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An Ambient Intelligence Architecture for Extracting Knowledge from Distributed Sensors

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ABSTRACT

Precisely monitoring the environmental conditions is an essential requirement for AmI projects, but the wealth of data generated by the sensing equipment may easily overwhelm the modules devoted to higher-level reasoning, clogging them with irrelevant details. The present work proposes a new approach to knowledge extraction from raw data that addresses this issue at different levels of abstraction. Wireless sensor networks are used as the pervasive sensory tool, and their computational capabilities are exploited to remotely perform preliminary data processing. A central intelligent unit subsequently extracts higher-level concepts represented in a geometrical space and carries on symbolic reasoning based on them. The same tiered architecture is replicated in order to provide further levels of abstraction.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**]: Distributed Systems – *distributed applications*

General Terms

Measurement, Design

Keywords

Wireless Sensor Networks, Conceptual Spaces, Ambient Intelligence.

1. INTRODUCTION

Ambient Intelligence (AmI) is a new paradigm in Artificial Intelligence that introduces a shift in perspective as regards the role of the end user [1]. Unlike other well established approaches, such as the human-in-the-loop design, where the contribution resulting from the exploitation of the human factor is limited to facilitate the system design process, or to infer more accurate models for the environment state, Ambient Intelligence aims to fully integrate the user's preference into the system. In this respect, the basic intrinsic requirement of any AmI system is the presence of pervasive and unobtrusive sensory devices [2], which is essential to ensure context-aware reasoning in order to act upon the environment, modify its state, and react to user-driven stimuli.

Today's advances in technology allow for cheap and unintrusive sensors that may be profitably employed as a distributed sensory means permeating the whole environment under observation. In this work, we discuss the use of Wireless Sensor Networks (WSNs) [3] to get precise and continuous monitoring of the physical quantities of interest; not only does this novel technology allow to perform remote sensing without causing disruption, but it may also perform basic in-network pre-processing of sensed data thanks to the limited computational capabilities of the nodes.

WSNs are however just one part of a comprehensive architecture aimed at overcoming the difficulty of efficiently managing the enormous stream of sensed data without overwhelming the upper-level reasoner with irrelevant details. The present proposal describes a multi-level cognitive architecture, where the process of knowledge extraction is carried on by several modules at increasing degrees of abstraction; this organization aims to gradually reduce the amount of data to be processed at each level, while increasing the information content of each information element.

The remote, distributed sensory device thus acts as the termination of a centralized sentient reasoner, where actual intelligent processing occurs; sensed data is processed in order to extract higher-level information, carrying on symbolic reasoning on the inferred concepts, and producing the necessary actions to adapt the environment to the users' requirements. A set of actuators finally takes care of putting the planned modifications to the environment state into practice.

The architecture described here has been purposefully designed so as to be easily specialized in different application scenarios such as industrial, social, or home environments. In particular, we consider here the issue of efficiently managing the premises of a University Department in order to accurately monitor the ambient conditions of office rooms, and common spaces, with the aim of taking proper actions for meeting the users' requirements, while satisfying energy constraints at the same time.

The remainder of the paper is organized as follows. Section 2 briefly discusses some related works presented in literature,

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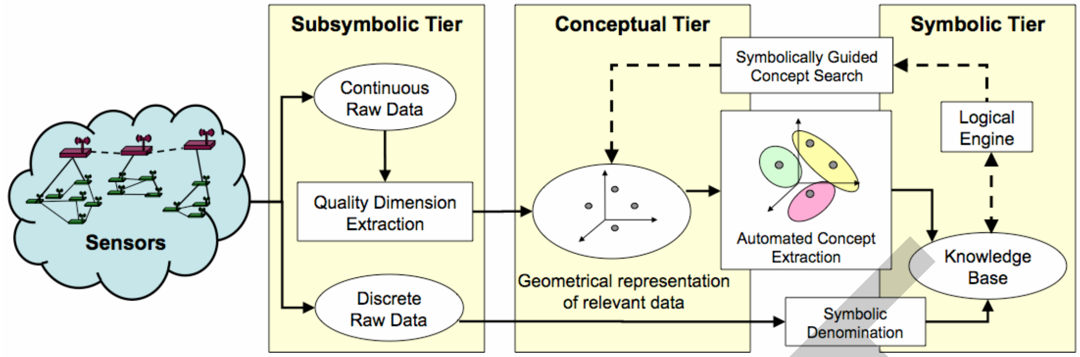

Figure 1. The three-tier paradigm for knowledge extraction.

Section 3 presents our idea for multi-tier knowledge representation, and Section 4 describes the full architecture. Finally, Section 5 discusses a specific case study, and Section 6 presents our conclusion.

2. RELATED WORKS

Many works in AmI-related literature have explored different approaches to the extraction of knowledge from the surrounding environment, and to inferring the behavior of the user from the raw data collected by ad hoc sensory systems.

In [4], the authors focus on the use of contextual knowledge for event classification in order to ease intrusion detection, exploiting heterogeneous sensors; in particular, the prototype integrates the information obtained by two coupled cameras and a badge reader in order to estimate the number of user log-ins within the area under observation, and mouse and keyboard activity sensors for controlling the users' behavior. In [5], the authors propose an application of an unsupervised learning technique based on fuzzy logic to the intelligent agents constituting the AmI system. The fuzzy rules are learned by examining the users' behavior and are dynamically adapted so that long-term goals may be satisfied. The system was developed to be integrated within the *iDorm* testbed, composed by a dorm equipped with a large number of embedded sensors.

In our work, we have selected the Wireless Sensor Networks technology as the underlying sensory system, also thanks to the technical and theoretical expertise acquired by our research group during the development of past projects in several application scenarios [6]. Their use both as a distributed sensory tool, and as a wireless network infrastructure has been widely documented also in AmI literature; however, to our best knowledge, none of those works fully exploits the potential computational capabilities of the sensor nodes; rather they are typically used as a mere data collection tool, with distributed sensors and communication capabilities. In [7][8], for instance, systems for healthcare are proposed, especially targeted to monitoring chronic illness, or for assistance to the elderly. Such works employ WSNs as the support infrastructure for biometrical data collection toward a central server; sensor nodes are thus required to simply route data packets through multiple hops without operating any distributed processing on them. In the work by Han, *et al.* [9], WSNs are used to provide inputs to an ambient robot system. Inside what the authors define a ubiquitous robotic space, a semantic representation is given to the information extracted from a WSN, but again this is used only as a sense-and-forward tool. Unlike those projects, the approach we are proposing here exploits an innovative architecture that regards the AmI system as a complex organism whose peripheral nervous system is represented by the WSN that acts as a preliminary filter and pre-processes raw sensed data in order to reduce the overall amount of collected data; the central nervous system, on the other hand, is realized according to a multi-tier cognitive architecture that allows for a compact representation of knowledge thanks to a progressive abstraction mechanism. The seminal idea underlying this kind of cognitive approach was originally presented in [10][11], where a three-tier cognitive architecture for artificial vision was proposed.

3. MULTI-TIER KNOWLEDGE REPRESENTATION

The proposed system is based on a multi-tier paradigm for performing knowledge extraction starting from sensory data. As shown in Figure 1, this paradigm provides three tiers of knowledge representation, corresponding to different abstraction degrees. Starting from the rightmost block in the figure, knowledge is represented at *linguistic* level, where information is described symbolically via a high-level language, whose input is provided by a *conceptual* level where grounding of symbols occurs, and used to connect the system to the lower, *subsymbolic* tier, where sensory data is first acquired. This structure resembles the ideas presented in [10][11] that were applied to an artificial vision scenario; our system enhances this knowledge representation paradigm with the introduction of WSNs as the lowest-level pervasive data acquisition means, and by reproducing the same 3-tier schema so that the abstract information extracted by the low-level modules of the architecture may be used as input for higher-level modules, thus producing more and more abstracted vision of the world surrounding the system itself.

The subsymbolic tier is devoted to process measurements collected by the pervasive sensory subsystem, although in specific cases part of this task may be delegated to the WSN. Data handled at the subsymbolic level may be continuous or discrete; in the former case, it is passed to the intermediate conceptual tier, where it will be provided with a representation in terms of continuous quality dimensions, otherwise it is outright handed over to the symbolic tier, where a linguistic representation will be given.

At the conceptual tier, data is endowed with a geometrical representation that allows for a straightforward management of the notion of concept similarity; measurements generated by the underlying measurement space are represented as vectors along some *quality dimensions* of interest. Concepts thus naturally arise from the geometric space as regions, identifiable through an automated classification process.

The symbolic tier finally produces a concise description of the environment by associating regions individuated inside the conceptual space to linguistic constructs, thus identifying basic concepts, while relations necessary to infer more complex concepts are described through an opportune ontology.

4. THE SYSTEM ARCHITECTURE

The architecture described here work is inspired to the structure and behavior of the nervous system of a complex organism, as preliminarily discussed in [12]. Such system may be regarded as an intelligent organism, immersed into the physical world; its actuator and sensory extremities are intertwined with the surrounding environment just like the terminations of the peripheral nervous system, whereas a single intelligent subsystem represents the central nervous system, and mimics the activity of the brain as regards the collection and processing of the sensory inputs, by performing high-level reasoning, and by planning the sequence of actions to be executed in order to satisfy some goals.

Four main components may be identified in our architecture: a *sensory* component, implemented as a WSN in order to allow for precise and continuous environmental monitoring; a component for *understanding*, representing part of the system's "brain" and implemented by reproducing our multi-tier knowledge extraction architecture over multiple levels, as detailed in Section 3; a *planning* component, that completes our artificial "brain" and uses the extracted knowledge to plan the necessary actions to steer the environmental conditions towards a desired state; finally, an *actuation* component translating the high-level inference of the intelligent system into actions that modify the physical environment.

4.1 Environmental Sensing through WSNs

In the proposed architecture, as well as in the human peripheral nervous system, some parts of the sensory organ may perform a preliminary pre-processing in order to filter, and possibly aggregate, data before forwarding it to the central system; the overall amount of transmitted data is thus reduced, although the information content is not affected.

The collected information is used to construct an internal representation of the surrounding environment, as well as to observe the user's behavior and learn their preferences. The former goal requires data for such physical quantities as temperature, relative humidity, and ambient noise, while the latter requires sensors able to monitor users' activities, such as the interaction with the air conditioning system, via a remote control.

As already mentioned, WSNs have been chosen as the sensory component, also in consideration of the possibility of executing limited on-board processing. We propose here for the network a clustered structure, in which each small cluster, constituted by heterogeneous nodes with different computational capabilities, distributedly processes homogeneous data. This pre-processing

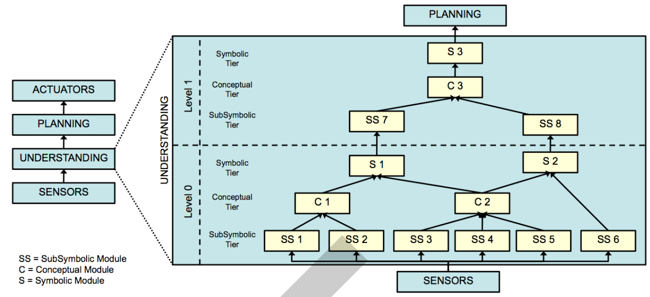

Figure 2. Layered architecture of the understanding component.

phase exploits spatio-temporal correlation of data, in order to compute a model that nodes will share thanks to their cluster coordinator, similarly to the approach proposed in [13]. This process serves the two-fold purpose of reducing the number of unnecessary transmissions (only data not fitting the model will be transmitted in order to update the model itself), and of performing a dimensionality reduction that is used to preserve only relevant features. It is also useful in this phase to extract statistical informations about specific physical quantities in order to obtain aggregate measures of the relative environmental features, while also getting rid of noisy data. For instance in our application scenario, ambient light measurements are preprocessed by all the sensor nodes deployed in one room in order to compute the average light exposure and the standard deviation among measurements, which the central system may use to infer the overall lighting degree and homogeneity.

4.2 Understanding the Environment: the Intelligent Core

The *understanding* component processes the collected data so as to obtain a higher-level representation of the environment at different abstraction degrees used to merge different types of perceptual stimuli, in a way functionally resembling the organization of the human brain.

Several studies in neurosciences [14] proved that different brain areas are functionally specialized for well-defined tasks for sensory signal processing. Besides functional specialization, also functional integration is performed in the different areas, and at different spatial and temporal scale. This suggests the design of a hierarchical and modular architecture, whose parts operate independently and in parallel on different environmental stimuli in order to provide a symbolic representation of them.

Figure 2 shows how the *understanding* component is in fact split into multiple levels, each implemented according to a 3-tier structure of interconnected modules for representing knowledge, as described in Section 3. Each module in a level belongs to one of the tiers, and the connections specify how the information must flow from bottom to top, i.e. from the subsymbolic toward the symbolic tier, through the conceptual one.

Knowledge extracted from the symbolic tier of a given level provides the input for upper levels, where it is regarded as a kind of "higher-level sensory data"; information is actually originated at the sensor network only for the lowest-level modules, but this approach allows us to reproduce the same multi-tier knowledge management scheme at different levels, or in other words *the knowledge base created by a given level is used to iterate the same knowledge extraction mechanisms at higher abstraction levels*.

The lowest-level subsymbolic modules are in most cases directly implemented on the WSN. It is in fact the sensor network that addresses the extraction of aggregate information from the wealth of collected sensory data, in the form of qualitative dimensions. This process is carried on at the central system, instead of the WSN, only for some particular kinds of sensors, such as *software sensors* used to monitor the user's activity at their workstation.

4.3 Planning and Acting

Besides constructing a faithful representation of the current state of the environment, our system is also able to plan a sequence of actions that will modify this state in order to bring it as close as possible to the users' desires, taking into account both the internal representation and the goals derived from the users' requirements.

The *planning* component of the system needs to reconcile possibly opposed goals, through an accurate constrained planning system. In the case study we are proposing here, such goals are for instance related to maintaining pleasantness in room ventilation, or an adequate lighting, while at the same time minimizing the overall energy consumption, or guaranteeing that other user-defined constraints are satisfied, and that the WSN lifetime is maximized.

The planning component exploits particular sensory information to adapt its internal representation of the user's requirements, such as information about the interaction of the user with the system actuators, through which an indirect indication of the user's preferences may be inferred. For instance, by switching on the light, the user is implicitly informing the system that the current lighting degree is inadequate; if this new piece of information is not consistent with the previous representation of the user's preferences, then it may be used to adapt the system's planning goals. Further details on the implicit feedback collection system are contained in [12].

The output of the planning system consists of a sequence of actions to be executed in order to reach the goals, while fulfilling the constraints. A toy example may be the case when the internal representation of the environment produced by *understanding* component indicates an insufficient ambient lighting for the user's desires, and an external light index superior to the internal one. Knowing that the actions of "opening the curtains" and "switching on the light" may both restore an adequate ambient lighting for the user, and that the energy consumption derived from the former action is lower than for the latter, the *planning* component outcome will be the action of "opening the curtains", which will trigger the actuators for the relative automatic engine.

5. CASE STUDY

The described architecture has been tested on a specific application scenario consisting in the management of an office environment, namely a University Department, in order to fulfill constraints deriving both from the specific user's preferences about the air quality, and room lighting and occupancy, and from considerations on the overall energy consumption. The present section focuses on a few specific *understanding* subsystems and the relative modules and sensory equipment; in particular the subsystem dealing with room occupancy and with the presence of a target user in their own office, and its integration with the subsystem that monitors lighting conditions will be considered.

5.1 The Deployed Sensory Component

The sensory component of this system is implemented through a WSN, whose nodes are equipped with off-the-shelf sensors for measuring such quantities as indoor and outdoor temperature, relative humidity, ambient light exposure and noise level. Sensor nodes have been deployed in various rooms close to "sensitive" indoor areas: by the door, by the window, and by the user's desk; additional nodes have also been installed on the building facade, close to the office windows, for monitoring outdoor temperature, relative humidity, and light exposure. Moreover, other nodes carry specific sensors, such as RFId readers, in order to perform basic access control. In our prototype, RFId tags have been embedded into ID badges for the department personnel, while RFId readers are installed close to the main entrance and to each office door; readings from each tag are collected via their coupled nodes, and forwarded by the WSN to the intelligent core, that will process them and will reason about the presence of users in the different areas of the department. RFId-triggered reasoning about users' locations is inherently imprecise and requires the integration with other sensory information, such as those collected by specialized software demons acting as virtual *software sensors* and used to detect the users' activity on their workstations. The users' interaction with actuators is also captured via ad-hoc sensor monitors. For instance, if the user manually triggers any of the provided actuators (e.g. the air conditioning, the motorized electric curtains, or the lighting systems) via the remote controls or traditional switches, specialized sensors capture the relative IR or electric signals so that the system may use them as implicit feedback. Finally, the overall energy consumption is also monitored by a sensor providing instantaneous information about active and reactive power, voltage and current. By analyzing specifically values related to active power, the system will be able to tune and modify its planned actions in order to satisfy some predefined energy consumption constraints.

5.2 Room Occupancy

A specific subsystem whose modules belong to the *understanding* component has been devised to reason on room occupancy. This subsystem only needs information directly obtainable from the sensory component, so it belongs to *Level 0*; the outcome of this subsystem provides an estimate about the number of people present in the user's office room, and a probability for the user's presence as well; this information will form part of the input for subsystems at higher levels.

Processing sensory data in order to extract the **<RoomOccupancy>** concept inevitably involves reasoning with uncertainty, therefore we decided to consider a model based on probabilistic Bayesian networks (as opposite, for instance, to logical inference engines). Indeed, rule-based expert systems are not suitable for dealing with environmental features characterized by a large uncertainty, as the set of logical rules constituting them is exclusively deterministic; our domain, on the other hand, requires the integration of intrinsically noisy sensory information

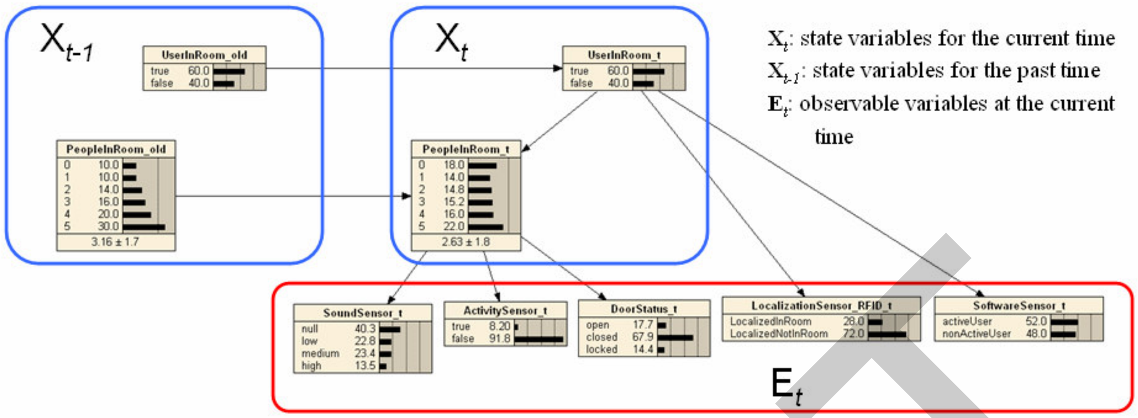

Figure 3. Markov chain for room occupancy evaluation.

that, moreover, can only provide partial observations of the system state.

Classical Bayesian networks [15], however, may only provide a static model for the environment, which would not be suitable for the proposed scenario; we therefore chose dynamic Bayesian networks or, more specifically, Markov chains to implement our models which thus allow for probabilistic reasoning on dynamic scenarios, where the estimate of the current system state depends not only on the instantaneous observations, but also on past states.

Figure 3 shows the Bayesian network designed for our case study, and clearly shows that sensory information are the only measurable manifestation of the system hidden state. State is here represented by the presence of the considered user in their own office room (associated to the **UserInRoom** variable), and the number of people in the same room (**PeopleInRoom**). The state is observable through sensory information associated to the noise level in the room (**SoundSensor**), to the sensed interaction of the user with the room actuators (**ActivitySensor**), to the open / closed / locked status of the room door (**DoorStatus**), to the RFId-based naive user localization (**Localization-Sensor-RFId**), and to the user's activity at their workstation monitored via software sensors (**SoftwareSensor**). Variables modeling this sensory information are connected with state variables through sensor probabilistic models, expressed by conditional probability tables that were learned from an opportune training data set.

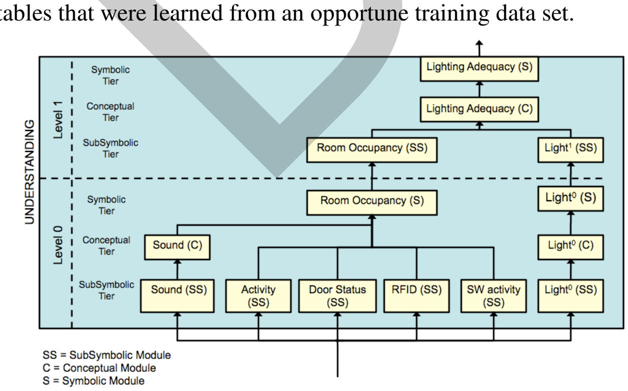

Figure 4. The subsystems for lighting adequacy and room occupancy.

Almost all of the above mentioned sensory information is discrete and does not require conceptual modules for extracting factual information from qualitative data, with the exception of the noise level, whose attached conceptual module uses a statistical characterization of room noise to classify it as `NegligibleNoise`, `LowNoise`, `MediumNoise`, or `HighNoise`.

Level 0, depicted in Figure 4, shows those architectural modules. The information outcome of the **Activity (SS)**, **DoorStatus (SS)**, **RFId (SS)**, **SW activity (SS)** subsymbolic modules is directly handed over to the **Room Occupancy (S)** symbolic module that implements the previously described Bayesian network, while qualitative information produced by the subsymbolic module **Sound (SS)** needs preliminary classification through the **Sound (C)** conceptual module, before passing to the **Room Occupancy (S)** module.

5.3 Lighting Adequacy

It is worth considering the subsystem reasoning on the adequacy of lighting in order to get a deeper understanding of the interplay of different levels for knowledge management. This subsystem takes into account current indoor lighting, estimated through ambient light sensor readings, and the presence of the considered user, estimated via the outcome of the room occupancy subsystem. As shown in Figure 4 input to the lighting adequacy subsystem are the outputs of lower-level modules, thus placing this system at *Level 1* of our architecture. The processing of the sensory information about current lighting follows the previously described multi-tier knowledge representation scheme. The subsymbolic module dealing with lighting data (**Light^0(SS)**) extracts statistical information, such as the average value and the variance of sensory readings, to provide a global qualitative description of the lighting of the room. The information about indoor and outdoor lighting constitutes the qualitative dimensions for the conceptual module dealing with the overall lighting (**Light^0(C)**), which classifies the actual lighting degree and translates this concept in factual knowledge for the connected symbolic module (**Light^0(S)**). The information generated by *Level 0*-symbolic modules **Light^0(S)** and **Room Occupancy (S)** is passed onto the upper level where it is interpreted as higher-level subsymbolic information. In general, each *Level i*-symbolic module connected to *Level i+1* corresponds to a *Level i+1*-subsymbolic module whose input virtually derives from those "pseudo-sensors"; the back translation from low-level-symbolic to high-level-raw information is performed by an ad-hoc mapping mechanism. The outcome of the **Room Occupancy (S)** module are the probability of the presence of the considered user is in their own office, and the estimated number of people in the same room; this kind of information can be directly interpreted as a qualitative dimension, so the *Level 1* **Room Occupancy (SS)** module only needs to bridge the gap with the *Level 1* **Lighting Adequacy (C)** conceptual module. The information about lighting extracted by the **Light^0(S)** module in symbolic form, requires a translation to numeric form through an ad-hoc mapping from logic predicates to numeric indices. This task is performed by the **Light^1(SS)** module that produces the needed qualitative dimension to complete the input for the **Lighting Adequacy (C)** conceptual module, which in turn classifies the obtained information about lighting in the room, in relation with its occupancy, as **`InsufficientLighting`**, **`Sufficient-Lighting`**, or **`OptimalLighting`**. Based on this factual knowledge, and on a room state representation in terms of the status of light switches and motorized curtains, the **Lighting Adequacy (S)** symbolic module is able to provide the planning component with a concise description of the current room lighting. The planning component will use this information and a description of the desired target state to carry on its reasoning and select the most appropriate sequence of actions.

6. CONCLUSION

The present work describes the design and implementation of a comprehensive architecture for knowledge management in the context of AmI applications. A precise representation of the state of the environment can be obtained only through continuous and pervasive monitoring, but this makes the management of the stream of sensory data very challenging, due to its huge amount. The discussed case study shows how the low-level sensory subsystem may be effectively implemented with the wireless sensor networks technology, and how a multi-level structure for the system may help to cope with the issue of knowledge extraction, by addressing different abstraction degrees at different levels. A multi-tier structure at each level is also used to keep the problem manageable.

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