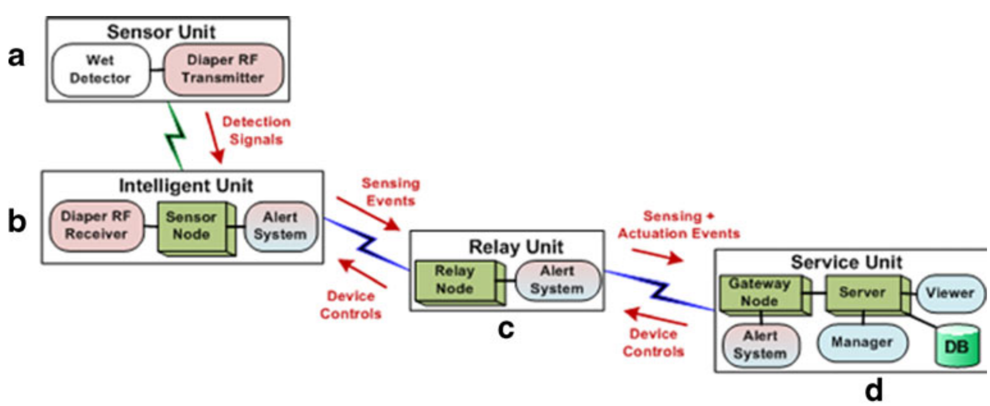


Fig. 8 Various system components **a** sensor unit, **b** intelligent unit, **c** relay unit, **d** service unit

minimum caregiver involvement. At first, the caregiver places the sensing unit inside the patient's diaper. The system automatically notifies the wetness event to the caregiver through appropriate alerts such as buzzers, LEDs, SMS, and 3D user interfaces. Finally, the caregiver interacts with provided user interface to acknowledge and provide the necessary care to the patient. The operations are designed to be simple and are only carried out when there is a wetness episode. The operation of the system is flexible for users and the wireless infrastructure supports full interconnectivity.

4.2 Discussion

The system was tested in the lab environment, simulating real-world scenarios and achieved the desired detection and reporting specs without false alarms. As a first step in conducting trials, the complete system was deployed at a local nursing home, and studies were carried out on a single elderly patient with high continence aid requirements. We deployed the sensor–signal receiver node in the vicinity of the patient, such as at the bedside or attached to the wheelchair. Two relay/actuator nodes were placed outside the patients' room and near the common dining area respectively, and the gateway node was placed just outside the nursing station. The PC with 3D user interface was installed in the nursing station for caregivers to monitor incontinence status and interact with the system when an incontinence episode occurs. Taking the advantages of wireless sensor network-based infrastructure, it is easy to set up the system even in new environments, and this can provide as a framework for other concurrent healthcare applications as well.

Preliminary trials of continuous operation for 1 week show strong promising results on robustness and stability of the system. Its outcomes provide the correct detection and notification of most incontinence episodes, but there is still a need to make improvements to achieve near 100% reliability. Sometimes, problems may come from improper user handling of the system such as incorrect placement of sensor, system not re-activated after diaper change, etc. We believe that we can build the trust of medical staff and caregivers on working with ICT-based solutions, since they see how these solutions can improve incontinence care. All these positive outcomes encourage us to continue building better smart continence management systems. Our next step will be to test the system on multiple patients concurrently, as well as to provide more features such as continence planning, personalization, etc.

4.3 Some additional remarks

Incontinence and its related problems are pressing problems in elder care and must be resolved efficiently in order to enhance quality of life to both elderly and caregivers. A sensor network-based smart continence management system is developed addressing end-user requirements and considerations from medical compliance, efficacy, and practicability. The initial system is deployed at a nursing home and tested out with incontinent dementia patients to see the usefulness and applicability in real-world scenarios. The promising results help us make possible extensions of the system with vital functionalities aiming to improve the current incontinence management practices.

5 Automated recognition of meal preparation and eating

The last application we discuss is that of automatically recognizing meal preparation and eating in a sensor-equipped smart kitchen. This application illustrates the design principles of micro-context and ambient intelligence. It uses the WDMS and ASMS for capturing data from wearable and ambient sensors. It does not use DSARS or RS since the focus is on activities and not on high-level behavior. DAWEFS is not used by this application, since the indoor sensor network used is assumed to be reliable and losses due to network are addressed by judicious sensor selection.

One of the determining factors that decide whether or not a person with mild dementia can live independently at home is his/her ability to carry out ADLs by themselves. To be realistic, they must be observed in isolation, that is, without the presence of the caregiver or family members. This means that there must be ambient intelligence within the home, based on sensor technology that is able to automatically detect when the subject carries out his/her ADLs.

Until now, smart homes have not been very successful in the continuous monitoring of people in their homes. Systems that detect fire hazards (based on ambient temperature sensors) or falls (based on wearable accelerometers) have been used in smart homes; however, these are sporadic event detection systems, and the events themselves are stand-alone, highly specific, localized, and do not make use of information or intelligence that may be present in the environment. Smart homes that do attempt to classify residents' activities stop short at summary statements such as “Mr. Jones was ‘performing kitchen activity’ between 7 pm and 9 pm or ‘performing dining room activity’ between 8 pm and 10 pm”. Summaries of this nature are minimally useful and do not give doctors and caregivers much information about the health and well-being status of the elderly residents who are being monitored. Ideally, an activity monitoring system should be capable of reporting what was the precise activity that the resident was engaged in, how long that activity took, and how well (meaning assigning some kind of rating) the activity was performed. For behavior monitoring (we take behavior to be meaningful sequences of activities leading to some well-defined goal), the reporting should essentially be the same, but with more semantics such as degrees of ease, degrees of prompting, or help that had to be provided, and so on. In our work, we are targeting the basic ADL of "Eating" and the instrumental ADL of "preparing food". In this section, we only discuss the eating recognition part.

In order to carry out recognition of ADLs in a smart home setting, some core technologies and capabilities are needed. First, a wireless sensor network comprising a variety of ambient and wearable sensors must be incorporated. Data acquisition, filtering, segmentation, and classification must be carried out at a low level, in order to extract features from sensor-produced data, into meaningful micro-context information which is stored in appropriate data archives. These data then becomes the basis for activity recognition, behavior understanding, and learning. Algorithms must be flexibly mixed and matched and therefore need to access micro-context stored in a generic format.

Our approach relies on multi-modal information fusion and activity primitive recognition at the low level and context aware reasoning at the high level. We also employ techniques based on information quality for adaptive sensor selection querying and responding to uncertainty in the environment and sensors.

5.1 Bridging the gap between sensors and applications

Monitoring of elderly in smart spaces (such as homes or hospital wards) [13] has been a research topic for a long time and has been applied to hospitals as well as homes. For example, a smart hospital [14] is equipped with monitoring aids that are able to detect the onset of agitated behavior in patients and notify staff to take appropriate action. A smart home for an elderly resident [15] is equipped with a variety of sensors for the purpose of gathering state information regarding how well the elderly resident is carrying out his ADLs. The EasyADL project [16] has the goal to recognize elderly peoples' ADLs in an automated fashion and have achieved good simulation results. In focused practical work, assistive systems have been built by [17, 18] focusing on video and acoustic sensors and have achieved promising results with certain types of behavior patterns such as aggression. These projects lack generality in terms of architecture and reuse of partial results in a common framework.

The work on ADLs, however, has been quite remote from sensors and sensor networks, being mostly restricted to usability studies of simple isolated sensors and devices [19], simulations of proposed large-scale deployments of a single sensor modality such as RFID [16, 20] and high level analysis of case studies of elderly living independently, their needs, and their monitored behavioral patterns extracted in the form of behavioral rules [21]. We see that a huge gap exists between sensors and applications.

Sensor-generated data may be used in their raw form or in various distilled forms. Once sensor data have been classified into features, the data are now information since semantics have been associated with it. In this section, we develop some generic ways of composing fragmented information gleaned through multi-modal sensors, into a form that might be usable by high-level agents. Basically, there are two approaches for recognizing higher-level states from sensor-observed data, statistical approaches, and

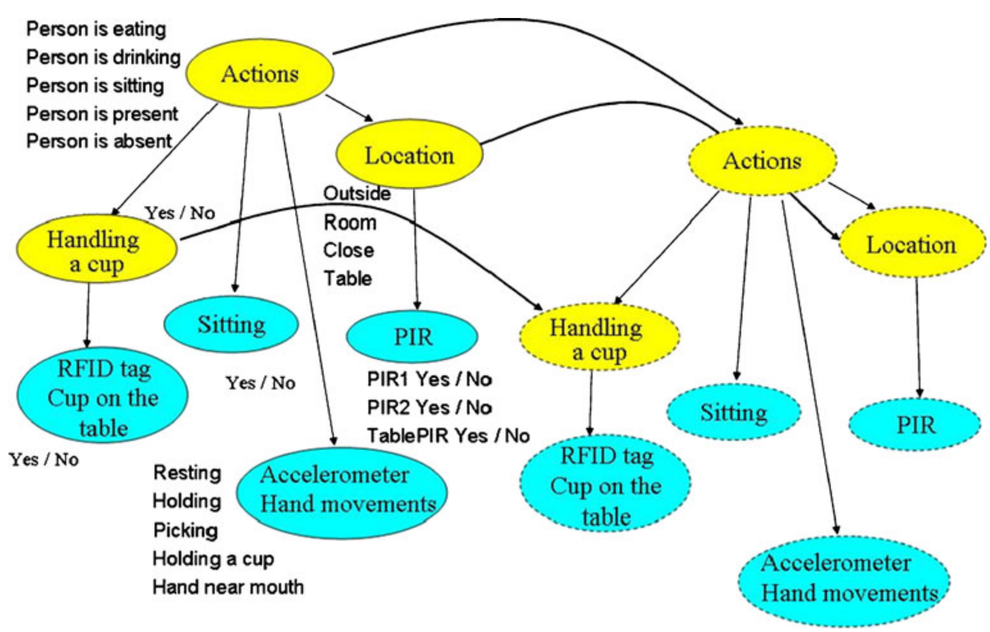


Fig. 9 The example of the dynamic Bayesian network used for detection of eating activity. *Blue* nodes are sensor nodes. *Yellow* nodes are temporal nodes. Non-temporal nodes, although possible, were not included to simplify the inference. Lists next to nodes contain the possible states of a variable represented by a node

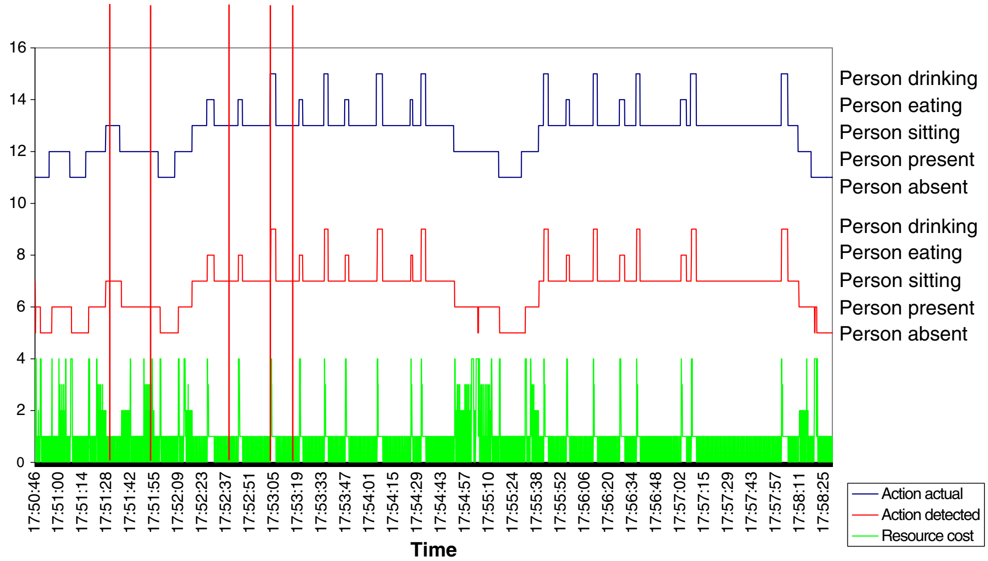


Fig. 10 Experimental data from the eating activity detection prototype. Five states are detected: *Person absent, person present, person sitting, person eating*, and *person drinking*. The *top graph* shows the actual action. The *graph* in the *middle* shows the activity detected using entropy only algorithm with threshold equal to 0.15. The graph at the bottom shows the cost of resources used

value-based approaches. *Statistical approaches* aim to combine raw data from all sensors at their lowest level, using statistical techniques such as hidden Markov models and other types of statistical models. These techniques may be employed for multiple sensors of the same modality (e.g., multiple video cameras) or for multiple sensors of multiple modalities. Although quite effective, we have found that calibration and information overload are two problems with this approach. *Value-based approaches* are hierarchical and compositional and work with intermediate states obtained from different sensors. They are able to limit the information flow towards the sink (query source) and thus, are suitable for large deployments of multi-modal sensors. They operate on the basis of thresholding and feature extraction. If the value of a sensor reading or an extracted feature has crossed a certain threshold, it may be assumed that a certain type of *Activity Primitive* has occurred. Based on the discrimination capability of a sensor, a set of features is defined for a particular modality and a particular algorithm.

5.2 Phenomena tracking using dynamic Bayesian network model

Activity tracking is the continuous process of estimating the most likely action at the time t based on the evidence obtained at the time t, selecting the sensors to be used at the next time moment and updating the probability distributions to update the dynamic Bayesian network (DBN) for the next time moment. Figure 9 shows an example of the DBN that we use in the application of eating activity recognition.

5.3 Activity detection implementation

We implemented the activity tracking system together with sensor selection for the scenario of monitoring the eating habits of an elderly person at home. The current scenario assumes that the person is alone at home, and, at some point, he may come to the kitchen and start eating some snacks and having some drink from a cup while sitting at the table. The goal of the system is to detect the fact that the person ate or drank and preferably have an estimation of the duration and count of each activity which later can be used for estimation of the amount of food consumed.

The current detection system is based on four sensor modalities. There is an RFID reader installed under the surface of the table which detects the presence or absence of the cup on the table. The cup has an RFID tag installed under the bottom. There is an accelerometer on the person's wrist which detects the movements of a hand. There is a pressure sensor on a chair in front of a table, and there is a

Fig. 11 Eating activity detection with prototype implementation. The fragments of video recording corresponding to the long vertical lines in the Fig. 10

Table 5 Achieved confidence and correctness levels for different entropy thresholds and algorithms

	Average confidence	Average correctness	Average cost
Entropy threshold 0.15	97.3%	94.6%	0.57
Entropy threshold 0.25	95.5%	92.4%	0.38
Entropy threshold 0.4	92.1%	89.8%	0.27

set of three passive infrared (PIR) motion detection sensors in the environment, one of which closer to the entrance door, one near the table, and one under the table surface. The set of PIR sensors are equivalent to the simple discreet location tracking system. For the activity detection, we used the DBN presented on the Fig. 9. There is a list of possible states next to each node of the first copy of the BN.

5.4 Activity detection results

Here, we present the comparison of the activity detected using the entropy threshold of 0.15, which roughly correspond to the confidence level of 98%. Here, we used simple cost model where each sensor modality used has a cost 1. The Fig. 10 shows the actual activities, the detected activities, and cost of the sensors, and Fig. 11 shows fragments of video corresponding to the long vertical lines on the Fig. 10. Video recording was not used for activity detection but for deriving the ground truth of actual activity by manually annotating the current activity.

We tried several entropy levels to check the algorithm. The experiments were performed on the same data set, using the same sensor readings and actual activities, with sensor selection algorithm being the only variable. The Table 5 holds the results for entropy levels of 0.15, 0.25, and 0.4 which roughly correspond to the confidence levels of 98%, 95%, and 90%. The column of average correctness shows the ratio of time steps when the system state was correctly identified.

However, we found that, with lower entropy thresholds, the system tends to refuse to choose any sensors for too long, therefore leading to situation when correctness level is satisfied, but short events important to the application are missed. For example, in the case of entropy level 0.4 on the Fig. 12, there is a missed eating event, and it happened exactly because the sensor input was ignored.

5.5 Some additional remarks

We have presented encouraging results of applying an algorithm for recognizing activities of daily living. The algorithm uses a dynamic Bayesian network-based approach to reduce the complexity of determining states. Initial results are quite promising and point to a general algorithmic approach that (a) uses multiple modalities of sensors for gathering data, (b) detects activity primitives, and (c) stores detected activity primitives as micro-context for future use. Since this is a part of the ongoing work, in the future, we will implement more sensor modalities to detect wider set of activities relevant to eating detection. It will include person tracking in space to detect the proximity to the table and fact that the person is sitting. Besides, within the framework of the phenomena-aware resource management [22], we will include sensor modalities which would offer alternative data in the case more information is needed to achieve reliable activity detection or efficient resource trade-off and implement sensor management.

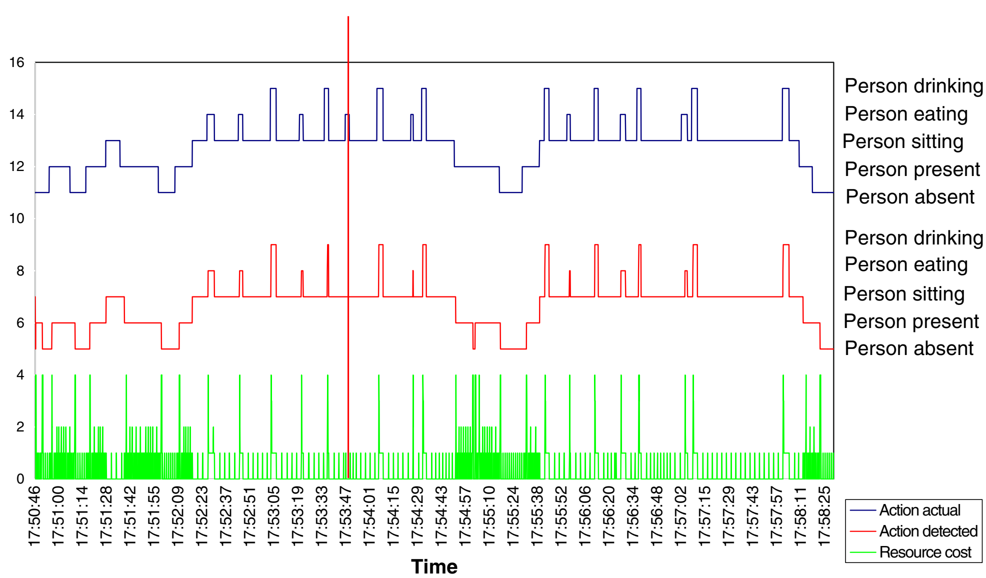


Fig. 12 Experimental data from the eating activity detection prototype similar to the one shown on Fig. 10, but the sensor selection algorithm used the threshold equal to 0.4. The *long vertical line* marks the moment when eating event was completely missed. Note that the achieved high confidence and correctness of results is not because the system is able to detect arbitrary activity with high confidence, but due to currently simple scenario and limited set of possible actions

6 Future directions and conclusions

The field of health and wellness management is an area of active research and development all around the world. Several organizations have embarked on use-case focused deployment, development, and targeted research. We have already mentioned Continua Alliance [1]. In addition, INTEL research [23], OHSU [24], Intel TRIL (Dublin) [25], and the Belfast-based European center for connected health [26] are also very active in this area in a variety of ways.

In this paper, we have presented three design principles for building applications and services for health and wellness monitoring in home environments. Exemplars of applications built on loosely connected services have also been presented. The targets for the applications presented in this paper are patients with mild dementia. In order to promote ease of reuse, reduction of development effort and fewer complications at runtime, it is our recommendation that applications and services should be kept simple and isolated as far as possible. If possible, there should be composition of subsystems within services; however, a methodology for doing this is not presented in this paper. We have found that intelligence should be kept agnostic of the sensing layer and sensing platform. Activity recognition is aided and abetted by the incorporation of micro-context, fine-grained information about a subject's (or object's) state which may become very useful in the reasoning towards monitoring or assisting the end-user. It is very important to capture knowledge from domain experts and encode this knowledge into flexible, reusable components and models within the application. Technical problems encountered by us along the way had to do with scalability, repeatability, predictability, and uncertainty in reasoning. Non-technical problems include privacy concerns and acceptance by healthcare professionals and other stakeholders.

It is our conclusion that, despite the problems and obvious challenges involved in successful exploitation of technology in the area of home-based health and wellness monitoring, the benefits are huge. Since the demand for home-based health and wellness monitoring continues to grow with the rapidly aging population all over the world, research and development in this area should continue with increasing emphasis on real-life testing and trials.

References

1. Continua Alliance: www.continuaalliance.org/ (accessed 6th May 2010)
2. ICOST – International Conference on Smart Homes and Health Telematics – http://handicom.it-sudparis.eu/icost2009/ (accessed 6th May 2010)
3. Functional Assessment Staging of Alzheimer's Disease (from http://geriatrics.uthscsa.edu/tools/FAST.pdf) (accessed 6th May 2010) ©1984 by Barry Reisberg, M.D. All rights reserved. Reisberg B (1988) Functional Assessment Staging (FAST). Psychopharmacol Bull 24:653–659
4. Biswas J, Jayachandran M, Shue L, Xiao W, Yap P (2007) An extensible system for sleep activity pattern monitoring. Proceedings of the International Conference on Intelligent Sensors, Sensor Networks and Information, (ISSNIP) 2007, pages 561–565, 3–6 Dec. 2007, Melbourne, Australia
5. Wai AAP, Fook VFS, Jayachandran M, Biswas J, Nugent CD, Mulvenna MD, Lee J-E, Yap P (2008) Smart wireless continence management system for persons with dementia. J Telemed e-Health, October 2008
6. Biswas TA, J Chen-Khong Tham Yap (2008) Eating activity primitives detection - a step towards ADL recognition, P.in HealthCom 2008. In the 10th International Conference on e-health Networking, Applications and Services, Singapore, 7th-9th July 2008, pp 35–41
7. Hongbo Ni, Xingshe Zhou, Daqing Zhang, Kejian Miao and Yaqi Fu (2009) Towards a task supporting system with CBR approach in smart home. Proceedings of International Conference on Smart Homes and Health Telematics, ICOST 2009, Paris, France, 1–3 July 2009
8. Feki MA, Biswas J, Tolstikov A (2009) Model and algorithmic framework for detection and correction of cognitive errors. J Healthcare Eng 17(3):203–219
9. Andrei Tolstikov, Chen-Khong Tham and Jit Biswas (2005) Data loss regulation to ensure information quality in sensor networks. Proceedings of the International Conference on Intelligent Sensors, Sensor Networks and Information, (ISSNIP) 2005, Melbourne, Australia, 5–8 Dec. 2005, pp 133–138
10. Jit Biswas, Felix Naumann and Qiang Qiu, Assessing the completeness of sensor data. Proceedings of the 11th International Conference on Database Systems for Advanced Applications, DASFAA 2006, LNCS 3882, Springer, pp 717–732
11. Jit Biswas, Chen-Khong Tham and Andrei Tolstikov (2008) Method for automatic configuration of sensor set selection for information quality guarantees. I^2R Technology Disclosure, 2nd October 2008, Institute for Infocomm Research, Singapore 138632
12. Hill J, Culler D (2002) Mica: a wireless platform for deeply embedded networks. IEEE Micro 22(6):12–24
13. Jit Biswas, Santos Kumar Das, Qiang Qui, Vijaya Saradhi Chava and Viet Thang Pham (2005) Quality aware elderly people monitoring using ultrasonic sensors. In Proceedings of the International Conference on Smart Homes and Health Telematics, ICOST 2005, Sherbrooke, Canada, 4–6 July 2005, pp 107–115
14. Jit Biswas, Daqing Zhang, Guopei Qiao, Victor Foo, Qiang Qui and Philip Yap (2006) A system for activity monitoring and patient tracking in a smart hospital. In Proceedings of the International Conference on Smart Homes and Health Telematics, ICOST 2006, Belfast, Northern Ireland, 26–28 June 2006, pp 196–203
15. Gregory Abowd, Aaron Bobick, Irfan Essa, Elizabeth Mynatt and Wendy Rogers (2002) The aware home: developing technologies for successful aging. In Proceedings of AAAI Workshop and Automation as a Care Giver, Workshop held in conjunction with American Association of Artificial Intelligence (AAAI) Conference 2002, Alberta, Canada, July 2002., pp 1–7
16. Backman A, Bodin K, Bucht G, Janlert L-E, Maxhall M, Pederson T, Sjölie D, Sondell B and Surie D (2006) easyADL – wearable support system for independent life despite dementia. In Workshop on Designing Technology for People with Cognitive Impairments CHI2006 April 22–23, 2006, Montreal, Canada
17. Hoey Jesse (2006) Tracking using flocks of features with application to assisted handwashing. In Proceedings of the British

Machine Vision Conference, Edinburgh, UK, 4-7 Sept. 2006, http://www.computing.dundee.ac.uk/staff/jessehoey/papers/hoeybmvc06.pdf, (accessed 6th May 2010)

18. Allin SJ, Bharucha A, Zimmerman J, Wilson D, Roberson MJ, Stevens S, Wactlar H, Atkeson CG (2003) Toward the automatic assessment of behavioral disturbances of dementia. Fifth International Conference on Ubiquitous Computing (UbiComp'03), 2nd International Workshop on Ubiquitous Computing for Pervasive Healthcare Applications, Seattle, WA, Oct 12–15, 2003
19. Demiris G, Skubic M, Parker Oliver DR, Rantz MJ, Aud MA, Lee J, Burks K, Keller J, Green N (2006) End-user involvement in interface design in smart home applications: the nursing perspective. Presented at the International Conference on Aging, Disability and Independence (ICADI) 2006, St. Petersburg, Florida, pp 21–23 February 2006
20. Donald J (2005) Fine-grained activity recognition by aggregating abstract object usage. Patterson and Dieter Fox and Henry Kautz and Matthai Philipose, ISWC '05: Proceedings of the Ninth IEEE International Symposium on Wearable Computers, Osaka, Japan, 18-21 October 2005, pp 44–51
21. Siddharth Dalal, Majd Alwan, Reza Seifrafi, Steve Kell, Donald Brown (2005) A rule-based approach to the analysis of Elders' activity data: detection of health and possible emergency conditions. AAAI Fall 2005 Symposium (EMBC), Shanghai, China, 1–4 Sep. 2005, http://marc.med.virginia.edu/pdfs/library/FS205DalalS.pdf (accessed 6th May 2010)
22. Andrei Tolstikov, Chen-Khong Tham, Wendong Xiao, Jit Biswas (2007) Information quality mapping in resource-constrained multimodal data fusion system over wireless sensor network with losses. In Proceedings of the International Conference on Information, Communications and Signal Processing, Singapore, pp 1–13 Dec. 2007
23. INTEL Labs, Seattle, Technology for Long Term Care http://seattle.intel-research.net/research.php (accessed 6th May 2010)
24. Oregon Health and Science University's Oregon Center for Ageing and Technology, http://www.orcatech.org (accessed 6th May 2010)
25. Technology Research for Independent Living TRIL http://www.trilcentre.org (accessed 6th May 2010)
26. European Center for Connected Health, http://www.eu-cch.org/ (accessed 6th May 2010)