Smart home context awareness based on Smart and Innovative Cities

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ABSTRACT

In the emerging Smart Cities - Smart Homes computing paradigms developing a formalization for context information is increasingly important. In the present paper, basedon the EU FIRE research project "Social and Smart"we aim to formalize and build a complete formal definition of context in both home and city scale. Using sensors as a Smart City service and local sensors installed locally in Smart Homes, it is possible to collect continuously context data, such as temperature, humidity, noise and pollution levels. This context information can be used to adapt to user-specific needs in the Smart Home environment via the incorporation of user defined home rules. Semantic web technologies are used to support the knowledge representation of this ecosystem. The overall architecture has been experimentally verified using input from the SmartSantander Smart City project and applying it to the SandS Smart Home within the FIRE and FIWARE framework. Finally, two examples are presented in order to stress how the smart home appliances adapt their function to home rules and context information.

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IPMSC2015 September 25–28, 2015, Island of Rhodes, Greece

DOI: 10.1145/1235

Keywords

Pervasive Human Computer Interaction, User Modeling, Context Awareness, Personalization, Smart Homes, Smart Cities, Innovative Cities, Semantic User and Pervasive Representation

1. INTRODUCTION

Although in their initial definition and development stages pervasive computing practices did not necessarily rely on the use of Internet, current trends show the emergence of many convergence points with the Internet of Things (IoT) paradigm, where objects are identified as Internet resources and can be accessed and utilized as such. In the same time, the Human-Computer Interaction (HCI) paradigm in the domain of domotics has widen its scope considerably, placing the human-inhabitant in a pervasive environment and in a continuous interaction with smart objects and appliances. Smart Homes that additionally adhere to the IoT approach consider that this data continuously produced by appliances, sensors and humans, can be processed and assessed collaboratively, remotely and even socially. In the present paper we try to build a new knowledge representation framework where we first place the human user in the center of this interaction. We then propose to break down the multitude of possible user behaviors to a few prototypical user models and then to resynthesize them using fuzzy reasoning. We further discuss the ubiquity of context information in relation to the user and the difficulty to propose a universal formalization framework for the open world. We show that by restricting user related context to the Smart Home environment, we can reliably define simple rule structures that correlate specific sensor input data and user actions that can be used to trigger arbitrary smart home events. This rationale is then evolved to a higher level semantic representation of the domotic ecosystem in which complex home rules can be defined using Semantic Web technologies.

A user model (UM) [22] is a computational representation of the existing information in a user's cognitive system, along with the processes acting on this information to produce an observable behavior. User stereotypes or personas is a quite common approach in UM due to its correlation with the actors and roles used in software engineering systems, its flexibility, extensibility, re-usability and applicability [26]. A persona is an archetypal user derived from specific profile data to create a representative user containing general characteristics about the users and user groups and is used as a powerful complement to other usability methods. The use of personas is an increasingly popular way to customize, incorporate and share the research about users [21]. The personas technique fulfills the need of mapping and grouping a huge number of users based on the profile data, aims and behavior which can be collected both during design and run time, users and usage design respectively.

Recently, the emergence of ubiquitous or pervasive computing technologies that offer "anytime, anywhere, anyone" computing by decoupling users from devices has introduced the challenge of context-aware user modeling. So far, most of context-aware systems focus on the external context known as physical context which refers to context data collected by physical sensors. Thus, they involve context data of physical environment, distance, temperature, sound, air pressure, lighting levels etc. The external context is important and very useful for context-aware systems, as context-aware systems provide recommended services. However, from a broader scope, context may be considered as information used to characterize the situation of an entity [36]. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including location, time, activities, and the preferences of each entity. A user model is context-aware if it can express aspects of the user's contextual information and subsequently help the system adapt its functionality to the context of use. Many aspects of contextual information used in modeling are discussed in [8].

The semantic formalization idea is to provide a functional ontological and reasoning platform that offers unified data access, processing and services on top of existing, Internet of Things (IoT) architecture ubiquitous services and to integrate heterogeneous home sensors and actuators in a uniform way. From an application perspective, a set of basic services encapsulates sensor and actuators network infrastructures hiding the underlying layers with the network communication details and heterogeneous sensor hardware and lower-level protocols. A heterogeneous networking environment indeed calls for means to hide the complexity from the end-user as well as applications by providing intelligent and adaptable connectivity services, thus providing an efficient application development framework. As a result, to face the coexistence of many heterogeneous sets of things and home appliances, a common trend in IoT applications is the adoption of an abstraction layer capable of harmonizing the access to the different devices with a common language and procedure [14]. Our approach is to further encapsulate this abstraction layer into "if then that" rule sets and then to Web Ontology Language (OWL)[23] ontologies that combined with home rules defined in Semantic Web Rule Language (SWRL) [20] form the domotic intelligence that continuously adapts home environment conditions to the user's actions and preferences.

To conclude with, the experimental results for the above framework are presented that have been conducted inside the "Social & Smart"(SandS) [1] FP7 European Project which aims to highlight the potential of IoT technologies in a concrete user-centric domestic pervasive environment. Large scale experiments are planned at SmartSantander [2], a city-scale experimental research facility in support of typical applications and services for a smart city, comprising a very large number of online ambient sensors inside a real-life human environment.

2. RELATED WORK

As correctly stated in [16], user modeling is the process through which systems gather information and knowledge about users and their individual characteristics. Therefore, a user model is considered a source of information about the user of the system, which contains several assumptions about several relevant behavior or adaptation data. Approaching user modeling from the HCI perspective, there is the potential that user modeling techniques will improve the collaborative nature of human-computer systems. During the last 20 years, there has been a lot of work done in this area. Authors attempted to cover all possible scenarios through the development of different definition for users and user modeling approaches respectively.

Reviewing how "user models" term has been approached, within the HCI literature, it is indicated that users are part of an enlarged communication group in which users change through time and according to the environmental conditions and the experience they gain. Thus, in the end, there are three types of users: "novel", "intermediate" and "expert" [16]. Another more oriented work, is that of [17], as it focuses on the specific group of elderly people with none, one, or more than one disabilities respectively, whose needs and capabilities change as they grow older underlying the need for having more diverse and dynamic computing systems for modeling users. A few years later, in terms of having rich adaptive output information, ontology-based approaches have been used for the design of the "Ec(h)o" audio reality system for museums to further support experience design and functionality related to museum visits. This work has been later extended [18] by incorporating rich contextual information such as social, cultural, historical and psychological aspects related to the user experience.

Finally, in 2004, the research in user modeling has started to shift from focusing on users' needs instead of users' capabilities. This work has incorporated the "Persona" concept [11], which has been introduced to distinguish between different user groups within an adaptive user interface domain. These "Persona" concepts have been proved really useful as a wide range of potential users could be covered by assigning random values to characteristics, such as: age, education, profession, family conditions, etc. From a computational perspective, using "personas" is a quite common approach in UM due to its correlation with the actors and roles used in software engineering systems, its flexibility, extensibility, re-usability and applicability [26]. It is thus observed, that from product design to multimedia and user interfaces adaptation, the approaches described above, even though they differ a lot with respect to the collected personal data characteristics which use to improve the system and user's satisfaction, still share the same goal.

Filling a home with sensors and controlling devices by a computer is nowadays not only possible, but commonly found in homes. Sensors are available off-the-shelf that localize movement in the home, provide readings for light and temperature levels and monitor usage of doors, phones and appliances. Small, inexpensive sensors are attached to objects not to only register their presence but also record histories of recent social interactions.

As social interaction is an aspect of our daily life, social signals have long been recognized as important for establishing relationships, but only with the introduction of sensed environments where researchers have become able to monitor these signals. Hence, it is possible to look at socialization within the smart home and cities (such as entertainment guests, interacting with residents, or making phone calls) and examine the correlation between the socialization parameters and productivity, behavioral patterns or even health. These results will help researchers not just to understand social interactions but also to design products and behavioral interventions that will promote more social interactions.

Proliferation of sensors in the home results in large amounts of raw data that must be analyzed to extract relevant information. Most smart-home data from environmental sensors can be processed with a small computer. Once data is gathered from wearable sensors and smart phones (largely accelerometers and gyroscopes; sometimes adding camera, microphone, and physiological data), the amount of data may get too large to handle on a single computer, and cloud computing might be more appropriate. Cloud computing is also useful if data are collected for an entire community of smart homes to analyze community-wide trends and behaviors.

Collecting and handing with concurrently enormous ubiquitous data, information and knowledge that have different formats within the SmartSantander [2] is a hard task. According to the level of abstraction of context-aware systems in HCI, context is divided into low-level context and high-level context respectively. The raw data of low-level context are usually gathered from different physical sensors. Data type, formats and abstraction level from different physical sensors are different. Devices and physical sensors of context-aware systems use various scale and unit, and low-level context has different elements. Context-aware systems store data, information and knowledge that have different relationship, format and abstraction level in the context base. Furthermore, context-aware systems collect context history storing sensor data over time to offer proactive service. Context history stores huge amount of data on location, temperature, lighting level, task, utilized devices, selected services, etc. To quickly provide suitable services to users, context-aware systems should manage variety, diversity and numerous amount of context. However, previous research suggested only a concept to control this problem. Therefore, our methodology ensures semantic interoperability by bridging the gap between the expressively rich natural language vocabulary used in the recipes and the low-level machine-readable instructions with very precise and restricted semantic content.

3. USER MODELING

3.1 Basic characteristics

The herein proposed approach for modeling user information following a personas-based inspiration is discussed within this subsection. Specifically, according to the notation followed within our system, the so called "eahouker profile" (E_p) is a set of properties of the system's users ("eahoukers", e) that can be exploited for determining eahoukers with similar characteristics. These properties are stored in a database, i.e., the Eahoukers Social Network's DataBase (EDB) and are continuously updated. The profile contents are rather static in the sense that the information is present in the database when the eahouker joins the SandS system and seldom changes in everyday activities. The interested reader should at this point note that a quasi-static approach would have been more accurate, since a number of user attributes, like for instance a user's marital status and the number of children she/he may have, can change over time. Basic information about the user is also included in the profile and consists of gender, age, number of children, social status and his house appliances and geographical position.

In a more formal manner the profile of an eahouker e, denoted E_p, contains the following information about the user: $E_p \in \{gender,\ age,\ children,\ city,\ houseRole,\ socialStatus\}$, where $gender \in \{male, female\}$ is the gender of e, $age \in N$ is the age of e, $children \in N$ denote the number of children of e, $city$ is a string describing the city of e, $houseRole \in \{owner, junior, senior\}$ is the house role of e and $socialStatus \in \{single, married, young\}$ corresponds to the marital status of e. Considering the above user profile definition at hand, the semantic description framework of the eahoukers can be directly interfaced and queried, but more importantly it enables us to define a personas-based user similarity measure.

3.2 Fuzzification

Let's consider a set of eahoukers $\mathcal{E}$ that interact with information objects and a set M of *meanings* that can be found or referred to in items. Within our approach, M is described as a set of semantic entities that the eahouker has interest for, to varying degrees. This interpretation provides a fairly precise, expressive and unified representational grounding, in which both user interests and content meaning are represented in the same space, in which they can be conveniently compared [12].

In addition, the use of ontologies for capturing knowledge from a domain of interest has grown significantly lately, thus we also consider a domain ontology $\mathcal{O}$ herein. According to one of the core ideas of the Semantic Web, i.e., that of sharing, linking, and reusing data from multiple sources, the availability of semantically described data sources and thus the uptake of Semantic Web technologies is important to applications in which rich domain descriptions can play a significant role. Still, considering the inherent complexity of a decent knowledge representation formalism (e.g. OWL) convincing domain experts, and thus, potential ontology authors, of the usefulness and benefits of using ontologies is one of the major barriers to broader ontology adoption [19].

Efficient user model representation formalism using ontologies [7], presents a number of advantages. In the context of this work, ontologies are suitable for expressing user modeling semantics in a formal, machine-processable representation. As an ontology is considered to be "a formal specification of a shared understanding of a domain", this formal specification is usually carried out using a subclass hierarchy with relationships among classes, where one can define complex class descriptions (e.g., in Description Logics (DLs) [7] or OWL).

As far as a relevant mathematical notation is concerned, given a universe $\mathcal{X}$ of eahoukers $\mathcal{E}$ one may identify two distinct sets of concepts, namely a crisp (i.e., non fuzzy) set and a fuzzy set. The crisp set of concepts on $\mathcal{X}$ may be described by a membership function $\mu_C : \mathcal{X} \rightarrow \{0, 1\}$, whereas the actual crisp set C may be defined as $C = \{c_i\}$, $i = 1, .., N$. Quite similarly a *fuzzy* set F on C may be described by a membership function $\mu_F : C \rightarrow [0, 1]$. We may describe the fuzzy set F using the well-known sum notation for fuzzy sets introduced by Miyamoto [25] as:

$$F = \sum_i c_i/w_i = \{c_1/w_1, c_2/w_2, \ldots, c_n/w_n\} \tag{1}$$

where: $i \in N_n$, $n = |C|$ is the well-known cardinality of the crisp set C, and $w_i = \mu_F(c_i)$ or, more simply $w_i = F(c_i)$, is the membership degree of concept $c_i \in C$. Consequently, equation (1) for a concept $c \in C$ can be written equivalently as:

$$F = \sum_{c \in C} c/\mu_F(c) = \sum_{c \in C} c/F(c) \tag{2}$$

In order to define, extract and use a set of concepts, we rely on the semantics of their fuzzy semantic relations. As discussed in the previous subsection, a *fuzzy binary relation* on C is defined as a function $R_i : C \times C \rightarrow [0, 1], i = 1, .., M$. The inverse relation of relation $R_i(x, y)$, $x, y \in C$ is defined as $R_i^{-1}(x, y) = R_i(y, x)$, following the prefix notation $R_i(x, y)$ for fuzzy relations. The definition of the *intersection*, *union* and sup-t *composition* of any two fuzzy relations R_1 and R_2 on the same set of concepts C are given by equations:

$$(R_1 \cap R_2)(x, y) = t(R_1(x, y), R_2(x, y)) \tag{3}$$

$$(R_1 \cup R_2)(x, y) = u(R_1(x, y), R_2(x, y)) \tag{4}$$

$$(R_1 \circ R_2)(x, y) = \sup_{w \in S} t(R_1(x, w), R_2(w, y)) \tag{5}$$

where t and u are a fuzzy t-norm and a fuzzy t-conorm, respectively.

3.3 Fuzzy personas similarity function

To provide a measure for the evaluation of similarity between two eahoukers' profiles, we first need to establish an evaluation of similarity for each profile component. In Table 1 we define a set of functions $\{CS_i| \ \le i \le size(E_p)\}$, one for each attribute of the eahouker' profile:

1. Two eahoukers are considered identical if their gender, city, role in the house and marital status are the same. This property is expressed through functions CS_1, CS_4, CS_5 and CS_6 that are collectively represented in Table 1 as $CS_{1/4/5/6}$.
2. Two eahoukers are considered identical if their difference of age is less than 5 years. Indeed, their behavior and habits inside the house can be considered the same even if they have a slight difference of age. This property is expressed by the function CS_2.
3. Finally, two eahoukers are considered identical if they have more or less the same number of children. This property is expressed by the function CS_3 in Table 1.

Table 1: User profile similarity functions

$$CS_{1/4/5/6}(x, y) = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{otherwise} \end{cases}$$

$$CS_2(x, y) = \begin{cases} 1 & \text{if } |x - y| \le 5 \\ 0 & \text{otherwise} \end{cases}$$

$$CS_3(x, y) = \begin{cases} 1 & \text{if } |x - y| \le 1 \\ 0 & \text{otherwise} \end{cases}$$

Having introduced the functions for the evaluation of profile similarity, we can define a function that uses these evaluations to provide the level of similarity of two eahoukers. Let E_{p_i} denote the i-th attribute of E_p. In addition, let E_{p_u} and E_{Pz} to be the profiles of eahoukers u and z respectively. The eahouker profile similarity function $\mathcal{S}$ is then defined as follows:

$$\mathcal{S}(u, z) = \frac{\sum_1^n CS_i(E_{p_{ui}}, E_{P_{zi}})}{n} \tag{6}$$

where n is actually the cardinality of E_p (which equals to six in the herein presented use case example).

4. CONTEXT

4.1 Context aware HCI

In everyday social contextual situations, humans are able to, in real-time, perceive, combine, process, evaluate and respond to a multitude of information including semantics meaning of the content of an interaction, nonverbal information such as facial and body gestures, subtle vocal cues, and context, i.e., events happening in the environment. Multimodal cues unfold, sometimes asynchronously and continuously express the interlocutors' underlying affective and cognitive states, which evolve through time and are often influenced by environmental and social contextual parameters that entail ambiguities. These ambiguities w.r.t. contextual aspect range from the multimodal nature of emotional expressions in different situational interactional patterns [9], the ongoing task [10], the natural expressiveness of the individual, to the intra- and interpersonal relational context. Additionally, in human communication, literature indicates that people evaluate situations based on contextual information such as past visual information [15], general situational understanding, cultural background, gender of the participants and the knowledge of the phenomenon that is taking place [10].

According to the first work which introduced the term context-awareness in CS, [33] the important aspects of context are: Who you are with, When, Where you are, What resources are nearby. Thus, context-aware applications look at the Who, Where, When and What (the user is doing) entities and use this information to determine Why the situation is occurring. In a similar definition, Brown et al. [10] define context as location, identities of the people around the user, the time of day, season, temperature, etc. Other approaches such as Ryan et al. [32] include context as the user's location, environment, identity and time while others have simply provided synonyms for context; e.g. referring to context as the environment or situation. However, to characterize a situation, the categories provided by [33] have been extended to include activity and timing of the HCI. [34] view context as the state of the application's surroundings and [31] define it to be the application's setting. For a more extended overview on context-awareness the reader is referred to [6].

Based on context's broader approach [6], context can be formalized as a combination of four contextual types: Identity (e.g. gender, age, children, social and marital status), Time, Location (e.g. geo-localization, proximity to other homes) and Activity (e.g. what is occurring in the situation) which are the primary context types for characterizing the situation of a particular entity and also act as induces to other sources of contextual information.

As far as real-world, context-aware HCI computing frameworks, context is defined as any information that can be used to characterize the situation that is relevant to the interaction between the users and the system [33]. Thus, this definition approaches better the understanding of human affect signals. An even more suitable definition is the one that summarizes the key aspects of context with respect to the human interaction behavior (who is involved (e.g. dyadic/triadic interactions among persons), what is communicated (e.g., "recipes" to perform a specific task), how the information is communicated (the person's cues), why, i.e., in which context the information is passed on, where the pro-active user is, what his current task is and which (re)action should be taken to participate actively in content creation [13].

Unfortunately, understanding human behavior data is usually context independent due to the fact that the human behavior signals are easily misinterpreted if the information about the situation in which the shown behavioral cues have been displayed is not taken into account. Thus, up to date the proposed methodology has approached one or more of the above presented contextual aspects either separately or in groups of two or three using the information extracted from multimodal input streams [35]. Overall, further research is needed in approaching this contextual information in a continuous way.

4.2 Ubiquitous contextual information

An issue related to the use of data collected continuously is that both psychologists and engineers tend to acquire their data in laboratories and artificial settings, to elicit explicitly the specific phenomena they want to observe. However, this is likely to simplify excessively the situation and to improve artificially the performance of the automatic approaches. Aligned with the aforementioned trend, there also has been much work in collecting large amounts of raw data that must be analyzed to extract relevant social contextual information. In this view, researchers have started to record smart-homes or work situations to further achieve such high levels of social naturalistic data. Once data is gathered from wearable sensors and smart appliances, the amount of data may get too large to handle. This reason underlines the need for more advancements w.r.t. such a situation: the diffusion of mobile devices equipped with multiple sensors [30] and the advent of Big-Data [24]. Typically, such data are defined according to utility for retrieval, coverage, diversity, availability and re-usability. Moreover, semantic concepts such as objects, locations, and activities in visual data can be easily automatically detected [27]. Recent approaches have also turned towards semantic concept-level analysis approaches.

Semantic context concept-based approaches [29] aim to grasp the conceptual and affective information associated with natural language semantic rules. Additionally, concept-based approaches can analyze multi-word expressions that don't explicitly convey emotion, but are related to concepts that do. Rather than gathering isolated rules about a whole item, users are generally more interested in comparing different products according to their specific features, or even sub-features. This taken-for-granted information referring to obvious things people normally know and usually leave unstated/uncommented, in particular, is necessary to properly deconstruct natural language text into rules.

4.3 Pervasive context awareness environments

4.3.1 *Context sources*

Context Data in a Smart Pervasive environment such as a Smart Home can come from various sources:

1. in-place sensors such as temperature, humidity, luminosity, noise or human presence sensors located in the various rooms or outside, in the vicinity of the house
2. power and water consumption meters of the house
3. Smart City sensors providing additional information such as pollution levels, temperature, total electrical power consumption of the city etc., optionally with geospatial information.

4.3.2 *Home rules*

Users sometimes need their appliances to perform a specific action in their house taking into account the context information. For example, they may not want to wash clothes when it is raining or the temperature in the city is quite low. For this reason there are defined some actions for the Smart Home system. These actions are called Home Rules. These Home Rules are handling whether the appliances should be switched on or off.

In a more high level approach, the structure of the Home Rules, illustrated in Figure 1, can be customized as "if it is valid, do/don't do that". It is consisted of three parts.

1. The "if it is valid", a trigger consists of:
   (a) an input type and the value of the input that is defined by pervasive and context information such as the ones described in Section 4.3.1
   (b) an operator $<, \leq, =, \neq, \geq, >$.
   (c) a reference value, which is input by the user (for example 20 degrees Celsius)
2. "do/don't", what to do when the rule is triggered, where any Smart Home system action/reaction can be inserted

3. "that", which consists of an optional parameter e.g. lower the house blinds by using that percentage

Moreover, more complex rules such as the temperature in specific interval of values are expressed with multiple rules that are logically joined together.

5. SEMANTIC REPRESENTATION

In this section, Semantic technologies are used in order to represent the knowledge of an ecosystem. This ecosystem consists of cities, comprising a number of houses. Additionally, in every city and in every house is located a number of sensors which give data for the environmental context e.g. humidity, temperature and so on. They are also able to give more specific information such as noise and pollution levels or information about the human presence inside the house. All these data are received from the sensors and are stored in a database.

In this ecosystem we can define a number of rules, which we will call home rules, for example defining under which conditions house appliances should be switched on or off. Another more concrete example would be "do not operate the air-condition when the outside temperature is high".

The OWL 2 Web Ontology Language (OWL 2), an ontology language for the Semantic Web with formally defined meaning was adopted for the Semantic Representation of our ecosystem. OWL 2 ontologies provide classes, properties, individuals and data values and are stored as Semantic Web entities. The following sections explain in a more detailed way on how the ecosystem is represented by our ontology. The ontology was created using the open source Protégé 4.2 platform [3].

5.1 Ontology Hierarchy

In the ontology, every different aspect of the ecosystem is described by a class. Figure 2a illustrates the ontology's classes an ecosystem. The "Appliances" is the class containing all the different types of the ecosystem's appliances, with a subclass for every different type of appliance in the ecosystem, e.g. the refrigerator,the washing machine the air-condition and the television. The "Location", contains both the individuals of every house and city, the "Sensor" is a class that contains the individuals of all the existing sensors and the "Person" contains all the people. Moreover, the "Gender", the "HouseRole" and the "SocialStatus" are for the different types of gender, house roles, and social status that implement the user model.

5.2 Properties

The ontology also comprises a series of properties. These properties are both object properties and data properties. Object properties relate two objects, of which the one is the domain and the other is the range. The object properties of the ontology of this ecosystem are mainly used to relate the sensors with a specific location and the inhabitants of the house and the appliances. The object properties may be "hasGender", which relates a person class with a gender class, "hasSensor", which relates a sensor class with a specific location, "hasHouseRole", which relates a Person class with a house role, or having to do with the location like "isLocatedIn", "livesIn" and "builtIn", relating a house with a city, a person with a house, and a house with a city, respectively.

On the other hand, data properties are similar to object properties with the sole difference that their domains are typed words. In our ontology, they relate the actual sensor values with a sensor, like "hasNoise" and "hasTemperature", relating a sensor with the actual captured noise value, (e.g. 40dB) or temperature value (e.g. 25°C). They can show the power on or off status of the appliances, e.g. "isOn" taking true value if the appliance is turned on, or false if the appliance is turned off. Finally, they can give some extra information about the people of the ecosystem with properties such as "numberOfChildren", relating a person in it with its number of his children. A small set of object's and the data's properties of the ontology appear in Figures 2b and 2c.

5.3 Individuals

The ecosystem in all contains a large number of appliances, sensors, houses and people. Every single appliance, sensor, house and person is represented in the ontology as an individual of the Appliance, Sensor, House or Person class respectively, as illustrated in Figure 2d.

5.4 Rules and Consistency Check

In the current section we provide a novel semantic representation of the home rules of the ecosystem. These home rules are expressed using the SWRL. SWRL has the full power of OWL DL, only at the price of decidability and practical implementations. However, decidability can be regained by restricting the form of admissible rules, typically by imposing a suitable safety condition. Rules have the form of an implication between an antecedent (body) and a consequent (head). This meaning can be read as: 'whenever the conditions that are specified in the antecedent may hold, the conditions that are specified in the consequent must also hold'. A critical property of our ontology is that the ontology should always be consistent, a condition that is verified with the use of a Pellet reasoner [28]. Thereat, whenever a home rule is violated an inconsistency must be detected. Taking that into account and whenever the conditions that are specified in the antecedent's hold, the conditions specified in the consequent must also hold, hence the home rule's violation is transformed to the respective antecedent of the SWRL.

For this reason, a data restriction has to be created in the Appliance class. A data property, called 'restriction' is created. Its domain is an appliance and its range is a boolean, but it is also restricted to exist an appliance with the restriction property. Then, every home rule is transformed to a SWRL, and if the left side of the rule is satisfied, it leads to the creation of the 'restriction' property for an appliance. This makes our ontology inconsistent restricting the appliance to start working. So, every time a database record changes, or a new one is added, the ontology individuals are populated with the new values querying the database. Then, using the Pellet reasoner, the system checks for a possible existence of any inconsistency. Finally, the inconsistency is being handled by forcing the appliance to switch off or switch on. Figure 2e presents some examples of home rules transformed to the respective SWRLs in Protégé. Their meaning is: 1) "The washing machine must not be operating if a Person is in the house and there exist noise more than 40dB", 2) "If it is earlier than 8a.m. the television must not be switched on, 3) "Do not operate any washing machine when the external temperature is greater than 26°C", 4) "If it is

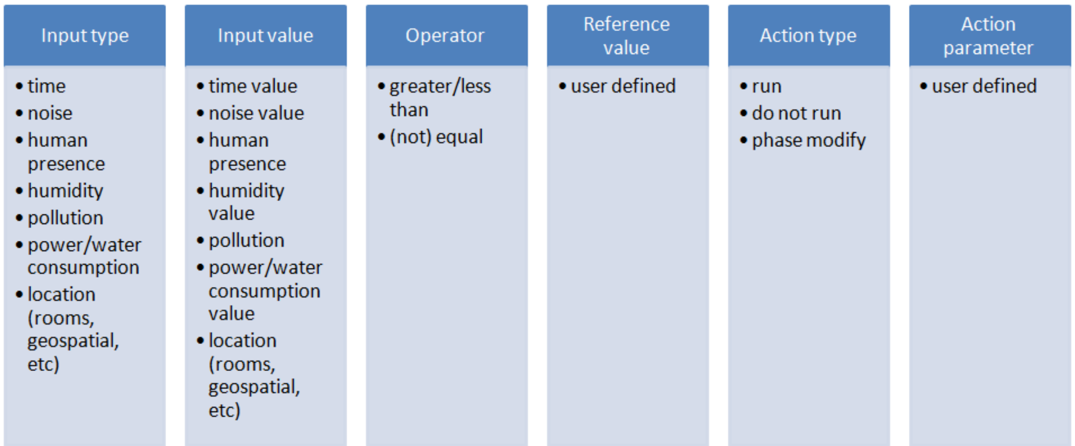


Figure 1: Home Rules Structure

later than 10p.m. the television must not be switched on, 5) "If the sensor detects high rates of pollution in the atmosphere and there exists and junior member in the house, none of the house appliances must operate", and 6) "The air-condition must not be switched on if the temperature inside the house is less than 26°C", respectively.

6. EXPERIMENTS

6.1 Data collection

6.1.1 User models

Regarding the experimental dataset to validate the formation of Personas, data was collected by the SandS consortium and partners during a small-scale mockup. SandS also opened up its user base towards the FIRE and related communities such as the Open Living Labs. The dissemination call for user participation pointed to a user registration form, illustrated in Figure 3. This registration form comprised several user-related fields: first name, last name, date of birth, senior/junior, gender, single/married, city.

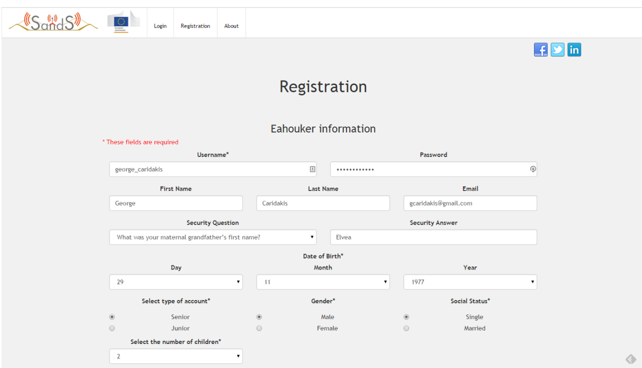


Figure 3: SandS user registration form

6.1.2 Smart City sensors

Large-scale tests of the unified user in a smart home in a smart city, SandS will use context sensor data gathered at SmartSantander. SmartSantander [2], born as an European Project is turning into a living experimental laboratory as part of the EU's Future Internet initiative. Major companies involved in the project include Telefonica Digital, the company's R&D wing, along with other smaller suppliers as well as utility and service companies. In terms of application areas five main areas have initially been targeted in the trials so far: traffic management and parking, street lighting, waste disposal management, pollution monitoring and parks and garden management. To this aim, the city of Santander, in Spain, has been equipped with a large number of sensors (Figure 4) used to collect a huge amount of information. These sensors can be divided into several categories based on the data they should collect.

1. Mobility sensors: placed on buses, taxis, and police cars. They are in charge of measuring main parameters associated to the vehicle (GPS position, altitude, speed, course and odometer).

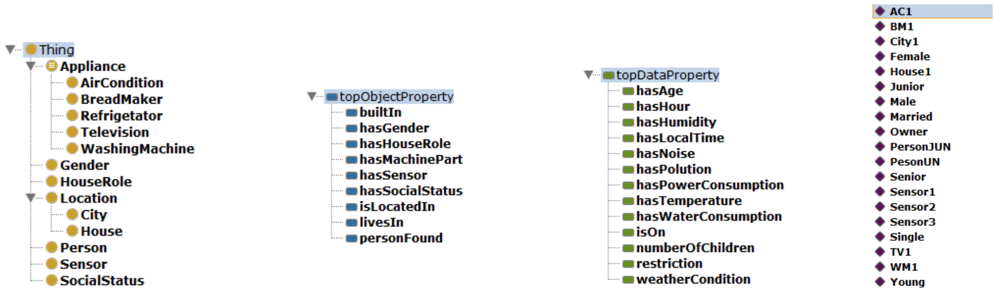
2. Traffic and parking sensors: buried under the asphalt, they are accountable for sensing the corresponding traffic parameters (traffic volumes, road occupancy, vehicle speed, queue length, free parking availability).

3. Environmental sensors: the task is to collect data concerning temperature, noise, light, humidity, wind speed, and detection of specific gases like CO, PM10, O3, and NO2.

4. Park and garden irrigation sensors: In order to control and make the irrigation in certain parks and gardens more efficient, these sensors register information about wind's speed, quantity of rain, soil temperature, soil humidity, atmospheric pressure, solar radiation, air humidity and temperature, as well as water consumption.

At the moment the data collected by these sensors are stored in the Intelligent Data Advanced Solution (USN/IDAS) SmartSantander cloud storage platform. This platform stores in its databases all the observations and measurements gathered by the sensors. It contains live and historical data. These databases are migrating on the Fi-lab platform as an instance of the FI-WARE [4] ecosystem.

In very minimal terms our experiments will manage the integration of the two systems only in one direction: by exploiting SmartSantander data in favor of SandS with special



(a) Ontology hierarchy (b) Ontology Properties (c) Data Properties (d) Ontology Individuals

House(?house), Person(?per), Sensor(?sens), WashingMachine(?wm), hasSensor(?house, ?sens), isLocatedIn(?wm, ?house), personFound(?sens, ?per), hasNoise(?sens, ?noise), isOn(?wm, true), greaterThan(?noise, 40) -> restriction(?wm, true)

House(?house), Sensor(?sens), Television(?tv), hasSensor(?house, ?sens), isLocatedIn(?tv, ?house), hasHour(?sens, ?hour), isOn(?tv, true), lessThan(?hour, 8) -> restriction(?tv, true)

City(?city), House(?house), Sensor(?sens), WashingMachine(?wm), builtIn(?house, ?city), hasSensor(?city, ?sens), isLocatedIn(?wm, ?house), hasTemperature(?sens, ?temp), isOn(?wm, true), greaterThan(?temp, 26) -> restriction(?wm, true)

House(?house), Sensor(?sens), Television(?tv), hasSensor(?house, ?sens), isLocatedIn(?tv, ?house), hasHour(?sens, ?hour), isOn(?tv, true), greaterThan(?hour, 22) -> restriction(?tv, true)

Appliance(?ap), House(?house), Person(?per), Sensor(?sens), hasHouseRole(?per, Junior), hasSensor(?house, ?sens), isLocatedIn(?ap, ?house), personFound(?sens, ?per), hasPolution(?sens, ?pol), isOn(?ap, true), greaterThan(?pol, 300.0) -> restriction(?ap, true)

AirCondition(?ac), House(?house), Sensor(?sens), hasSensor(?house, ?sens), isLocatedIn(?ac, ?house), hasTemperature(?sens, ?temp), isOn(?ac, true), greaterThan(?temp, 26) -> restriction(?ac, true)

(e) Examples of transformed Home Rules to the respective SWRLs in Protégé

Figure 2: Ontology classes, Object Properties, Individuals and Home Rules of an ecosystem

Figure 4: SmartSantander sensors locations

regards to the empowerment of the home rules used by the DI. Hence the contact between the two systems will happen via the home rules which may be feed by the SmartCity sensor data either in their current version or in an enlarged one to be capable of profiting from the data. Available sensor data, related to the SandS domain include: temperature, noise, light, humidity and quantity of rain. Other data, for instance those concerning traffic, could be considered in a more longterm planning and scheduling approach.

Finally, our goal would be to stress the following case studies:

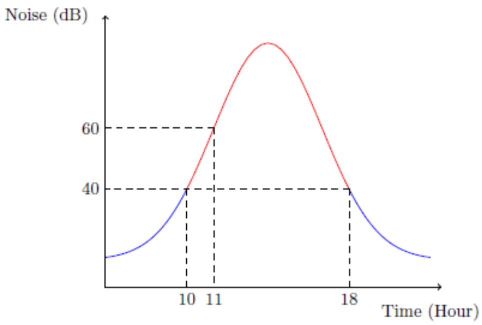
1. feeding the home rules with the signals provided by the SmartCity system. It represents a simple interoperability test,

2. introducing limitations on the use of the appliances related to environment conditions, such as the power or water consumption reckoned by the city environment sensors, the short term weather forecasting, etc. It represents a logical test on the DI scheduler and consistency checker,

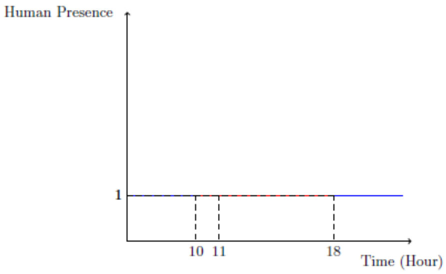
3. managing alarm messages sent by the municipality. It will represent a stress test for the entire system.

6.1.3 Sensor Integration

In the ecosystem, there are sensors both in every house and for the whole city. The sensors send periodically information about the temperature, the luminosity and the humidity. Both the in-house and the city sensors send the values of the sensors periodically to the ecosystem. These values are stored to a specific table of a database overwriting the previous record that was stored. The in-house sensors send information about the humidity in the house, the inside house temperature, the human presence in it, the power consumption and the water consumption of all the appliances inside it, the location where the sensor is installed (e.g. the kitchen, the bathroom, or the bedroom), the noise and the local timeStamp. Moreover, the city sensor values are collected in a specific moment using the FIWARE Ops tools [5]. The data of the sensors are periodically sent to the system in a JSON format using an HTTP connection. Then, the JSONs are parsed and the information is stored to the database. The city sensors, like the SmartSantander [2], are sending information of the noise inside the city, the temperature and the exact location that they are installed. Adding all these information of the sensors to a database, it is every time feasible for the system to identify the exact condition inside and outside the house, where the sensors are installed, just doing a simple query in the database. Due to the structure of the home rules it is possible in a very short time for the ecosystem to know if a home rule is triggered and if an appliance in a house should be switched on or off.



(a) Plot of the noise per hour



(b) Plot of the human presence per hour

Figure 5: In-house Sensor plots of the noise and the human presence

6.2 Experimental validation

The system is periodically querying the database and especially the collection where the sensor values are stored. Then, by using the home rules, which exist in the ecosystem, it checks the consistency. If any of the home rules is triggered for an appliance, it means that the appliance is switched off, until the home rules for this appliance are consistent again. As it was mentioned before, a home rule may be triggered with both the in-house values of the sensors and the values of the SmartSantander sensors. For example, Figure 5a illustrates the noise values, which follow the Gaussian function, and are received by the in-house sensors and stored for a specific period of time. In addition, Figure 5b shows any human presence in the house at the same period of time. If this house exists in an ecosystem the home rules presented in Section 5.4 are defined. Then the first home rule is triggered. In the beginning the washing machine is working, until the noise volume tides over 40dB at 10:00. Then, the appliance is switched off until 18:00, when the noise levels falls below 40dB.

Moreover, if the system receives from a city sensor, such as the SmartSantander sensors, a temperature value equal to 26°C, then the third home rule is triggered because there is detected an inconsistency and as a result the house's washing machine is switched off. Such an example is presented in Figure 6. Between 11:00 and 15:00 a city sensor receives higher temperature values than 26°C having as a result an inconsistency and forcing the house's washing machine to switch off. Then, after 15:00 when the temperature is lower than 26°C, the washing machine is switched on again.

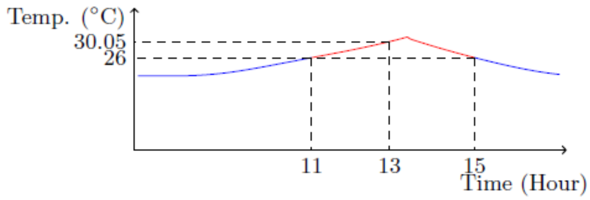


Figure 6: SmartSantander sensor values of the temperature in a day

7. CONCLUSIONS AND FUTURE WORK

In this paper we proved how the emerging semantics of the Smart Home environments can be captured through a novel formalism and how expert knowledge can be used to ensure semantic interoperability. User stereotypes or personas on the one hand provide flexibility, extensibility, reusability and applicability and on the other hand knowledge management is incorporated as an efficient user and context model representation formalism. In addition, this formal, machine-processable representation is used in order to define, extract and use both a set of concepts and their fuzzy semantic relations. This user modeling approach is put into a rich smart home context representation which abstracts raw sensor data to a high level semantic representation language in which complex home rules can be defined.

Moreover, future work will include further incorporation of user, usage and context information, through a unified semantic representation, driving an adaptation mechanism aiming to provide a personalized service and optimizing the user experience. Among the aspects of the architecture that will be stressed through experimental validation is the computational cost and the scaling of SandS to a wider user group. Based on the SandS architecture the cloud infrastructure ensures the optimal handling of the computational load since the intermediate processes are not computationally demanding. On the other hand, issues that may arise from the scaling of the platform application are part of the experimental validation since the load is directly correlated with the user activity. The large scale validation at SmartSantander will provide us with useful insights about the latter.

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