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Interaction Modeling and Prediction in Smart Spaces: a Bio-Inspired Approach Based on Autobiographical Memory

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Abstract—In Smart Spaces the capability of learning from experience is fundamental for autonomous adaptation to environmental changes and for proactive interaction with users. New research trends for reaching such a goal are based on neurophysiological observations of human brain structure and functioning. A learning technique to provide a Smart Space with a so called Autobiographical Memory is here presented drawing inspiration from a bio-inspired model of the dynamics occurring between the system and the user. Starting from the hypothesis that users actions have a direct influence on the internal system state variables and vice versa, a statistical voting algorithm is proposed for inferring the cause/effect relationships among such instantaneous variations. The main contribution of this paper lies in proposing a general framework able to allow a Smart Space to be aware of its present state as well as of the behavior of its users and to be able to predict, with a quantified probability estimation, the expected consequences of users actions.

Index Terms—Smart Space, Bio-inspired Learning, Dynamic Interactions Modeling, Event Prediction

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GLOSSARY

Proto State $X_P(t)$	vector of values acquired by sensors related to the internal status of the system
Core State $X_C(t)$	vector of values acquired by sensors related to the external status of the system
Proto Super-state $Sx_P(t)$	semantic representation of the internal state obtained through a SOM feature reduction process
Core Super-state $Sx_C(t)$	semantic representation of the external state obtained through a SOM feature reduction process
Proto Event $\epsilon_P(t)$	modification of the Proto Super-state
Core Event $\epsilon_C(t)$	modification of the Core Super-state

I. INTRODUCTION

The rather new discipline of Ambient Intelligence (*AmI*) has grown in recent years and the design of AmI systems has opened the path to different definitions, issues, related studies and proposed solutions [1],

[2]. An intelligent environment or *Smart Space* (*SS*) is characterized by a complete absorption of technology into everyday common objects. This point of view, shared by the whole AmI research community, helps in providing the user with a more natural interaction with the system and hence to overcome the obtrusion due to the massive use of electronic devices [3]. In [4], McAra-McWilliam pointed out that AmI systems are capable of interacting with humans by creating an environment that is responsive to people's activities. In order to establish efficient interactions in SSs between these two players, research focused its attention on how to understand user's behaviors and needs for being aware of the current environmental situation and for being proactive in everyday life support.

Learning human activities [5], [6] is an important aspect in building SSs, in order to understand complex interactions with human users [7]. In this scenario, new paradigms, inspired by cognitive sciences [8], [9] and neurophysiology [10], can be appropriate solutions, as it is demonstrated in Artificial Intelligence and Robotics [11]. Modeling cognitive and conscious capabilities [12], [13] in intelligent systems according to the natural understanding, reasoning, acting and learning criteria of human brain [14], [15] can be used for solving complex problems such as natural interaction with users [16] in AmI systems [17].

In this paper, these concepts are explored in order to point out the relevant role of the structural coupling between system and environment (i.e. interaction with the user) in the development of context-aware SSs. In fact a model is here proposed for learning [18] in dynamic cognitive systems [19] that is able to understand the cause/effect relationships between the changes in system state and the environmental perturbations due to the presence of the user. An algorithm based on neuro-physiological studies on how human self-consciousness arises and evolves is proposed to extract contextual information from heterogeneous sensors signals and to learn and predict interactions involving users present in a Smart Space.

A. Related Works

Since the end of the Nineties different visions of AmI systems have been proposed both from academic and industrial players. Examples of these strong efforts can be found in the Philips' PHENOM [20] or HomeLab [21] projects, such as in MIT's Oxygen project [22], Intel's Human Activity Recognition [23]–[25], and in the Italian Virtual Immersive COMmunication (VICOM) project [26]. Other particular systems which consider cars as the responsive environment are introduced by Trivedi *et al.* [27] for enhancing driver safety and security.

All the previously cited systems share some generic principles in architecture design. As a matter of fact, they contemplate a structure composed by a set of heterogeneous sensors, tools for analyzing the gathered data, dynamic planners for responding (in short or long time periods) to interactional stimuli and learning methods for understanding environmental changes. The last element is especially important for providing Smart Spaces with the flexibility required for naturally interacting with human users. The human adaptability should be considered as a reference point for building dynamic systems, as pointed out by Perlovsky [28]. From an engineering point of view, this characteristic has been the final goal of a different way of representing intelligence, evolving from the cognitive [11] semantic reasoning of classical AI (Artificial Intelligence) systems [29], where all the knowledge was hardwired into the system by human *experts* [30], to emergent and dynamics systems [31] able to learn models of human interaction behavior [32]. The

former ones are constructed on an extensional knowledge representation [33], where rules are the fundamental atomic bricks [34]. The deterministic approach founded on rule-sets definition/extraction and on the inferential relationships, which link different sets together, can lead to system instability, when they have to face the complexity of human/machine interactions and its unpredictability. Furthermore, rule-based approach can be not comprehensive of all the sensors states and all the semantic events that a human can produce during its activity with the system. Moreover, rule-based systems have an intrinsic difficulty in representing the effects of the interactions in the time domain, as well as a reduced predictive capability. An intensional representation [33] can overcome these limitations. The statistical description of the events allows one to avoid any deadlocking condition, due to the intrinsic completeness of the represented knowledge.

Different works can be found in the literature focused on learning algorithms specifically designed for AmI applications. For example, in [35] a fuzzy learning technique, which extracts fuzzy rules to represent the user's behavior in an AmI system installed in a dormitory, is presented. The learned rules relate two sets of state variables, regarding respectively sensors and actuators, acquired simultaneously, without considering their temporal consequentiality. In [36], the authors propose an activity recognition method for Smart Hospitals. The system is based on multiple Hidden Markov Models (HMMs) which interpret the interactions between hospital staff, clinical objects, and patients. The statistical model is based on a two layer HMMs where at a first stage people and object interactions are modeled in order to be fused in the second layer in order to recognize activities. Layered HMMs has been used also in other works, as in [37], [38], where complex actions can

be decomposed in sub-activities. Many other statistical models have been proposed to handle these problems. Coupled Hidden Markov Models [39] have been used to model and recognize human interactions derived from analysis of trajectories. In [40] a Hierarchical Hidden Markov Model (HHMM) allows the decomposition of complex activities in simpler ones in order to recognize behaviors in a domestic scenario. Similarly the work proposed by Du *et al.* [41] introduces a new statistical model, called Coupled Hierarchical Duration-State Dynamic Bayesian Network (CHDS-DBN), to represent interactions by considering features extracted at different levels of detail. These approaches based on graphical models need the a priori definition of the graph structure, i.e. the relationships between the state and observation node, and an off-line learning procedure to estimate the conditional probability density functions relating them. Another example of a learning system is ADA [42]: involving groups of users in a big audio/visual game, Eng *et al.* built up a system able to learn the proper actions that have to be used to condition human behavior. The active learning strategy, based on various pre-codified stimuli available to the system, was used to parametrize a neural based adaptive system. Through an interactive psychology-based strategy the system is able to memorize causal relationships (stimulus-answer) between the system and the users and to select the most appropriate actions to be performed. A neural based learning system was also used by Marchesotti *et al.* in [43] in order to estimate the amount of usage/occupation of a University laboratory. core of the method was a Self Organizing Map (SOM) Neural Network used as a hierarchic fusion method for integrating the external and the internal status of the system.

B. Motivations and Objectives

The proposed algorithm named, *Autobiographical Memory*, is intended as the first step into a new way of building interacting systems whose learning and predicting capabilities are inspired by the human ones.

The innovative aspect of this work is the new way of modeling the interactions between user and system and its engineering implication in the development of context aware learning/predicting strategies. To do so multiple heterogeneous data coming from a set of sensors are jointly processed with the aim of detecting internal and external contextual events. Then a non-parametric probabilistic interaction model is learned that can be used to predict future events to be able to design anticipative decision strategies. The proposed mechanism, applied for processing and passively learning interactions between system and users introduces new functionalities and modeling capabilities with respect to other works in the state of the art, which can be exploited in Smart Space design.

The paper is organized as follows: in Section II an approach for learning interactions between Smart Spaces and users being inspired by neurophysiological studies is proposed. A procedure is introduced for using these memorized data to predict changes in the system internal status, which are caused by users interactions, potentially allowing self-reaction and self-adaptation capabilities. In Section III described algorithms are extensively tested in the scenario of a Smart space, installed in a University laboratory, that monitors internal status of its devices and external events produced by users actions. Section IV presents comparisons with other learning approaches for Ambient Intelligence applications. Finally in Section V we conclude commenting on open issues and possible future improvements.

II. A Bio-inspired Algorithm for Learning Interactions

A possible starting point to provide an Ambient Intelligence system with two basics capabilities, like context awareness and reasoning, is to understand how *consciousness*, interpreted as the capability of differentiation between itself (*self*) and the external world, can be translated into an AmI system.

In this paper, taking inspiration from the work of the neurophysiologist A. Damasio [44], a model is developed where two key players, the intelligent organism and the perceived object, are involved by considering their interactional relationships. In this context, the organism can be addressed as the Smart Space system whereas the object is any entity that gets to be known by the system for possible interactions; the temporal stream of causal relationships between the organism and the object provides the contents of the knowledge one can call consciousness. From this point of view, consciousness can be associated with the construction and the use of knowledge base resulting from two occurrences: 1) the organism is involved in the relation to some objects; 2) the object in the relation causes a (potential) change in the organism. Using this information a framework for an AmI system is proposed that is able to predict the evolution of the change of the system state conditioned to user's actions and when this modification can occur.

A. Neurophysiologic foundation

Through his experiments, Damasio [44] states that consciousness probably arises from the relationship of the organism with the representation of an object. More in details according to Damasio's view, consciousness derives from the construction of knowledge about dynamic changes of the state of the organism while interacting with an object and its modifications following

the relationship with the other entity. This aspect is particularly suited for an Ambient Intelligence application where the focus is the interaction between the system and the user to efficiently supply services.

Damasio refers to *images* as the brain representations of some objects or feelings in terms of the sensory perceptions related to them. In this sense, images are therefore not just visual, but also dependent to other sensory modalities, that is visual, auditory, olfactory, gustatory, somatosensory (i.e. coming from the body feelings, touch, temperature, pain, etc.). The pattern of neural activities, namely the set of neurons involved in the sensory process, from which images arise (in a yet unknown way) are called *neural patterns*. According to this, *proto-self* and *core self* are images of the internal and external activities, deriving from *first-order neural patterns*. However, core consciousness, namely the consciousness of what is external to the organism, emerges from *causal* relationships between an object and the organism.

This element is related to *second-order neural patterns* since it accounts the object coming into sensory representation and the consequent modification in the proto-self. Moreover, considering that the interacting entity triggers the core self in an impulsive way it can be observed that core consciousness is created in pulses caused by objects affecting the organism. A second-order neural pattern can be represented as in Figure 1 where the proto-self at the inaugural instant, i.e. before the interaction, the object giving rise to the core self, and the consequent modification in the proto-self are outlined.

[Fig. 1 about here.]

This structure allows one to capture the *causal relationships* between an object and the organism in the sense of modifications of the internal state of the cognitive entity caused by the interaction with an external element.

In neurophysiologic experiments Damasio observed that core consciousness is continuously generated while the interaction with an external element occurs. The more the interaction lasts, the more core consciousness occurrences will be observed and analyzed. This is implicitly the learning process which allows one to have memory of the past and to anticipate the future through previous experience, and it consists in the building of the *Autobiographical Memory*. Therefore, essentially, the Autobiographical Memory is composed by a set of *objects* relating an event with its consequences on the organism, i.e. the images generated in the core consciousness process. The capability of retaining experiences represented by the core consciousness mechanism is the basis of the formation of the *memory* of the past. This information is then used in the *extended consciousness* to connect the consciousness (i.e. the functional assembly of two distinct parts, self and other-than-self) and the lived past in order to anticipate future. In this process a new component of the brain is fundamental, that is the *autobiographical self*. This element is responsible for reactivating and displaying records of past experiences retained in the Autobiographical Memory concerned to the object which is currently generating the core self. The difference between the core self and the autobiographical self resides in the fact that core self is a transient entity emerging in core consciousness when interacting with some objects while autobiographical self is linked to the idea of identity and corresponds to a non-transient collection of unique facts and ways of beings which characterize the interactions of a person.

The autobiographical self is a record of dispositional (i.e. dormant, potential, implicit) core self experiences related to an object, as, for example, the sensory aspects (e.g. color, shape of the object) but also the motor

activities to better gather sensor signal and emotional reaction to the object. This object is recalled when a core self caused by the same element emerges and these records become explicit and sensory, motor and emotional data connected to the object are retrieved. In some sense that will be clear later in this paper (see Sect. II-D), we could say that autobiographical self adds a set of possible predictions about the trend of the dynamics of ongoing interaction to the current core self.

B. A Bio-inspired Model of Interactions

In Ambient Intelligence one of the main targets is to predict actions that will occur in the monitored area in order to establish beforehand the correct activity to accomplish the required tasks. To reach this goal, a possible approach consists in memorizing interactions occurred between the system and the relating entity in an area associated with an AmI system, in order to acquire a knowledge base to be used for prediction purposes. Since this capacity is one of the crucial aspects for surviving and for the evolution of life beings, a bio-inspired learning approach turns out to be particularly appropriate.

The aim is to learn the interaction through the cause/effect relationships taking place between two entities, namely the system and the user. In particular, two opposite aspects of the interaction can be taken into account for the memorization process: 1) how external events affect the internal status of an entity is examined when we want to describe the *effects* on the analyzed entity *caused* by external occurrences produced by the other entity/entities; 2) how modifications of internal status change the external status is analyzed when we want to describe the *effects* on the interacting entities *caused* by an internal modification of the state. The first way of learning interactions resembles the Autobiographical Memory formation described above in Sect. II-A. The names of the variables defined in the proposed model directly recall the above mentioned neurophysiological concepts. Anyway, such names are not intended as an exact representation in mathematical terms of biologic constructions, but just as a link between the engineering framework and the biologic world.

In our model it can be also important to memorize how the system affects the user behaviors by its actions since this can be significant to predict his future behavior conditioned to system activities. We will address these two aspects of learning interactions as:

1) *passive memory*: external cause / internal effect

2) *active memory*: internal cause / external effect

The rest of the paper only deals with the problem of constructing the passive memory for an Ambient Intelligent system. However, the described approach can be extended to the development and maintenance of the active memory in a straightforward way, as it is commented in Sect. V-B

1) Proto and Core Events Representation: In the proposed model to consider the duality between internal and external states, two vectors respectively describing internal (*proto*) and external (*core*) status are defined:

$$X_P(t) = \{x_{P1}(t), x_{P2}(t), \ldots, x_{P_N}(t)\} \qquad (1)$$

$$X_C(t) = \{x_{C1}(t), x_{C2}(t), \ldots, x_{C_M}(t)\} \qquad (2)$$

where x_{Pn} and x_{Cm} represent, respectively, the data acquired by proto and core sensors considered to describe the internal and the external (with respect to the system) situation. Therefore, a set of heterogeneous sensors are positioned in the Smart Space to monitor the scene and the state of the components of the systems and the acquired signals are used to compose the state vectors $X_P(t)$ and $X_C(t)$. However, in order to provide a significant representation of these elements in terms of

contextual situation to be analyzed a clustering procedure is required to provide a more semantically meaningful description of the ongoing situation detected by sensors. In general, given the complexity and the high number of signals, a pre-processing technique can be useful to fill the memory with meaningful information. In other words, the efficiency of the memory can take advantage of assigning some sub-symbolic labels to each occurrence of the vectors in Eqs. (1 - 2) which, otherwise, can be of difficult interpretation.

A Self Organizing Map [45] (SOM) unsupervised classifier can be employed to convert the multidimensional proto and core vectors $\boldsymbol{X}_P(t)$ and $\boldsymbol{X}_C(t)$ to a lower dimensional M-D, where M is the dimension (from here on we consider $M = 2$ without losing generality) map (layer) where the input vectors are clustered according to their similarities and to each cluster is assigned a label. Labels can be associated in a supervised way, by a human operator or according to a priori information, to an ongoing situation that belongs to a set of conditions to be identified pertaining to the specific application. The choice of SOMs to perform feature reduction and clustering processes is due to their capabilities to reproduce in a plausible mathematical way the global behavior of the winner-takes-all and lateral inhibition mechanism shown by distributed bio-inspired decision mechanisms. Furthermore, SOMs always provide an output with all the sensory data condition. Their intrinsic robustness, due to the unsupervised Kohonen [45] learning mechanism, ensure that new, but correlated to the training data, input patterns are properly recognized. Through this processing step it is possible to provide the system with a contextual representation of internal and external states in terms of maps recalling the brain neural patterns (see Sect. II-A). Worth of note is that the semantic labels are not necessary for

the system functioning since they can be automatically assigned as sub-symbolic tags whose contextual meaning can be understood by the system in an explorative way during the interaction with the external environment. Though, the unsupervised approaches to label states are interesting for fully autonomous AmI spaces, they are out of the scope of this paper.

The clustering process, applied to internal and external data allows one to obtain a mapping of proto and core vectors $\boldsymbol{X}_P(t)$ and $\boldsymbol{X}_C(t)$ in 2-D vectors, corresponding to the positions of the neurons in the SOM map, that we call, respectively, proto *Super-states* Sx_P and core *Super-states* Sx_C. Each cluster of Super-states, deriving from the SOM classifiers, is then associated with a semantic label related to the contextual situation:

$$\begin{aligned} Sx_P^i \mapsto l_P^i, \quad i = 1, \ldots, N_P \\ Sx_C^j \mapsto l_C^j, \quad j = 1, \ldots, N_C \end{aligned} \quad (3)$$

where the notation Sx_P^i and Sx_C^j indicates that the Super-state belongs, respectively, to the i-th proto label and to the j-th core label; N_P and N_C are, respectively, the maximum number of the proto and core Super-states labels.

Then, the result of this process is the building of a 2D map divided in connected regions labeled with a meaningful identifier related to the ongoing situation. Using this representation it is possible to interpret the changes of state vectors $\boldsymbol{X}_P(t)$ and $\boldsymbol{X}_C(t)$ from instant to instant as movements in a plane (*map*) where each position is representative of a super state, i.e. of a particular circumstance. If changes of the vector states $\boldsymbol{X}_P(t)$ and $\boldsymbol{X}_C(t)$ do not imply a change of Super-state labels $Sx_P^i \mapsto l_P^i$ and $Sx_C^j \mapsto l_C^j$ it means that the modifications are irrelevant from the point of view of the chosen semantic representation of the situation. On the other hand, when the Super-state labels Sx_P^i and Sx_C^j

change in subsequent time instants, this fact entails a contextual situation modification, i.e. an *event*. Then, by sequentially analyzing the dynamic evolution of Super-states, proto and core events can be detected. Appropriate sequences of proto and core events can be described as *core self* events that can be assembled as in Fig. 2.

The resulting information becomes an approximation of what Damasio calls the *Autobiographical Memory* where the interaction between user and system are memorized.

2) Autobiographical Memory Model: According to above considerations, the Autobiographical Memory formation is characterized by learning the changes in proto Super-state caused by a core Super-state modification (*core event*). Therefore, the proto Super-state preceding the core event, the core event itself and the proto Super-state must be memorized. More precisely, considering a core event (ϵ_C) taking place at time T_1 the effects on the internal state must be taken into account to learn how the interaction with the external entity, which provoked the core event, occurred. To do that, a time window of duration T_{max}^- is taken into account to detect what was the proto Super-state $Sx_P^-(t)$, with $T_1 - T_{max}^- < t < T_1$ (i.e. the initial internal condition) and its modification subsequent to the core event, i.e. $Sx_P^+(t)$, with $T_1 < t < T_1 + T_{max}^+$. Note that T_{max}^+ is the maximum time after which we consider reasonable that the proto modification has been caused by the core event and it was not occurred autonomously.

Three events are, then, memorized:

- $\epsilon_P^- = Sx_P^0 \rightarrow Sx_P^-$: proto event at the initial instant. It represents the modification of the proto Super-state from $Sx_P^0 \mapsto l_P^i$ to $Sx_P^- \mapsto l_P^j$ occurring before the core event. The two labels l_P^i and l_P^j are the ones associated, respectively, with the Super-states Sx_P^0 and Sx_P^-. The event ϵ_P^- stores

the initial internal state Sx_P^- and at the same time, if it changed in the time window T_{max}^-.

- $\epsilon_C = Sx_C^- \rightarrow Sx_C^+$: core event. It describes the change of the external super state from $Sx_C^- \mapsto l_C^m$ to $Sx_C^+ \mapsto l_C^n$.
- $\epsilon_P^+ = Sx_P^- \rightarrow Sx_P^+$: proto event following to the core event. It represents the change of the proto super state from $Sx_P^- = l_P^j$ to $Sx_P^+ = l_P^k$.

The above triplet $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$ represents a core self instantiation that is associated with an element of the Autobiographical Memory, namely what, in the Damasio work, is called core consciousness.

This model of interactions relies on the following assumptions: 1) the sequence of events considered to describe the interaction to be stored in the passive memory is: proto - core - proto (i.e. internal - external - internal with respect to the system); 2) just one core event is involved in the interaction, i.e. the proto state change is caused by only *one* core event; 3) an interaction takes place only if a proto event, i.e. a change in proto super state, follows the core event within T_{max}^+; 4) if a proto event, preceding the core event, is involved in the interaction it must occur within T_{max}^-. Note that, to model an interaction, it is not necessary that a proto event takes place before the core event within a time range; in fact the system could have been in a stable state for a long period of time since a core event modified the internal status. In our model since we want to memorize events, the steady condition before the core event will be considered as a pseudo event where the label of the super states does not change, i.e. $\epsilon_P^- = (Sx_P^0 \rightarrow Sx_P^-) \mapsto (l_P^i \rightarrow l_P^i)$.

3) Model Discussion: In the neurophysiological description of the Autobiographical Memory it has been outlined that its constituting elements derive from the second order neural patterns (see Sect. II-A), i.e. by the

conjunction of two first order neural patterns relating proto-self and core self. According to this fact, in the proposed model, the Autobiographical Memory can be represented mathematically as a system of two first order derivative equations deriving from the activities in the SOM maps. Each derivative equation describes the proto Super-state modification conditioned to a core Super-state. A core event changes the core Super-state then another equation is necessary to describe the proto super state evolution with the new core Super-state.

The sequence of events and of Super-state modifications can be represented as in Fig. 2 where the proto and core Super-states $Sx_{P,C}$ map to the corresponding labels $l_{P,C}$ and it is outlined that causal relationship can be represented as the effect of the external event on the internal state depending on the same internal state.

[Fig. 2 about here.]

The equations can be written as follows:

$$
\begin{cases}
H_1 \left(\frac{d\,Sx_P(t)}{dt}, Sx_P(t) \right) = F_1\left(Sx_C(t)\right) \\
\qquad\qquad\qquad t = T_1 - T_{max}^-, \ldots, T_1 \\
\\
H_2 \left(\frac{d\,Sx_P(t)}{dt}, Sx_P(t) \right) = F_2\left(Sx_C(t)\right) \\
\qquad\qquad\qquad t = T_1, \ldots, T_1 + T_{max}^+
\end{cases}
\tag{4}
$$

where H_1, H_2, F_1, and F_2 can be non-linear, non-continuous, time varying functions defined according to the application. It must be pointed out that the initial condition for the second equation $Sx_P(T_1^+)$ derives from the first differential equation.

[Fig. 3 about here.]

In Fig. 3 the representation of (4) by means of proto and core events is graphically shown. The drawn trajectories are dotted to represent non linearity and discontinuity due to the modification of the Super-states

in the proto/core map. Maintaining the analogy with the neurophysiology, the trajectories connect neurons which are fired in the proto-self, core self, and core consciousness processes. Neurons are properly the Super-states Sx_P and Sx_C which are the elements of the SOM map. The cube represents the occurrence of the particular triplet of events and, inside it, the evolution trajectories in the Super-state space are drawn to outline the mapping of the differential equations in (4) to the event space. For what concerns the operative usage of the stored memory, the second equation in (4) can be considered as the prediction of the future proto-self change when a core event takes place. In fact, when a core event happens, and knowing what was the previous proto-state, it is possible to predict what can be the consequence on the proto-state by employing the second differential equation.

C. Learning Technique Based on a Voting Procedure

In Section II-B a model mathematically coherent with the Damasio's description of the generation of consciousness is presented. However, for its digital engineering implementation an algorithm is proposed to construct the Autobiographical Memory by appropriately storing triplets of events $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$ to be used for predicting future situations without the need of defining or estimating the non-linear, non continuous, time varying functions H_1, H_2, F_1, and F_2 that appear in (4).

During its functioning the system perceives and computes continuously the data collected by its internal (*proto*) and external (*core*) sensors, relating with, respectively, the observed internal and external phenomena. Such data are collected in the proto state $\boldsymbol{X}_P(t)$ and in the core state vector $\boldsymbol{X}_C(t)$ (see (1)-(2)) at each time frame t. The SOM clustering process associates these states with the correspondent Super-states $Sx_P(t)$ and $Sx_C(t)$ which are mapped at each instant t into

a semantic label $l_P(t)$ and $l_C(t)$. Then we define two vectors containing the time evolution of these labels, as follow:

$$\boldsymbol{L}_P = \{l_P(0), \ldots, l_P(t), \ldots\} \tag{5}$$

$$\boldsymbol{L}_C = \{l_C(0), \ldots, l_C(t), \ldots\} \tag{6}$$

A method based on a voting procedure is therefore implemented to accomplish this task. In this way an approximation of the probability distribution of cause/effect relationship can be constructed. More in details, the Autobiographical Memory is composed by a collection of all the possible combinations of the core consciousness triplets $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$, each of them receiving a vote when the consequences of the relative proto/core/proto events takes place. Since we want to statistically describe, through the learning process, what is the probability of the evolution of the proto state in consequence of a core event, i.e. we intend to assess the conditional probability density function (pdf) $p(\epsilon_P^+|\epsilon_P^-, \epsilon_C)$, the normalization must be performed to sum up to one with respect to ϵ_P^+. In fact, when the learning process is reasonably accurate, this enables predictions to be made about the possible consequence on the internal state provoked by an external event considering the previous internal state. In addition, in order to provide a short term prediction of the effects of a certain external event on the internal state, each element of the Autobiographical Memory can be associated with a structure memorizing the temporal information relative to the interaction.

Then resuming, the Autobiographical Memory is composed by the following elements:

- a set of representations of the possible interactions, described by the triplets $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$ (i.e. the *core consciousness*), each of them associated with a point in the 3D space shown in Fig. 3

- each of these elements is associated with a prob-

ability, deriving from an estimate of the pdf $p(\epsilon_P^+|\epsilon_P^-, \epsilon_C)$, which is proportional to the number of votes that the particular triplet received, i.e. the number of occurrences observed during the learning process.

- each element of the Autobiographical Memory is also associated with a temporal histogram ($Hist(\epsilon_P^-, \epsilon_C, \epsilon_P^+)$) storing the temporal information regarding the triplet $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$. The selection of the histogram bin dimension must be performed taking into account a trade off between the precision of the temporal prediction that it is required by the application and the number of training examples available. If the temporal prediction needs to be very accurate a large number of training examples is needed to well represent the temporal distribution of the events. An example of one of the learned temporal histogram is shown in Figure 4.

[Fig. 4 about here.]

Operatively, in order to build the Autobiographical Memory the core label vector $\boldsymbol{L}_C$ is monitored, by comparing its subsequent elements, to detect core Super-state label $l_C^m(t)$ changes in order to detect the core event $\epsilon_C = l_C^m(t_C) \rightarrow l_C^n(t_C + \delta t_C)$. The value δt_C accounts for the time window considered to detect events in the label vector $\boldsymbol{L}_C$. When this happens, the proto label vector $\boldsymbol{L}_P$ is analyzed to establish if, within a time window of duration T_{max}^- preceding the core event, a proto event took place; in this case the proto event $l_P^i(t_P^-) \rightarrow l_P^j(t_P^- + \delta t_P^-)$ is memorized as the initial proto event ϵ_P^-. On the contrary, if no label change related to the proto Super-state happened the value of the label l_P^i is considered as the initial state and the proto initial event is given by $\epsilon_P^- = l_P^i(t_P^-) \rightarrow l_P^j(t_P^- + \delta t_P^-)$. The proto label vector $\boldsymbol{L}_P$ is examined to detect if,

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Algorithm 1 Pseudo-Code of the Autobiographical Memory (***AM***) formation

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1: **while** $l_C(t_C) = l_C(t_C + \delta t_C)$ **do**

2:    **analyze** ($\boldsymbol{L}_C$)

3: **end while**

4: **set** $\epsilon_{C(m,n)} = l_C^m(t_C) \rightarrow l_C^n(t_C + \delta t_C)$

5: **analyze** ($\boldsymbol{L}_P$)

6: **for** $t_C - T_{max}^- < t_P < t_C$ **do**

7:    **if** $l_P(t_P^-) \neq l_P(t_P^- + \delta t_P^-)$ **then**

8:       **set** $\epsilon_{P(i,j)}^- = l_P^i(t_P^-) \rightarrow l_P^j(t_P^- + \delta t_P^-)$

9:    **else if** $l_P(t_P^-) = l_P(t_P^- + \delta t_P^-)$ **then**

10:       **set** $\epsilon_{P(j,j)}^- = l_P^j(t_P^-) \rightarrow l_P^j(t_P^- + \delta t_P^-)$

11:    **end if**

12: **end for**

13: **analyze** ($\boldsymbol{L}_P$)

14: **for** $t_C < t_P < t_C + T_{max}^+$ **do**

15:    **if** $l_P(t_P^+) \neq l_C(t_P^+ + \delta t_P^+)$ **then**

16:       **set** $\epsilon_{P(j,k)}^+ = l_P^j(t_P^+) \rightarrow l_P^k(t_P^+ + \delta t_P^+)$

17:    **else if** $l_P(t_P^+) = l_C(t_P^+ + \delta t_P^+)$ **then**

18:       **set** $\epsilon_{P(j,j)}^+ = l_P^j(t_P^+) \rightarrow l_P^j(t_P^+ + \delta t_P^+)$

19:    **end if**

20: **end for**

21: **add vote** $\{\epsilon_{P(i,j)}^-, \epsilon_{C(m,n)}, \epsilon_{P(j,k)}^+\}$++

22: **update** $\text{Hist}(\epsilon_{P(i,j)}^-, \epsilon_{C(m,n)}, \epsilon_{P(j,k)}^+)$

   with $t_P^+ + \delta t_P^+ - (t_C + \delta t_C)$

23: **normalize** w.r.t. (ϵ_P^+)

24: **update** $\boldsymbol{AM}\left(\epsilon_{P(i,j)}^-, \epsilon_{C(m,n)}, \epsilon_{P(j,k)}^+\right)$

---

after $t_C + \delta t_C$, when the core event occurred, a proto event $\epsilon_P^+ = l_P^j(t_P^+) \rightarrow l_P^k(t_P^+ + \delta t_P^+)$ follows within a time window T_{max}^+. When this happens a vote is added to the corresponding triplet $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$ in the three dimensional space constituting the Autobiographical Memory (see Fig. 3). Also the temporal histogram

$Hist(\epsilon_{P(i,j)}^-, \epsilon_{C(m,n)}, \epsilon_{P(j,k)}^+)$, storing the temporal information of the interaction, is updated by incrementing the bin associated with $t_P^+ + \delta t_P^+ - (t_C + \delta t_C)$. In this way, the time occurring between the external cause (core event) and the internal consequence on the system (proto event) is memorized. In the case that no proto event ϵ_P^+ comes after the core event, there are two possibilities to be considered: a) the core event did not affect the system, i.e. no interaction took place; b) the reaction of the system to ϵ_C is not to change its internal status (or to change not so significantly to be considered as an event by the clustering and labeling procedure). The situation a) should not be taken into account in our memory, but since it is not possible to automatically discriminate between these two cases, the subsequent proto event ϵ_P^+ is set equal to $l_P^j(t_P^+) \rightarrow l_P^j(t_P^+ + \delta t_P^+)$ and the cell in the Autobiographical Memory corresponding to the three events detected will be increased by one. Finally, having updated the memory as described above, a normalization procedure with respect to the row where $\epsilon_C = l_C^m \rightarrow l_C^n$ and $\epsilon_P = l_P^i \rightarrow l_P^j$ (or $\epsilon_P = l_P^i \rightarrow l_P^i$ if it is the occurrence observed) is fulfilled to obtain an estimate of the probability $p(\epsilon_P^+|\epsilon_C, \epsilon_P^-)$. The pseudo code of the algorithm for the construction of the Autobiographical Memory is presented in Algorithm 1.

It is worth noting that the proposed method to derive the probabilistic model of the cause/effect relationship can be modeled also by a statistical graphical model (e.g. HMM). In particular, for modeling interactions between internal and external events Coupled Hidden Markov Models (CHMMs) or Hierarchical Hidden Markov Models (HHMMs) are well suited as demonstrated by the state of the art work described in Sect. I-A. In our case the states of the models would be the proto and core events and the conditional probability densities are the estimated probability densities $p(\epsilon_P^+|\epsilon_C, \epsilon_P^-)$. The

proposed approach is here preferred with respect to an HMM since it can be implemented by a simple voting method and easily learned online without requiring a previously acquired training set.

D. Usage of Autobiographical Memory for Prediction

The knowledge base within the Autobiographical Memory built as presented in II-C can be used to predict near future events by observing and processing internal and external events occurring within the scope of the system. This capability resembles the activation of the autobiographical self (see Sect. II-A), which is the brain process of recovering neural *images* related to the arisen core self.

The reference architecture describing the Autobiographical Memory algorithm is presented in Figure 5.

[Fig. 5 about here.]

To perform the prediction task when an external event $\epsilon_{C(m,n)}$ is detected by the the system the proto map is analyzed to establish which was the previously occurred internal event $\epsilon^-_{P(i,j)}$. The Autobiographical Memory is then examined to establish which is the internal event $\widehat{\epsilon}^+_{P(j,*)}$ that is more likely to occur, carrying the internal state to the Super-state l^*_P, that is:

$$\widehat{\epsilon}^+_{P(j,*)} : \quad \max_{\epsilon^+_{P(j,*)}} p\left(\epsilon^+_{P(j,*)}|\epsilon_{C(m,n)},\epsilon^-_{P(i,j)}\right) \quad (7)$$

Moreover the temporal histogram can provide information about the time at which the $\epsilon^+_{P(j,*)}$ might take place. All these data can be very useful for an Ambient Intelligence application to anticipate operations or arrange the elements of the system that can be involved in the interaction with the external world. Operatively the procedure to predict events is similar to the learning process described in Sect. II-C and Algorithm 1. In particular, steps 1-4 and steps 5-12 of the pseudocode

presented in Algorithm 1 do not change. In fact, the core vector $\boldsymbol{L}_C$ (see (6)) is analyzed until a core event, for example $\epsilon_{C(m,n)}$, is detected. When this occurrence is observed the proto vector $\boldsymbol{L}_P$ (see (5)) is checked to establish which proto event ($\epsilon^-_{P(i,j)}$) happened before the core event within a time window of T^-_{max}. Steps 13-16 consist in extracting from the learned Autobiographical Memory the most likely proto event $\widehat{\epsilon}^+_{P(j,*)}$ between the ones that have been detected to occur after the observed proto and core events ($\epsilon^-_{P(i,j)}$ and $\epsilon_{C(m,n)}$). Then also the temporal histogram associated with the two observed events ($\epsilon^-_{P(i,j)}$ and $\epsilon_{C(m,n)}$) and to the predicted one ($\widehat{\epsilon}^+_{P(j,*)}$) is retrieved from the Autobiographical Memory. The resulting pseudocode for the usage of the Autobiographical Memory for prediction is presented in Algorithm 2.

The predicted proto event is then the one that maximizes the learned probability distribution $p(\epsilon^+_P|\epsilon_{C(m,n)},\epsilon^-_{P(i,j)})$. Different choices can be made to foresee the time when this event will take place as, for example, either the mean or the median value of the temporal histogram related to the triplet $\{\epsilon^-_{P(i,j)},\epsilon_{C(m,n)},\widehat{\epsilon}^+_{P(j,*)}\}$ or the value related to the most frequent bin.

The computational complexity of the Autobiographical Memory algorithm is related to number of proto and core Super-states, respectively N_P and N_C. In particular the number of possible proto and core events is N_P^2 and N_C^2 since they are detected as connection of Super-states. Therefore, the maximum number of the passive memory element is $N_P^2 \times N_C^2 \times N_P^2$ considering all the possible combinations of proto and core events for constructing the triplets $\{\epsilon^+_P,\epsilon_C,\epsilon^-_P\}$. However, it should be noted that N_P and N_C are typically small values as shown in the experimental scenario (see Section III). This property is due to the SOM clustering process that allows one to

---

Algorithm 2 Pseudo-Code for prediction using learned Autobiographical Memory (**AM**)

1: **while** $l_C(t_C) = l_C(t_C + \delta t_C)$ **do**

2:     **analyze** $(\boldsymbol{L}_C)$

3: **end while**

4: **set** $\epsilon_{C(m,n)} = l_C^m(t_C) \rightarrow l_C^n(t_C + \delta t_C)$

5: **analyze** $(\boldsymbol{L}_P)$

6: **for** $t_C - T_{max}^- < t_P < t_C$ **do**

7:     **if** $l_P(t_P^-) \neq l_P(t_P^- + \delta t_P^-)$ **then**

8:         **set** $\epsilon_{P(i,j)}^- = l_P^i(t_P^-) \rightarrow l_P^j(t_P^- + \delta t_P^-)$

9:     **else if** $l_P(t_P^-) = l_P(t_P^- + \delta t_P^-)$ **then**

10:         **set** $\epsilon_{P(j,j)}^- = l_P^j(t_P^-) \rightarrow l_P^j(t_P^- + \delta t_P^-)$

11:     **end if**

12: **end for**

13: **retrieve** $\widehat{\epsilon}_{P(j,*)}^+$ from **AM**

    $\widehat{\epsilon}_{P(j,*)}^+ = \max_{\epsilon_P^+} p(\epsilon_P^+ | \epsilon_{C(m,n)}, \epsilon_{P(i,j)}^-)$

14: **retrieve** $\text{Hist}(\epsilon_{P(i,j)}^-, \epsilon_{C(m,n)}, \widehat{\epsilon}_{P(j,*)}^+)$

15: **predict** $\epsilon_P^+ = \widehat{\epsilon}_{P(j,*)}^+$

16: **predict** $t_P^+ \overset{from}{\rightarrow} \text{Hist}(\epsilon_{P(i,j)}^-, \epsilon_{C(m,n)}, \widehat{\epsilon}_{P(j,*)}^+)$

---

encode the large variety of sensors data into contextual low-dimensional labels providing a-priori limitation (see [46]) to the learning complexity. Moreover, the algorithm tends to exclude those unlikely memory elements, i.e. the ones that occur rarely during the learning phase.

III. RESULTS

A. Case Study - The Smart Lab

The developed system is a Smart space controlling a University laboratory where two sensors sets monitor the activity of people entering and using laboratory resources (external sensors) and the internal activity of the devices themselves (internal sensors). In particular, the approach of the present work lies in the study of the related evolution of the two state vectors representing user and

system. The definition of events occurring in the two opposite vectors and the properly filtered collection of these events yields data about delay and probability of the expected relationships and provides new and automatically found associations. In other words, we define a learning technique in order to allow a Smart Space to be able to predict with a reasonable probability the logical consequence of a user action. This knowledge gives the system an inference capacity to try and foresee its own devices behavior and the users requirements and to adapt accordingly. In this way, it would be possible, for example, to guide the user, using multimodal communication devices belonging to the Smart Space (e.g. speakers, screens, mobile devices handled by the user, etc.), toward the PC with more computational or network resources available (e.g. not used remotely).

As previously stated, the implemented system is made up of two sensors sets grouped according to their target: the adjectives internal and external do not refer to the hardware features but to the nature of the observed quantity. That is to say, the former group collects information about the system behavior (proto-self), the latter one about the user (core self). For instance this justifies the fact that a mouse activity sensor is an external sensor because it is useful to guarantee the presence of a human user in front of a personal computer. In the current implementation the involved machines are three: two computers used by the students (*PC1-2*) and a third one, called Processing Unit (*PU*), collecting data and running the central fusion and processing tasks.

The exerted sensors are partly hardware devices and partly software routines. For the external (core) set we employ (refer to Figure 6): a software simulated badge reader (*BR*); two video cameras with partially overlapped fields of view to cover the room and locate the users by employing a blob tracker and a calibration tool to obtain

the position in the map plane of the lab (*TLC*); two mouse activity sensors (*MOU*) and two keyboard sensors (*KEY*) to let the system distinguish whether the resources load on a PC is due to the automatic simulations or to the user activity. On the internal variables sensing side we use: two login controllers (*LOG*); two CPU computational load sensors (*CPU*); two network adapter activity monitors (*LAN*); two hard disk usage meters (*HD*). They collect data at a rate of 1 Hz and send them to the PU where they are filtered and put in the two following vectors (where the numerical subscripts indicate the PC):

$$\boldsymbol{X}_P(t) = \{CPU_1(t), CPU_2(t), LAN_1(t), LAN_2(t),$$
$$HD_1(t), HD_2(t), LOG_1(t), LOG_2(t)\}$$
$$\tag{8}$$

$$\boldsymbol{X}_C(t) = \{TLC_1(t), TLC_2(t), MOU_1(t),$$
$$MOU_2(t), KEY_1(t), KEY_2(t), BR(t)\}$$
$$\tag{9}$$

[Fig. 6 about here.]

Then the information is stored and processed in order to locate significant events: the concept of Autobiographical Memory cited in the model arises here, in the collection of significant events, as described in the following Section III-B.

B. Detect cause/effect relationships

In the central processing unit *PU*, vectors (8) and (9) are processed to obtain, respectively, the two global Super-states (Sx_P and Sx_C) defining the instantaneous situation of the two system sides (internal and external). These labels are obtained through appropriately trained Self Organizing Maps (SOM) neural network classifiers. Seven different situations of interest have been identified and played several times by human "actors" in order to

train the SOMs. The same number is coherently mirrored in the number of clusters identified and labeled with the corresponding l_P and l_C by both the external and the internal state (see Table I) SOM classifiers. Considering that the classifiers provide the system with these two global states once per second, we are interested in evaluating which differential relationships are connecting state changes occurring on the two maps. As stated in Sect. II-B1 events are defined as transitions between two Super-states; this implies a transition between two different clusters, not necessarily contiguous, on the SOM map (Figure 7), that is the Unified-distance Matrix.

[TABLE 1 about here.]

[Fig. 7 about here.]

Events are symbolized as in Sect. II-B1, then by writing:

$$\epsilon_{(P,C)}(t) = l^i_{(P,C)} \to l^j_{(P,C)} \tag{10}$$

we mean that the global internal state is changing at time t from a situation in which the proto/core Super-states labels change from the value $l^i_{(P,C)}$ to $l^j_{(P,C)}$. For instance, the event $\epsilon_P(t) = WL1 \to WLA$ corresponds to a condition in which PC1 sensors observe a working load state to the situation of high load on both the computers.

C. Autobiographical Memory Learning

The AmI system has been trained using the data gathered over different session of acquisition in the normal working condition of the laboratory where students working on their thesis projects could freely enter and uses the hardware and software resources. There is no need for specific *ad-hoc* training by human experts, since, as described in the following, the learning methodology is designed to be robust to noisy conditions and to

adapt to new conditions thanks to the incremental voting mechanism. During the learning phase, the activities performed by the students were, after accessing the lab, login, operative system common operations (file browsing, file opening, etc.), Internet browsing, and text writing (documents or programming) with common text editors. After having collected a representative training set in on-line working mode, we process the time-ordered series of the internal and external SOM classifier outputs to vote and infer frequent logical relationships. The voting procedure is driven by the events of the core self: for each triggering event $\epsilon_C(t)$ a vote is assigned to the interaction triplet $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$. After having processed the whole training set, noisy non significant votes are eliminated by cutting all the sequences receiving a number of votes below threshold Th, which has been set in order to preserve the 75 % of the assigned votes. This threshold has been chosen opportunely by several tests in order to preserve the maximum amount of information carried by detected cause/event relationship but eliminating those which are not frequent. This process, clearly, prevents from memorizing anomalous situations which are not handled by the proposed system. In Table II some training parameters are reported. The learning phase has been performed over different days and at different hours collecting 1800 minutes of activities performed by five different students allowed to use the two laboratory PCs acquiring sensors data every second at 1 Hz rate. Moreover the PCs have been accessible also remotely and a multi-user Linux platform enable their contemporary utilization. Data acquisition was automatically stopped when no activity was detected on the sensors for more than 5 minutes in order to use only relevant data for training. It must be pointed out that a correct evaluation of T_{max}^- and T_{max}^+ is determinant to produce a significant set of events. The duration of these time windows is assessed empirically processing training data with different values in order to be able to detect a meaningful configuration of events. In fact when the most probable third event is not one of those considered in the training phase, it means that the threshold does not allow correct consideration of the causal relationship. For example, when $T_{max}^- = T_{max}^+ = 10sec$ some occurrences of Autobiographical Memory elements (triplet of events) observed in the training set are significantly rare and not representative of the simulated cause/event relationships. One of the expected situations that is not represented with $T_{max}^- = T_{max}^+ = 10sec$ is when there is not work load on either PCs (ϵ_P^-), a user enters (ϵ_C), and no log in is observed. This happens because the log in typically needs more than 10 seconds to be performed. The most appropriate T_{max}^+ and T_{max}^- are chosen by analyzing different memories trained with a predefined set of real life scenarios to find those whose temporal histograms contain the highest number of values, that is they are able to capture most of the considered situations.

Another aspect of this experiment that is worth noting is that the number of the cause/effect relationships learned, i.e. the elements of the Autobiographical Memory, is 2634. This shows both the complexity of the analyzed scenario and the capability of the algorithm to memorize only a subset of all the possible causal relationships, that are $7^6 \approx 116000$ (see Section IV for detailed explanation about the computational complexity).

[TABLE 2 about here.]

Finally, what we obtain is an Autobiographical Memory representation that can be interpreted as a statistical knowledge database carrying information on more frequently experienced passive cause/effect relationships as well as on their distribution along the

time axis. For example, by processing the information stored in the Autobiographical Memory, data can be obtained about $p(\epsilon^+_{P(j,k)}(t_C + \tau)|\epsilon_{C(m,n)}, \epsilon^+_{P(i,j)}) = p(\epsilon^+_{P(j,k)}|\epsilon_{C(m,n)}, \epsilon^-_{P(i,j)}) \cdot p(\tau|\epsilon^-_{P(i,j)}, \epsilon_{C(m,n)}, \epsilon^+_{P(j,k)})$ that is the estimated probability that the proto event $\epsilon^+_{P(j,k)}$ takes place τ seconds after the core event $\epsilon_{C(m,n)}$ given that the the latest proto-self event is $\epsilon^-_{P(i,j)}$. Also in this case the probability $p(\tau|\epsilon^-_{P(i,j)}, \epsilon_{C(m,n)}, \epsilon^+_{P(j,k)})$ is estimated from the temporal histogram relative to the triplet $\{\epsilon^-_{P(i,j)}, \epsilon_{C(m,n)}, \epsilon^+_{P(j,k)}\}$.

D. Predicting Events using Learned Autobiographical Memory

In the on-line phase, the triggering of the Autobiographical Memory by means of the observed couples of $\{\epsilon^-_{P(i,j)}, \epsilon_{C(m,n)}\}$ events at time t_C can produce the activation of a row of the Autobiographical Memory, identifying a distribution regarding the proto events $\epsilon^+_{P(j,*)}$ and the related temporal histograms $Hist(\epsilon^-_{P(i,j)}, \epsilon_{C(m,n)}, \epsilon_{P(j,*)})$. This information resembles the activation of the autobiographical self (see Sect. II-A), the brain process of recovering neural images related to the emergences of a particular core self. Similarly to the autobiographical self that contains data regarding activities to react to the object that has produced the core self, here the estimated probability distribution deriving from the Autobiographical Memory formation can be employed for prediction purposes directed to accomplish a suitable action.

[TABLE 3 about here.]

An example of the foreseen response is shown in Table III, where only the most likely internal event is indicated. The complete table of the detected cause/effect relationships is composed by approximately 800 elements which corresponds to the number of possible types of interaction observed during the training of the system.

It is also interesting to note (see first row of Table III) that the system is able to autonomously figure out that when an access into the empty lab ($EMPTY \rightarrow ARRIVE$) is detected it is likely that the system internal status passes from stand-by ($NULL \rightarrow NULL$) to a login event in one of the PCs ($NULL \rightarrow LOGIN$). This example shows the capability of the system of learning meaningful contextual information regarding the interaction with the user of the Smart space.

Tests on the trained system have been performed in order to evaluate the predictive performances: the knowledge base was built through an approximately 1800 minutes long training set. The system found 13800 core events and 13800 proto events. Setting the voting filtering threshold to a minimum of 100 votes, approximately 75% of the votes were considered somehow significant. To prove the predicting capabilities of the proposed approach, users accessing to lab resources during normal and non controlled working sections have been monitored. Two agent modules, the proto and core Event detector, are responsible for transforming raw data gathered from sensors into a meaningful contextual representation. When a core event is detected, the prediction module investigates the list of previous proto events in a time window of duration T^-_{max} preceding ϵ_C: the proto event occurred before the core event is considered as the initial proto event ϵ^-_P. If more than one proto event is detected, the closest is selected; on the other hand if no proto event happens before ϵ_C, then, as mentioned in Sect. II-C, it is defined $\epsilon^-_P = l^i_P \rightarrow l^i_P$, where l^i_P is the internal status label observed before ϵ_C. The value of the couple $\{\epsilon^-_P, \epsilon_C\}$ is used to perform a query to the memory and retrieve the most likely subsequent proto event ϵ^+_P and its most probable time delay.

Results of this process are compared to the Ground Truth obtaining encouraging performances as summarized in Table IV. It can be seen that both the prediction of the upcoming proto event after that a core event has happened and the temporal evaluation of the interaction are assessed with satisfactory accuracy considering the proposed scenario and the training and test conditions. As a matter of fact results show that the method is sufficiently robust to handle the different situations observed during training and test phase which have been performed in different days and different hours. Moreover, it must be outlined that the output of the algorithm is intended to provide an anticipative basis to decide actions to be performed by the Smart Space. Then, eventual wrong predictions, when they are detected, can be handled by specific decision techniques and online memory updating strategies (see Section IV) to avoid a successive occurrence of the same problem. Also the probabilistic nature of the prediction derived from $p(\epsilon^{+}_{P(j,k)}|\epsilon_{C(m,n)}, \epsilon^{-}_{P(i,j)})$ can provide further useful information and the possibility of realizing multiple hypothesis decision approaches that will be not immediately available with, for example, a linear regression approach.

[TABLE 4 about here.]

IV. DISCUSSION AND COMPARISONS

The Autobiographical Memory has been used to allow a Smart Space to learn user/system interaction by a bio-inspired causal relationship model and to predict near future events together with their temporal occurrence with the aim of enabling preventive or proactive actions on the environment. Moreover, it is worth noting that the Autobiographical Memory can model different types of interaction to perform event prediction in a wide range of Ambient Intelligence scenarios, just by appropriately defining what it is to be considered the internal and external states of the system and the corresponding events. For example, in [47] the Autobiographical Memory is applied in a security scenario where a guardian chases an intruder by following guidance messages sent on a mobile device (e.g. PDA or 3G/4G mobile phone) by an intelligent surveillance system monitoring the environment. In this application the active memory (core-proto-core) is used to predict if the *proto event* (change of guidance message) leads to a better *core event* (change of position in a map of guard and intruder) with the aim of reducing the distance between the two players. In this way the learned interaction model allows the user to understand if the pursuing strategy (intent) of the guard is effective and can lead to reduce the distance between him and the intruder. It must be pointed out that, in this case, the usage of the active memory directly allows definition of the action to be performed to help the user in his task, that is to pursue the intruder. Instead, in the case study presented in Section III, the prediction is not directly related to the action to be taken. The prediction of the future state of the system (e.g. work load on PC1, no activity, etc.) has been considered to indicate the PC on which the user should login. A simple rule-based approach associates the situation to a message to be communicated to the user (for example on a palm) to guide him/her towards the most appropriate PC.

[TABLE 5 about here.]

These examples show possible usage of the predictive capabilities of the Autobiographical Memory in Ambient Intelligence applications. As already described in Section I-A, other learning algorithms have been proposed in this domain. Though the other algorithms have different objectives and they are therefore specifically designed

for their scopes, it is interesting to outline some of the features that motivated the usage of Autobiographical Memory for modeling and predicting interaction in Smart spaces. Table V summarizes the characteristics that makes the proposed algorithm particularly suitable in many systems aiming at proactively interacting with humans. In particular, the Autobiographical Memory creates a probabilistic (intensional) and neurophysiologically motivated model of interaction by distinguishing between the internal or external nature of the events and organizing them in a second-order structure where the consequence of an external event on the internal state is memorized. Instead, in most of the existing works internal and external data are combined for recognizing events (e.g. [43] and [36]) and the interaction modeling is limited to a first order (if-then rules or stimulus-answer) analysis (e.g. [35] and [42]) that does not allow a *context aware* representation of the causal relationship between the Smart Space and the user. As a matter of fact the interaction modeling and prediction based just on core event and the following proto event misses the initial condition, i.e. the context. Therefore, these characteristics, with the capability of predicting the temporal occurrence of future events can represent an improvement in the design of Ambient Intelligent systems able to proactively interact with its users. It should be noted that a quantitative performance evaluation of these methods is not presented since the aim of the proposed approach is to provide new functionality to learning approaches oriented to improve the interaction between human and a Smart Space rather than improve the predicting capability of future events. Moreover, the presented methods are strongly application dependent and their different domains of usage are very difficult to be compared one another.

An AmI system should be able to manage the *innovation*, i.e. the new events that can be detected during the functioning. However recalling the concept of embodied cognition [48] that is consistent with the proposed approach, the system creates its knowledge based on its physical capabilities. It can be said that the memory is embodied, i.e. it is established according to the "body" of the system, namely the controlled devices and the sensors that monitor the external world. In this way it is reasonable to say that new states can arise only if a relevant contextual (i.e. detectable at the Super-state level) change of the system and environment configuration occurs. A relevant consequence of this consideration is that, when the Super-state values are defined, the Autobiographical Memory can be easily employed in an on-line way by just sequentially applying the learning and predicting algorithms (see Algorithm 1 and 2) during the unsupervised usage of the system.

V. CONCLUSION

A. Summary

The described work has the purpose of building a framework for automatic learning interactions occurring between an Ambient Intelligence system and its users for predicting future events. A learning technique named Autobiographical Memory, which is inspired by neurophysiological evidences of how consciousness arises in the human brain, has been presented. The goal of the method is to train a multisensor system and to create a knowledge base keeping track of the cause/effect relationships taking place in a system described in terms of instantaneous internal and external states. These states are derived by a pair of trained SOM neural network classifiers. Given the observations of the user activity (mapped in the external state), the knowledge provided to the Smart Space by the voting algorithm can be used

to predict near future events occurring in the system internal state. Experimental tests show promising results of learning interactions and predicting their evolution in the scenario of the "Smart Lab". The prediction capability aims at optimizing the interaction with users, through the possibility to autonomously react and adapt to the ongoing relationships between the components of the system and the users.

B. Issues and Future Work

In this work, only the passive memory learning problem, namely the collection of instances of internal effects given external causes (see Sect. II-B), has been addressed. However, by using the same procedure, the *active memory* learning can be performed in order to store instances of triplets of core/proto/core events, enabling the possibility of predicting future external events given an internal modification and the preceding core event. The active memory allows the system to be able to make predictions on the influences on the external world caused by an internal action. One of the possible improvements of the predictive capability of a cognitive system can be based on the combination of the data stored in the passive and the active memories. Practically, the two interdependent triplets $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$ and $\{\epsilon_C, \epsilon_P^+, \epsilon_C^+\}$ must be learned. Although the passive memory can be efficiently employed for predictive purposes, as demonstrated by results in Section III-D, the combination of active and passive memory can be very useful to select an action to be performed by the system to cope with external environment changes.

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Fig. 1: Second order neural pattern representation (as presented in [44])
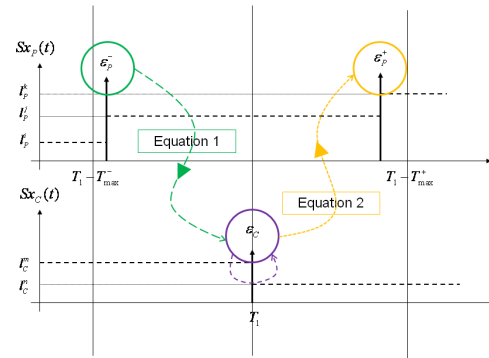
Fig. 2: Sequence of proto/core events in the Autobiographical Memory formation. On the ordinate axes the label changes of the proto/core Super-states are outlined
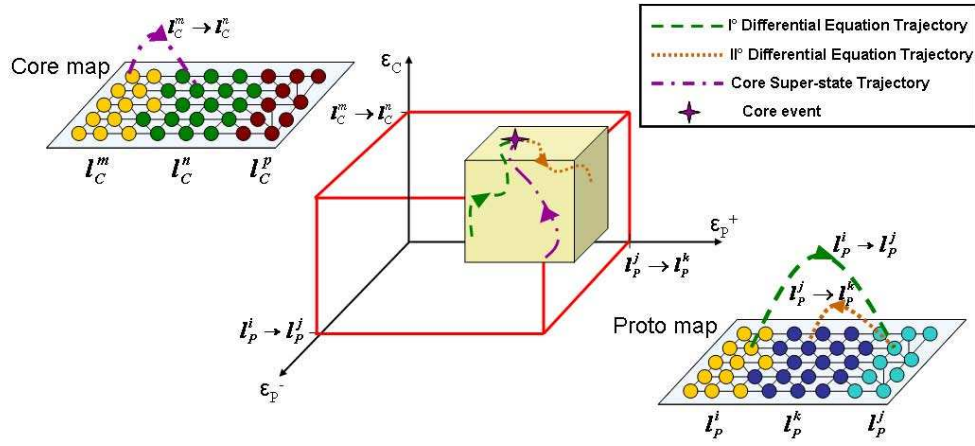
Fig. 3: Graphical representation of the mapping of the differential equations in (4) to the event space $\{\epsilon_P^-, \epsilon_C, \epsilon_P^+\}$ (see the text for further details). Proto and Core maps represents the result of the SOM clustering procedure on the data collected by sensors. Symbols $l_{P/C}^x$ are the contextual labels associated with each cluster
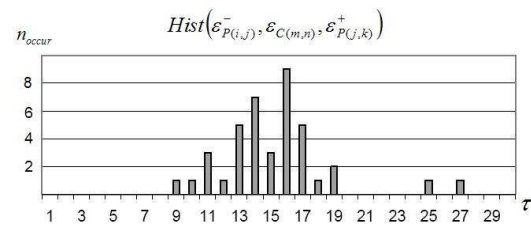
Fig. 4: Example of learned temporal histogram from which is possible to evaluate the probability that a proto event $\epsilon^+_{P(j,k)}$ takes place τ seconds after the core event $\epsilon_{C(m,n)}$ given that the latest proto event is $\epsilon^-_{P(i,j)}$
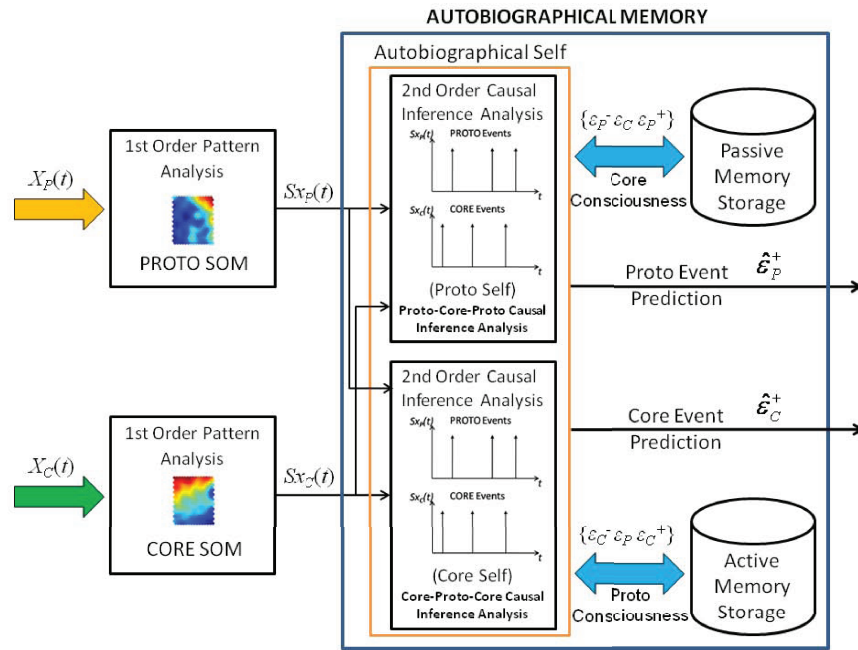
Fig. 5: Reference Architecture for the Autobiographical Memory (Learning and Prediction). Note that the Active Memory part is not considered in this work
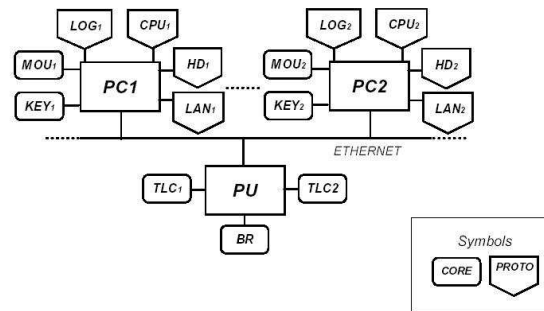
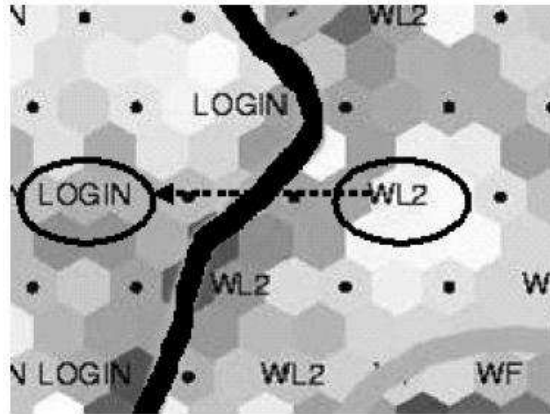Fig. 6: Smart space logical/physical architecture

Fig. 7: Internal state event represented as a transition between two different clusters on the map, that is the Unified-distance Matrix

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TABLE I: Meaning of the labels of internal (l_P) and external (l_C) Super states obtained by SOM clustering

Proto label l_P	Meaning	core label l_C	Meaning
LOGIN	New login to a PC	EMPTY	Empty lab
LOGOUT	User disconnection	ARRIVE	New user entering
WL1	Work load on PC1	EXIT	A user goes out the lab
WL2	Work load on PC2	WH1	User(s) presence near PC1
WF	PC1 and PC2 in low work load	WH2	User(s) presence near PC2
WLA	High work load on both PCs	WHA	Users presence near both PCs
NULL	No activity	WA	No user detected close to both PCs

TABLE II: Main parameters and data for the training phase

PARAMETER	VALUE
T_{max}^{-}	10 sec.
T_{max}^{+}	30 sec.
Duration of training set acquisition	1800 min.
Number of Proto Super States Observed	105030
Number of Proto events Observed	13800
Number of Core Super States Observed	103020
Number of Core events Observed	13800
Cause/effect relationships voted after thresholding	2634

TABLE III: Example of learned Autobiographical Memory with estimated probability associated with the most probable event and to the related most likely time delay $\overline{\tau}$ (mean value of $Hist(\epsilon_P^-, \epsilon_C, \epsilon_P^+)$) of the distribution)

ϵ_P^-	ϵ_C	$\hat{\epsilon}_P^+$	$p(\hat{\epsilon}_P^+ | \epsilon_C, \epsilon_P^-)$	$\overline{\tau}$
NULL→NULL	EMPTY→ARRIVE	NULL→LOGIN	0.24	17 sec.
WL1→WF	EXIT→WH1	WF→WF	0.45	5 sec.
LOGOUT→WL1	WHA→WH1	WL1→WF	0.50	26 sec.
WL1→WL1	ARRIVE→WH1	WL1→LOGIN	0.23	13 sec.
WL2→WF	WA→WH2	WF→WL2	0.50	5 sec.
WL1→WL1	WH1→EXIT	WL1→WF	0.54	17 sec.
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$

TABLE IV: Real-time prediction test results

NUMBER OF TEST SECTIONS	50
TEST SECTION LENGHT	20 min.
NUMBER OF PREDICTED PROTO EVENTS	1232
CORRECT PREDICTION RATIO	85% (1047/1232)
TIME OFFSET MEAN ERROR	2.5 sec.

TABLE V: Comparison of characteristics and capabilities of learning algorithms for prediction in Smart Space applications

	Learning technique	Internal/external event separation	Intensional context interpretation	Second-order causality model	Event prediction capability	Prediction event temp. occur.
Marchesotti *et al.* [43]	Self Organizing Map	No	Yes	No	No	No
Doctor *et al.* [35]	Fuzzy	Yes	No	No	Yes	No
Eng *et al.* [42]	Distributed Adaptive Control	Yes	Yes	No	No	No
Sánchez *et al.* [36]	Hidden Markov Model	No	Yes	No	Yes	No
Proposed method	Autobiographical Memory	Yes	Yes	Yes	Yes	Yes