UNIVERSITÀ
DEGLI STUDI
DI PALERMO

NDS
NETWORKING AND DISTRIBUTED SYSTEMS
RESEARCH GROUP

Exploiting the human factor in a WSN-based system for ambient intelligence

Article

Accepted version

A. De Paola, A. Farruggia, S. Gaglio, G. Lo Re, M. Ortolani

In Proceedings of the International Conference on Complex, Intelligent and Software Intensive Systems, 2009. CISIS '09, pp. 748-753

It is advisable to refer to the publisher's version if you intend to cite from the work.

Publisher: IEEE

http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5066872

NDS LAB - Networking and Distributed Systems
http://www.dicgim.unipa.it/networks/

Exploiting the Human Factor in a WSN-based System for Ambient Intelligence

Alessandra De Paola, Alfonso Farruggia, Salvatore Gaglio, Giuseppe Lo Re, and Marco Ortolani
Dipartimento di Ingegneria Informatica
Università degli Studi di Palermo
{depaola, gaglio, lore, ortolani}@unipa.it, a.farruggia@dinfo.unipa.it

Abstract

Practical applications of Ambient Intelligence cannot leave aside requirements about ubiquity, scalability, and trasparency to the user. An enabling technology to comply with this goal is represented by Wireless Sensor Networks (WSNs); however, although capable of limited in-network processing, they lack the computational power to act as a comprehensive intelligent system. By taking inspiration from the sensory processing model of complex biological organisms, we propose here a cognitive architecture able to perceive, decide upon, and control the environment of which the system is part. WSNs act as a transparent interface that allows the system to understand human requirements through implicit feedback, and consequently adapt its behavior. A central unit will carry on symbolic reasoning based on the concepts extracted from sensory inputs collected and pre-processed by pervasively deployed WSNs.

1 Introduction

From an Ambient Intelligence perspective [1, 10], the human user is the center of a pervasive digital intelligent environment, whose primary goal consists in satisfying users' requirements as regards controlling the conditions of their surroundings. One of the enabling technologies in this field is represented by Wireless Sensor Networks (WSNs) [3, 11], thanks to their capacity of providing a pervasive and unintrusive means for sensing the environment.

A WSN is made up of a potential large number of distributed computational units; those small sensor nodes are programmable, energetically autonomous, and able to wirelessly communicate with each other; moreover, they may be equipped with different sensors in order to measure several environmental characteristics. By exploiting the cooperation among nodes, a WSN allows for low-level preprocessing of the sensed data, in order to select, for instance, only relevant information from the huge amount of measurements. The possibility of a low-cost and low-intrusiveness, but pervasive deployment paves the way for the development of a ubiquitous and scalable system which is one of the primary requirements for Ambient Intelligence applications [5]. The sensory subsystem permeates the environment almost transparently to the users; moreover, the possibility of tuning the execution of the program running in the sensor nodes on the fly, allows us to modify the behavior of the WSN without a direct intervention. However, despite their potential, WSNs cannot by themselves be a tool for collecting and, above all, *understanding* all of the sensed data.

Our work proposes a novel cognitive system able to perceive, decide upon, and control the environment of which it is part. Such a system may be regarded as an intelligent entity embodied in the environment itself, and whose decisions are guided by goals related to the well-being both of the system, and of the other entities populating the environment.

This intelligent organism employs WSNs as its sensory organ in order to perceive precise information on the environment. This technology enables the system to collect measurements at the preferred rate regardless of space constraints. The difficulty of managing the generated large amount of data requires the design of a new architectural scheme capable to make full use of the programmability of the sensor nodes. The idea underlying our work is inspired to the nervous system of complex biological organisms, that typically include some peripheral pre-processing mechanisms for extracting more significative information from the wealth of data. Striking examples may be found in some parts of the human nervous system, whose peripheral component deals with collecting sensory inputs, filtering them, and transferring them in an aggregated form to the central nervous system, where high-level processing will be performed.

The cognitive architecture we propose here exploits its distributed sensory component in order to obtain necessary information to carry on cognitive, decision, and control activities. The middle-layer component of our system is also inspired to the functional organization of human brain. Sev-

DRAFT

eral studies in neurosciences [21, 16] 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 components operate independently and in parallel on different environmental stimuli in order to provide a symbolic representation of them. The interconnection among the different modules lets lower-lever modules transfer their knowledge as input for higher-level ones that accept several simpler information streams and integrate them to provide a complex representation of the environment. Modules are organized according to a multi-tier cognitive scheme, similarly to what happens in the functional areas of the brain that are divided into functional clusters of neurons operating at increasing abstraction degrees [21]; our scheme comprises three tiers representing knowledge in a *subsymbolic*, *conceptual*, and *symbolic* way respectively.

Also from a biological inspiration comes the possibility of learning by interacting with the external world. In our case, the external world is represented by the users populating the intelligent environment. Their interactions with the system are in fact used to steer a learning process able to adapt the mechanisms of knowledge representation and management, and the decision processes, to the users' requirements.

Our main contribution lies in the design of a cognitive architecture relying on a flexible and scalable paradigm for knowledge representation in order to efficiently extract environmental information from a pervasive sensory system and to turn it into a symbolic representation of the environment. The case study proposed in this paper regards the management of an indoor environment, namely the premises of a university department, where clashing goals are present, such as keeping a pleasant temperature, minimizing the overall power consumpion and maxizing the WSN time of life.

The remainder of the paper is organized as follows. Section 2 briefly describes other approaches to the use of WSNs and biologically inspired behavior for Ambient Intelligence. Section 3 presents the overall organization of the proposed architecture; details about the knowledge representation model and the learning scheme are given in Sections 4 and 5 respectively. Finally, Section 6 summarizes our conclusions.

2 Related Works

Many works presented in Ambient Intelligence literature make use of WSNs both as a distributed sensory tool, and as a wireless network infrastructure. However, to our best knowledge, none of them 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 [17, 15], systems for healthcare are proposed, especially targeted to monitoring chronic illness, of 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.* [14], 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.

In [20], a WSN-based infrastructure is described targeting the development of wildfire prevention system, whose architecture is based on three layers, the lowest of which relies on a sensor network for measurement gathering. Also the work presented in [2] employs a WSN, but the goal is the collection of information about the occupancy of the monitored premises; collected data are aggregated in order to compute predictions about the occupant behaviour.

Several works on Ambient Intelligence are inspired to biological models for reasoning and learning. In some cases the biological model is taken as an example for the formalization of a logical architecture reflecting the logical structures that concur to the arising of consciousness, as described by cognitive science research; in other works, the starting point is the capability of learning through the interaction with the surrounding environment that is typical of complex biological systems.

In [18], a logical structure for an Ambient Intelligence system is proposed that is inspired to the neuro-biological model of human brain, The authors focus on the use of contextual knowledge for the classification of events occurring in the considered environment, with the aim of facilitating intrusion detection. The classification step is based on an initial off-line training, based on a significant amount of training data, followed by an on-line phase, where a human operator provides explicit feedback about the quality of classification, so that the system may dynamically adapt its parameters. The same architectural scheme has been proposed in [9] and applied to the "classification of risk zones in a smart space"; the learning phase of the classifier is inspired here on the biological mechanisms that exploit memory of the past interactions between the intelligent entity and the other entities in the environment for learning.

In [8], the authors propose an application of an unsupervised learning technique based on fuzzy logic to the intelligent agents constituting the Ambient Intelligence system. The fuzzy rules are learned by examining the users' behavior and are dynamically changed so that long-term goals

DRAFT

may be satisfied. The inputs for the learning machine are gathered via the interactions between the user and the actuators allowing for manual environmental control.

With respect to the previously mentioned works, we also refer to a biological model to design our architecture. Unlike [18] and [9], we do not delve into the deep mechanisms regulating the arising of consciousness, rather we propose an architecture inspired to the hierarchical model for processing sensory stimuli in the human nervous system. On the other hand, a higher similarity between our proposal and the previously cited works is represented by the idea of exploiting feedback from users in order to adapt the system behaviour. In particular, we devised a system based both on explicit feedback, similarly to what proposed in [18, 9], and to implicit feedback, similarly to [8].

3 System Architecture

As already mentioned, the architecture proposed in this work is inspired by the human nervous system, in which signals gathered by the peripheral system are filtered, aggregated and then sent to the central system for high-level processing.

We consider as case study a home automation application instantiated for a work environment, with the aim to provide constant monitoring of the environmental conditions in the rooms of the teaching staff of our department. After describing the designed WSN, representing the peripheral system that permeates the environment, and allows for distributed data pre-processing, this section outlines the modular structure of the intelligent system.

3.1 Peripheral Information Processing - WSN

We regard the aggregation and selection of environmental data as analogous to the processing of perceptual signals occurring in the human nervous system. Some components of the peripheral system filter perceptual information by means of distributed processing among several neurons. A remarkable example is the processing of visual information occurring in the retina [16]: in the human eye, photoreceptors convert light into electrical signals that are passed to a network of retinal neurons, and are modified before being transmitted to gangliar neurons; eventually, they are handed to the optic nerve that carries the information up to the brain. The retinal neuron network does not restrict itself to carrying signals from photoreceptors, but rather combines them to obtain an aggregate heavily dependent on the spatial and temporal features of the original light signal.

In our architecture the terminal sensory component performing is represented by WSNs pervasively deployed in the environment. Figure 1, partially drawn from [19, 22],

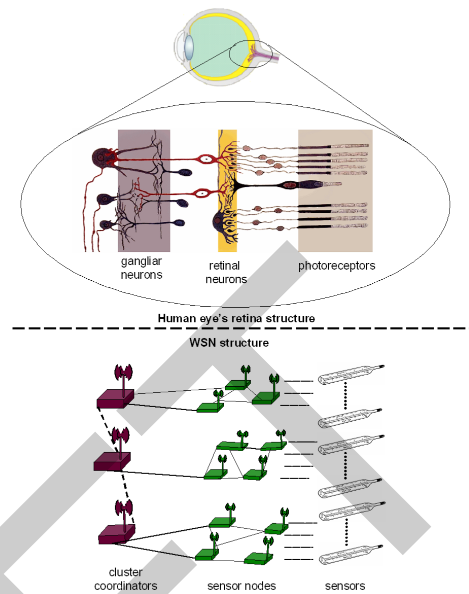

Figure 1. Comparison between the structures of the human retina and the proposed WSN.

highlights the similarity between the structures of the human visual organ and of the WSN employed here.

We propose a clustered network structure in which each small cluster, constituted by heterogeneous nodes with different computational capabilities, distributedly processes homogeneous data. This pre-processing 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.

The implemented WSN is equipped with off-the-shelf sensors for measuring such quantities as temperature, relative humidity, noise, and ambient light exposure. Sensor nodes (in our implementation we have used MICAz nodes and Stargate microservers) have been deployed in various rooms close to "sensitive" areas: by the door, by the window, and by the user's desk. Moreover, we are integrating this basic infrastructure with more specific sensors, i.e. RFId readers, that will provide information to be used for access control, and naive localization of people inside the premises.

3.2 Central Information Processing - Modular Architecture

The proposed system is organized according to a hierarchical structure whose modules are combined together in

DRAFT

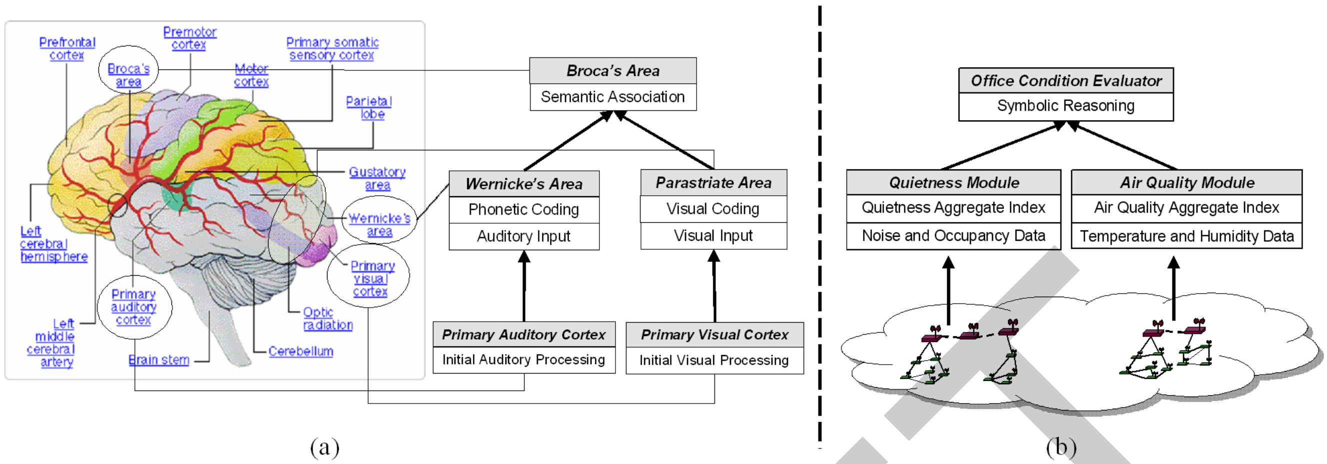

Figure 2. The human language comprehension model vs the proposed hierarchical reasoning model.

order to carry on specific reasoning on the environment at different levels of abstraction and on different kinds of perceptions. The overall behavior mimics that of the human brain, where the emerging complex behavior is the result of the interaction among smaller subsystems. From the design point of view, the modular organization allows for the realization of a scalable sofware architecture, able to effectively manage the huge amount of sensory data.

Figure 2, partially taken from [4], draws a parallel between the human brain model and our system model. In our modular architecture, the outcome of lower-level reasoning is fed into the upper levels, that deal with the integration of information originated by multiple lower-level modules. Each module independently measures environmental quantities, conceptualizes them, and describes the extracted concepts linguistically, as will be detailed in the following section where the multi-tier knowledge representation is presented. Moreover various modules process both direct and indirect measurements; the former occur at modules located at the lowest level in the hierarchy, while the latter are carried on at the upper layers, mediated by their lower-layer counterparts.

Considering a particular scenario, the human language comprehension model, described in [16], provides a significant example of interaction patterns among specific areas of the brain, as schematically presented in the left side of Figure 2. Different anatomic structures are devoted to different phases of language processing: the primary auditory cortex initially processes the auditory signals while at the same time the primary visul cortex processes the visual signals. Pieces of information separately obtained by each low-level structure are sent to the areas devoted to phonetic and visual coding respectively. The outcome of the two intermediate modules are passed to the semantic association area, where they are merged.

In our architecture, an analogous example may be recognized in the modules devoted to assess whether environmental conditions are acceptable for a pleasant working activity, as shown in the right side of Figure 2. Low-level modules independently reason about air quality and room quietness, and the produced information is aggregated by a higher-level module; thanks to a broader knowledge of the environment, it may perform more complex reasoning, without being overwhelmed by the incoming information thanks to the previous filtering.

4 Multi-tier Knowledge Representation

Each module of our architecture implements the three-tier structure shown in Figure 3, in which the lower subsymbolic tier applies only basic preprocessing to raw sensed quantities, and the higher symbolic tier provides a linguistic representation of knowledge; those two tiers are connected through an intermediate tier where ground concepts are represented in a geometric space, inspired by the "conceptual spaces" described in [12].

This structure resembles the ideas presented in [6] that were applied to an artificial vision scenario. The whole system is implemented on a central node with no strict resource constraints, with the exception of the subsymbolic tier of the lowest module that is localized on the WSN. For clarity's sake we only focus here on the description of this lowest architectural module.

The subsymbolic tier processes the measurements collected by the pervasive sensory subsystem. As already mentioned, the purpose of the WSN-based infrastructure is not limited to the basic gathering of sensed data, but comprises also a preliminary processing aimed at the selection of the relevant information. Sensed measurements can be classified into two main categories, namely continuous or discrete; data belonging to the former class are fed to the intermediate conceptual tier, where they will be provided with

DRAFT

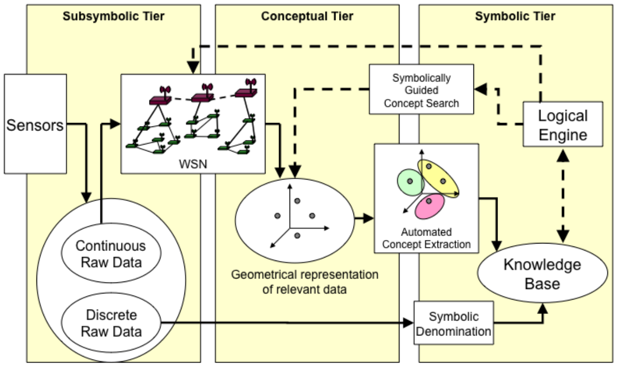

Figure 3. The three-tier structure of a low level module.

a representation in terms of continuous quality dimensions. On the other hand, discrete data are outright handed over to the symbolic tier, where a linguistic representation will be given.

At the conceptual tier, data are endowed with a geometrical representation that allows for a straightforward management of the notion of concept similarity, as long as a proper metric is chosen for the quality dimensions. Points populating the conceptual space, originally generated by the underlying measurement space, are represented as vectors, whose components are the quality measurements of interest. Concepts thus naturally arise from the geometric space as regions, identifiable through an automated classification process, and points will belong to one of those regions. In our implementation the identification of regions associated to concepts occurs after a supervised training of the classifier. As will be detailed in the following, the classifier is also able to dynamically adjust its internal representation of the concepts based on direct and indirect feedback from the user.

The symbolic tier in each module produces a concise description of the environment by means of a high-level logical language. At this level, regions individuated inside the conceptual space are associated to a linguistic construct, thus identifying basic concepts, while relations necessary to infer more complex concepts are described through an opportune ontology. The gap between a concept and its linguistic description is filled through two separate mechanisms inspired to the work of [6]: an "automated concept extractor" deals with the translation of the regions in the conceptual space into symbolic elements, whereas a "symbolically guided concept search" identifies further points in the conceptual space as a consequence of the activation of some of the logical rules contained at the symbolic tier.

The created knowledge base is used to iterate the same knowledge extraction mechanisms at a higher abstraction level. In the considered case study, the concepts asserted at the symbolic tier are also employed for the activation of the control rules of the actuators, represented by the controllers of the heat, air conditioning, and lighting systems. Moreover, a subset of those rules is devoted to providing feedback to the WSN in order to guide its self-maintenance activity; for instance, under steady environmental conditions, the higher tier will opt for a reduction of the sensor sampling rate in order to reduce the overall energy consumption.

5 Learning from Human Interaction

The conceptual and symbolic layers of our knowledge representation paradigm are based respectively on a classification system that associates qualitative concepts to sensory data, and on a set of logic rules that, by carrying out reasoning on the description of the environment, will trigger the proper actions. Those cognitive layers enclose the high-level modeling, and logical inference functionalities, that together constitute the core of the central reasoning system.

In complex biological systems, such functionalities are tipically refined by a learning process based on the interaction with the surrounding environment; analogously, the architecture described here includes specialized learning schemes that allow the system to acquire new information from the users populating the intelligent environment. Object of this further learning phase are both the classification carried on at the conceptual layer, and the rules defined at the symbolic one.

In the proposed system, two separate mechanisms are provided for collecting feedback from people inside the same intelligent environment; they are classified as *explicit* or *implicit*, depending on the way the additional information is collected. In the former case, the user is intentionally communicating their needs to the intelligent system, in order to support the learning phase. In the latter case, this explicit interaction is missing, so the system resorts to analyzing the actions carried on by users, in order to extract implicit knowledge.

The explicit feedback collection mechanism is based on a simple GUI enabling the users to assess the current environmental conditions so to express their likes and dislikes. For instance, by entering the appropriate choices into a web-based interface, any user may indicate that "air quality" is "pleasant", but "room quietness" is "unsatisfactory". The provided labeling will be referred to the geometrical representation of the current environmental state and will contribute as additional training samples for the classifier. In the initial design phase, a sufficient number of previously collected data will be used for off-line training; on-line assessments, collected during normal operation, will then be used to dynamically adapt the classification scheme. The automated concept extractor, suited for the outcome of the previously described WSN, includes a classifier employ-

DRAFT

ing a kernel-based method, i.e. Support Vector Machines (SVM) [7], designed to extract such concepts as "air quality".

Implicit feedbacks, on the other hand, rely on the possibility of "perceiving" the actions of the users in response to the environmental conditions as decided by the intelligent environment. Through specialized sensors installed on the manual controls available to the user, the system is for instance enabled to detect that a temperature decrease was requested. This kind of information is useful to associate the undertaken action (representing the user's preference) to the current environment state at the symbolic level; it will thus be possible for the system to learn new logical rules that better fit the intelligent environment inhabitants' demands.

6 Conclusion

The cognitive architecture presented here is an example of a flexible and scalable approach to knowledge extraction from the environment by means of the integration of a pervasive sensory framework and a central intelligent entity capable of symbolic reasoning. Unlike previous works, WSNs here are not merely used for data sensing and gathering purposes, rather their computational capabilities are effectively exploited in order to perform an initial preprocessing phase that constitutes the preliminary step for the overall reasoning. The structure and functionalities of the human nervous system have inspired us during the design of this modular architecture so that reasoning at different levels of abstractions was implemented. Preliminary tests conducted with an initial prototype have shown the potential of the proposed system in terms of expressivity for modeling the environment.

References

[1] E. Aarts and J. L. Encarnação. *True Visions: The Emergence of Ambient Intelligence*. Springer, 2006.

[2] M. Akhlaghinia, A. Lotfi, C. Langensiepen, and N. Sherkat. Occupant behaviour prediction in ambient intelligence computing environment. *Journal of Uncertain Systems*, 2(2):85–100, May 2008.

[3] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci. A survey on sensor networks. *IEEE Communication Magazine*, 40(8):102–114, August 2002.

[4] American Medical Association. Website. `http://braininfo.rprc.washington.edu`.

[5] T. Basten, L. Benini, A. Chandrakasan, M. Lindwer, J. Liu, R. Min, and F. Zhao. Scaling into ambient intelligence. In *Proc. of Design Automation and Test in Europe (DATE'03)*, pages 76–81, March 2003.

[6] A. Chella, M. Frixione, and S. Gaglio. Understanding dynamic scenes. *Artificial Intelligence*, 123(1-2):89–132, 2000.

[7] N. Cristianini and J. Shawe-Taylor. *An Introduction to Support Vector Machines*. Cambridge University Press, 2000.

[8] F. Doctor, H. Hagras, and V. Callaghan. A fuzzy embedded agent-based approach for realizing ambient intelligence in intelligent inhabited environments. *IEEE Transactions on Systems, Man and Cybernetics, Part A*, 35(1):55–65, Jan 2005.

[9] A. Dore, M. Pinasco, and C. S. Regazzoni. A bio-inspired learning approach for the classification of risk zones in a smart space. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR '07)*, pages 1–8, June 2007.

[10] K. Ducatel, M. Bogdanowicz, F. Scapolo, and J.-C. Burgelman. *Scenarios for Ambient Intelligence in 2010, Tech. Rep.* Information Soc. Technol., Advisory Group (ISTAG), Inst. Prospective Technol. Studies (IPTS), Seville, Feb 2001.

[11] D. Estrin, L. Girod, G. Pottie, and M. Srivastava. Instrumenting the world with wireless sensor networks. In *Proc. of Int. Conference on Acoustics, Speech, and Signal Processing (ICASSP 2001)*, Salt Lake City, Utah, May 2001.

[12] P. Gärdenfors. *Conceptual Spaces The Geometry of Thought*. MIT Press, Cambridge MA, 2000.

[13] S. Goel, T. Imielinski, and A. Passarella. Using buddies to live longer in a boring world. In *Proc. IEEE PerCom Workshop*, volume 422, pages 342–346, Pisa, Italy, 2006.

[14] K. Han, J. Lee, S. Na, and W. You. An ambient robot system based on sensor network: Concept and contents of ubiquitous robotic space. In *Mobile Ubiquitous Computing, Systems, Services and Technologies (UBICOMM'07)*, pages 155–159, Nov. 2007.

[15] S. Jimenez-Fernandez, A. Araujo-Pinto, A. C.-S. de Rojas, F. del Pozo-Guerrero, O. Nieto-Taladriz, P. de Toledo-Heras, and J. Moya-Fernandez. PERSEIA: a biomedical wireless sensor network to support healthcare delivery for the elderly and chronically ill. In *Proc. of IEEE Conference on Engineering in Medicine and Biology Society (EMBS '06)*, pages 2064 – 2066, New York City, USA, Aug 2006.

[16] E. Kandel, J. Schwartz, and T. Jessell. *Essential of Neural Science and Behavior*. Appleton & Lange, New York, 1995.

[17] R.-G. Lee, C.-C. Lai, S.-S. Chiang, H.-S. Liu, C.-C. Chen, and G.-Y. Hsieh. Design and implementation of a mobile-care system over wireless sensor network for home healthcare applications. In *Proc. of IEEE Conference on Engineering in Medicine and Biology Society (EMBS '06)*, pages 6004–6007, New York City, USA, Aug 2006.

[18] L. Marchesotti, S. Piva, and C. Regazzoni. Structured context-analysis techniques in biologically inspired ambient-intelligence systems. *IEEE Trans. on Systems, Man and Cybernetics, Part A*, 35(1):106–120, Jan 2005.

[19] Santiago Ramon y Cajal. Structure of the mammalian retina. Website. `http://en.wikipedia.org/wiki/Retina`.

[20] D. Stipanicev, L. Bodrozic, and M. Stula. Environmental intelligence based on advanced sensor networks. In *Workshop on Systems, Signals and Image Processing 2007 (in EURASIP'07)*, pages 209–212, June 2007.

[21] G. Tononi and G. Edelman. Consciousness and complexity. *Science*, 282(5395):1846–1851, 1998.

[22] Wikipedia. Evolution of the eye. Website. `http://en.wikipedia.org/wiki/Eye`.

DRAFT