Intelligent and Adaptive Pervasive Future Internet: Smart Cities for the Citizens

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Abstract. Current article discusses the human centered perspective adopted in the European project SandS within the Internet of Things (IoT) framework. SandS is a complete ecosystem of users within a social network developing a collective intelligence and adapting its operation through appropriately processed feedback. In the research work discussed in this paper we will investigate SandS from the user perspective and how users can be modeled through a number of fuzzy knowledge formalism through stereotypical user profiles. Additionally, context modeling in pervasive computing systems and especially in the SandS smart home paradigm is examined through appropriate representation of context cues during overall interaction.

Keywords: Smart Cities, Smart Homes, Intelligent Systems, User Modeling, Context Aware Services, Future Internet.

1 Introduction

Thanks to pervasive computing practices, the IoT framework supports and enhances the cooperation between humans and devices in terms of: 1) facilitating communication between the (Internet of) Things and people, and among Things through a collective network intelligence driven by users in the SandS context, 2) people's ability to exploit the benefits of this communication with the increasing familiarity with ICT technologies, 3) a mashup vision where in certain respects people and things are homogeneous agents endowed with fixed computational tools. However, the ways of deploying the IoT paradigm may differ significantly, from the logistics-driven idea where individual consumer items are being tracked to the co-creative design approach where the user participates in a proactive manner in all stages of the product or system creation process.

Following a pragmatic approach, the FP7 European Project and FIRE framework Social & Smart (SandS)[1] aims to highlight the potential of IoT technologies

[1] http://www.sandsproject.eu

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in a concrete user-centric framework. The aim is for the user to collectively, via the SNS (Social Network Service), and intelligently, via the adaptive network intelligence, interface with and finally control his household appliances. The overall interface is orchestrated through a domestic infrastructure. The central role of the user is reflected on all aspects of the ecosystem, from the family of Things which are socially governed to the household appliances that affect our everyday life. This entire procedure is devised so as to optimally carry out usual housekeeping tasks with a minimal low level intervention from the part of the user.

By giving the means to the eahooker to intelligently control his domestic appliances and by placing him inside the ESN (Eahookers Social Network), SandS follows clearly a human and user centric approach. More precisely, User Modeling (UM) emerges as an important research direction inside the project. More precisely, UM not in a general sense, but relatively to the users activity inside the ESN and with respect to the task on hand, the efficient orchestration of his household appliances (context). We are considering in particular a context-aware UM of eahookers, that is taking into account all the contextual information that could characterize the situation and condition of the systems entities. In SandS case this could be context information about the eahooker (distance to his house, communication device used, time of the day, weather, etc.), usage information (recipes used, feedback provided by user, frequency of use,..), information about the homes (geolocalisation, proximity to other homes, surface area, number of rooms, etc.), about the appliances (location inside house, energy consumption levels etc) and information specific to the social network itself (friendship statements, content exchanged between users, graph structure, communities formation, etc.). As soon as the eahookers activity will start producing this data, Computational Intelligence algorithms will extract knowledge about groups of similar users and construct for these groups stereotypical users (or Personas). Ultimately, we will investigate how each individual eahooker could be modeled with a simple user model, consisting of a fuzzy combination of the extracted Personas.

2 Internet of People

A user model [23] is a computational representation of the information existent in a user's cognitive system, along with the processes acting on this information to produce an observable behavior. Concretely, a model receives inputs in a similar capacity to a person, performs mental and cognitive operations and outputs a response. Within the extended Human Computer Interaction framework, User Modeling serves to make systems more usable, useful, and to provide users with experiences fitting their specific background, knowledge and objectives. User profiling, on the other hand, is achieved by understanding user individual characteristics, including information related to age, gender, skills, education, experience, and cultural level or higher representations of these characteristics. User features could also include online usage log statistics or patterns.

Construction of user stereotypes or personas is quite common due to its correlation with the actors and roles used in software engineering systems, its flexibility, extensibility, reusability and applicability. A persona is an archetypal user that is 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 optimisation methods. The use of personas is a growing popular way to customize, incorporate and share research about the 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.

User modeling utilizes also Artificial Intelligence, Machine Learning (ML) and Data Mining techniques. In [2] the authors propose a user modeling framework addressing the issue of cost-intensiveness by integrating supervised and unsupervised machine learning. The application domain for the framework is learning during interaction with the Adaptive Coach for Exploration (ACE) environment using both interface and eye-tracking data. An unsupervised learning (K-means clustering) algorithm using vectors derived from offline and online interaction as input to form groups according to their similarity can be considered. Clustering is a very popular and effective approach for user modeling based on ML and many standard ML techniques are prime candidates for straightforward application to user modeling.

3 Future Internet in Context

Emerging ubiquitous or pervasive computing technologies offer "anytime, anywhere, anyone" computing by decoupling users from devices. To provide adequate service for the users, applications and services should be aware of their context and automatically adapt to their changing context, known as context-awareness. Context is any information that can be used to characterize the situation of an entity. 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. Context-awareness means that one is able to use con-text information. A system is context-aware if it can extract, interpret and use context information and adapt its functionality to the current context of use.

Context models are used for representing, storing and exchanging contextual information [4]. A growing body of research investigates different approaches of context modeling and additionally reasoning techniques for context information [5]. The existence of well-designed context information models facilitates the development and deployment of future applications. Moreover, a formal representation of context data within a model is necessary for consistency checking, as well as to ensure that sound reasoning is performed on context data.Most of the context-aware systems [20] focus on the external context, called physical context. External context means context data collected by physical sensors. It involves context data of the physical environment, location data, distance, function on to other objects, temperature, sound, air pressure, time, lighting levels surrounding users, and so on. However, a few authors have addressed utilizing the cognitive elements of a user's context.

4 User Modeling via Fuzzy Personas

Before going further into the details of our approach, the motivation and development of our knowledge modeling notion and methods are grounded on a set of problems, assumptions, views and design decisions, which are stated next. We consider following settings: A set of users $\mathcal{U}$ interact with information objects, typically (though not mandatorily) containing a fair amount of unstructured or semi-structured content, e.g. text and/or multimedia objects and/or documents. The information objects are annotated with metadata, consisting of concepts, properties and values defined according to a domain ontology $\mathcal{O}$, and stored in a Knowledge Base (KB). At this point it should be made clear that the latter constitutes a clear assumption of this work and ontology matching or semantic similarity issues are not tackled herein.

Following the above common view, we define P as a set of *meanings* that can be found or referred to in items. Beyond raw keywords and multimedia descriptors, which are commonly used as semantic representation bricks for user needs, ontologies are being investigated in the field as enablers of qualitatively higher expressivity and precision in such descriptions [8], [16], [24], [30]. In our approach, P is described as a set of semantic entities that the user has interest for to varying degrees. This 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 [9].

It is rather true that in the seek of an efficient user model representation formalism, ontologies ([3], [17]), present 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) [3] or in Web Ontology Language (OWL) [32]).

4.1 Mathematical Background of Fuzzy Personas

Given a universe $\mathcal{V}$ of users $\mathcal{U}$, a crisp (i.e., non fuzzy) set S of concepts on $\mathcal{V}$ is described by a membership function $\mu_S : \mathcal{V} \rightarrow \{0, 1\}$. The crisp set S may be defined as $S = \{s_i\}$, $i = 1, .., N$. A *fuzzy* set F on S may be described by a membership function $\mu_F : S \rightarrow [0, 1]$. We may describe the fuzzy set F using the well-known sum notation for fuzzy sets [25] as:

$$F = \sum_i s_i/w_i = \{s_1/w_1, s_2/w_2, \ldots, s_n/w_n\} \quad (1)$$

where:

- $i \in N_n$, $n = |S|$ is the cardinality of the crisp set S,
- $w_i = \mu_F(s_i)$ or, more simply $w_i = F(s_i)$, is the membership degree of concept $s_i \in S$.

Consequently, equation (1) for a concept $s \in S$ can be written equivalently as:

$$F = \sum_{s \in S} s/\mu_F(s) = \sum_{s \in S} s/F(s) \tag{2}$$

Let now R be the crisp set of fuzzy relations defined as:

$$R = \{R_i\}, R_i : S \times S \to [0,1], \quad i = 1, .., M \tag{3}$$

Then the proposed fuzzy ontology contains concepts and relations and may be formalized as follows:

$$\mathcal{O} = \{S, R\} \tag{4}$$

In equation (4), $\mathcal{O}$ is a fuzzy ontology, S is the crisp set of concepts described by the ontology and R is the crisp set of fuzzy semantic relations amongst these concepts.

Given the set of all fuzzy sets on S, $\mathcal{F}_S$, then $F \in \mathcal{F}_S$. Let $\mathcal{U}$ be the set of all users $\widehat{u}$ in our framework, i.e. a user $\widehat{u} \in \mathcal{U}$. Let $\mathcal{P}$ be the set of all user meanings and $\mathcal{P}_{\mathcal{O}}$ be the set of all user meanings on $\mathcal{O}$. Then $\mathcal{P}_{\mathcal{O}} \subset \mathcal{F}_S$ and $\mathcal{P}_{\mathcal{O}} = \mathcal{F}_Z \subset \mathcal{F}_S$, whereas $P_{\widehat{u}} \in \mathcal{P}_{\mathcal{O}}$ depicts a specific user meaning.

4.2 Definition of Fuzzy Relations

In order to define, extract and use both 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 S is defined as a function $R_i : S \times S \to [0,1], i = 1, .., M$. The inverse relation of $R_i(x,y)$, $x, y \in S$ is defined as $R_i^{-1}(x,y) = R_i(y,x)$. We use the prefix notation $R_i(x,y)$ for fuzzy relations, rather than the infix notation xR_iy, since the former is considered to be more convenient for the reader. The *intersection*, *union* and sup-t *composition* of any two fuzzy relations R_1 and R_2 defined on the same set of concepts S are given by:

$$(R_1 \cap R_2)(x,y) = t(R_1(x,y), R_2(x,y)) \tag{5}$$

$$(R_1 \cup R_2)(x,y) = u(R_1(x,y), R_2(x,y)) \tag{6}$$

$$(R_1 \circ R_2)(x,y) = \sup_{w \in S} t(R_1(x,w), R_2(w,y)) \tag{7}$$

where t and u are a fuzzy t-norm and a fuzzy t-conorm, respectively. The standard t-norm and t-conorm are the *min* and *max* functions, respectively, but others may be used if appropriate. The operation of the union of fuzzy relations can be generalized to M relations. If $R_1, R_2, ..., R_M$ are fuzzy relations in $S \times S$ then their union R^u is a relation defined in $S \times S$ such that for all $(x,y) \in S \times S$, $R^u(x,y) = u(R_i(x,y))$. A transitive closure of a relation R_i is the smallest transitive relation that contains the original relation and has the fewest possible members. In general, the closure of a relation is the smallest extension of the relation that has a certain specific property such as the reflexivity, symmetry or transitivity, as the latter are defined in [22]. The sup-t transitive closure $Tr^t(R_i)$ of a fuzzy relation R_i is formally given by:

$$Tr^t(R_i) = \bigcup_{j=1}^{\infty} R_i^{(j)} \tag{8}$$

where $R_i^{(j)} = R_i \circ R_i^{(j-1)}$ and $R_i^{(1)} = R_i$. It is proved that if R_i is reflexive, then its transitive closure is given by $Tr^t(R_i) = R_i^{(n-1)}$, where $n = |S|$ [22].

Based on the relations R_i we first construct the following combined relation T utilized in the definition of the taxonomic context C:

$$T = Tr^t(\bigcup_i R_i^{p_i}), \quad p_i \in \{-1, 0, 1\}, \quad i = 1 \dots M \tag{9}$$

where the value of p_i is determined by the semantics of each relation R_i used in the construction of T. More specifically:

- $p_i = 1$, if the semantics of R_i imply it should be considered as is
- $p_i = -1$, if the semantics of R_i imply its inverse should be considered
- $p_i = 0$, if the semantics of R_i do not allow its participation in the construction of the combined relation T.

The transitive closure in equation (9) is required in order for T to be taxonomic, as the union of transitive relations is not necessarily transitive, independently of the fuzzy t-conorm used. In the above context, a fuzzy semantic relation defines, for each element $s \in S$, the fuzzy set of its ancestors and its descendants. For instance, if our knowledge states that "American Civil War" is before "WWI" and "WWI" is before "WWII", it is not certain that it also states that "American Civil War" is before "WWII". A transitive closure would correct this inconsistency. Similarly, by performing the respective closures on relations that correlate pair of concepts of the same set, we enforce their consistency.

Similarly, based on a different subset of relations R_i, we construct the combined relation $\widehat{T}$ for use in the determination of the runtime context $\widehat{C}$:

$$\widehat{T} = \bigcup_i (R_i^{\widehat{p}_i}), \quad \widehat{p}_i \in \{0, 1\}, \quad i = 1 \dots \widehat{M} \tag{10}$$

For the purpose of analyzing textual descriptions, relation T has been generated with the use of a small set of fuzzy taxonomic relations, whose semantics are derived primarily both from the MPEG-7 standard and specific user requirements and are summarized in Table 1. On the other hand, relation $\widehat{T}$ has been constructed with the use of the entire set of relations available in the knowledge base. This approach is ideal for the user modeling interpretation followed herein; initially, when dealing with generic user information, focus is given on the semantics of high level abstract concepts, whereas additional precision and a more specific view is required as the runtime user modeling expansion comes into play. The latter demands the use of all available information in the KB. Of course,

Table 1. Semantic relations used for generation of combined relation T

Name	Inverse	Symbol	Meaning	Example	
				a	b
Belongs	Owns	$Bel(a, b)$	b belongs to a	house	device
Manufactured by	Constructs	$Made(a, b)$	b is manufactured by a	Siemens	fridge
Friend	NotRelated	$Fr(a, b)$	b is a friend of a	George	Bruno
Execute	ExecutedBy	$Exec(a, b)$	b is executed by a, or b undergoes the action of a	user	recipe
Triggers	TriggeredBy	$Trig(a, b)$	b is triggered by a	rule	recipe

as the construction of relation $\widehat{T}$ implies, an intermediate step of removing its possible cycles, that are present due to the utilization of all relations and their inverses, is necessary before the application of the taxonomy-based expansion process.

The aforementioned relations are traditionally defined as crisp relations. However, in this work we consider them to be fuzzy, where fuzziness has the following meaning: high values of $Bel(a, b)$, for instance, imply that the meaning of b approaches the meaning of a, while as $Bel(a, b)$ decreases, the meaning of b becomes narrower than the meaning of a. A similar meaning is given to fuzziness of the rest semantic relations of Table 1, as well. Based on the fuzzy roles and semantic interpretations of R_i, it is easy to see that both aforementioned relations (9) and (10), combine them in a straightforward and meaningful way, utilizing inverse functionality where it is semantically appropriate. More specifically, relation T utilizes the following subset of relations:

$$T = Tr^t(Bel \cup Made^{-1} \cup Fr \cup Exec \cup Trig^{-1}) \tag{11}$$

Relation T is of great importance, as it allows us to define, extract and use contextual aspects of a set of concepts. All relations used for its generation are partial taxonomic relations, thus abandoning properties like synonymity. Still, this does not entail that their union is also antisymmetric. Quite the contrary, T may vary from being a partial taxonomic to being an equivalence relation. This is an important observation, as true semantic relations also fit in this range (total symmetricity, as well as total antisymmetricity often have to be abandoned when modeling real-life relationships). Still, the taxonomic assumption and the semantics of the used individual relations, as well as our experiments, indicate that T is “almost” antisymmetric and we may refer to it as “almost” taxonomic. Relying on its semantics, one may define the crisp taxonomic context C' of a single concept $s \in S$ as the set of its antecedents provided by relation T in the ontology. Considering the semantics of the T relation, it is easy to realize that when the concepts in a set are highly related to a common meaning, the context will have high degrees of membership for the concepts that represent this common meaning. Understanding the great importance of the latter observation, we plan to integrate such contextual aspects of user models in our future work.

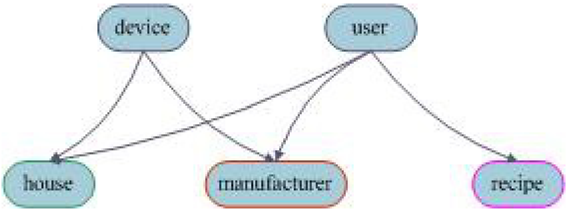

Fig. 1. Concepts and relations example

As observed in Figure 1, concepts *device* and *user* are the antecedents of concepts *house* and *manufacturer* in relation T, whereas concept *user* is the only antecedent of concept *recipe*.

5 Context Modeling

Existing approaches to context modeling differ in the ease with which they capture real world concepts, in their expressive power, in the support they provide for reasoning and in the computational performance of the reasoning. Early approaches to context modeling include key-value models and markup scheme models. Key-value models use simple key-value pairs to define the list of attributes and their values to describe context information. Markup based context information models use a variety of markup languages including XML. Fact-based context modeling like approaches that are based in database conceptual modeling and support query processing and reasoning. A special case of fact-based models are spatial context models that organise their context information by physical location, geometric or symbolic. Ontology based models of context information consider context as a specific kind of knowledge and use Web Ontology Language and Description Logics (OWL-DL) to augment the models' expressiveness and the complexity of reasoning.

Context modeling in SandS low level may seem to have strong similarities with context modeling in pervasive computing systems [18] because of the wirelessly interconnected appliances but considering the entire SandS architecture, many more modeling aspects become apparent. By giving the means to the eahouker, people who rule household appliances, to intelligently control his domestic appliances and by placing him inside the ESN, SandS follows clearly a human and user centric approach. We are considering in particular a context-aware user modeling of eahookers, that is taking into account all the contextual information that could characterize the situation and condition of the systems entities. In SandS case this could be context information about the eahooker (distance to his house, communication device used, time of the day, weather), usage information (recipes used, feedback provided by user, frequency of use), information about the homes (geolocalisation, proximity to other homes, surface area, number of rooms) and about the appliances (location inside house, energy consumption levels, etc.)

In order to be able to model these various aspects of context information inside SandS, several context models can be considered (see for example [6]). Of particular interest is the Context Broker Architecture (CoBrA) [10] which introduces a broker agent that maintains a shared model of the context for all computing entities in the space through a common ontology defined by using Semantic Web languages. Context Management Systems (CMS), an extension of the context server described in section 3, could also be considered in SandS case. As defined in [14], the role of a CMS is to acquire information coming from various sources, such as physical sensors, user activities, and applications in process or internet applications and to subsequently combine or abstract these pieces of information into context information to be provided to context aware services. The concept of CMS has also been used in the very relevant to SandS Amigo ("Ambient intelligence for the networked home environment") project[2]. From the projects description: "The Amigo project develops middleware that dynamically integrates heterogeneous systems to achieve interoperability between services and devices. For example, home appliances (heating systems, lighting systems, washing machines, refrigerators), multimedia players and renderers (that communicate by means of UPnP) and personal devices (mobile phones, PDAs) are connected in the home network to work in an interoperable way. This interoperability across different application domains can also be extended across different homes and locations.". Hence, the context server approach extended to a full CMS seems, at this project's early vision stage, as an adequate solution for context-aware user modeling in SandS.

6 Discussion on Related Datasets

In order to experimentally validate the proposed modeling and formalization architecture discussed in this paper as well as the adaptation mechanisms described as future work user, context and usage datasets are required. Datasets could be acquired in two ways: derived from SandS system integrated application or provided by a related project. Within SandS a small scale mockup and large scale experiments and validation will take place within WP7 and WP8 respectively. Related projects capable of providing a related dataset have been researched within the FIRE or related frameworks such as European Network of Living Labs (ENoLL).

A small scale mockup that will replicate the overall SandS system will be composed of a physical site located in Cartif[3] and seven virtual sites each one located in a server for each partner. Such a setting will allow validation of the entire system and its functionalities aiming to highlight problems while still on a manageable scale. On the other hand such a restricted application scale will also affect the completeness of the collected data. Additionally, such data, even if appropriate in terms of breadth and volume, will not be available during the SandS design and implementation stage constituting them usable only for a purely research objective.

[2] http://www.extra.research.philips.com/amigochallenge/
[3] http://www.cartif.com/en/

Large scale validation of the SandS system will include deploying the on Crew (w-iLab.t Ghent), OpenLab and SmartSantander [4] FIRE facilities to stress different aspects of applicability. Namely the respective aspects are, robustness and deliverability, large scale cooperation and communication of the different layers and finally, embedding the system in real life. Although the nature of the collected data, especially the ones corresponding to the SmartSantander application, will be appropriate, the timing of their availability almost excludes the integration of the research based on them within the SandS context. Analysis of the collected data in terms of stereotype personas and usage/context analysis is required in order to construct the knowledge base and fuzzify the ontology definition. This analysis will be followed by integration of its analysis to the adaptation mechanisms into the SandS system. Since large scale validation ends at M24 the integration and most importantly its validation is unfeasible constituting adoption of datasets from previous or ongoing (but more mature) research within related projects the only viable solution.

Attempting to pursuit this only viable solution we initially research bibliography in the related research area in order to detect a dataset close to the requirements set during the design of the user and context modeling process described in the respective sections of the current article. Our research yielded some results that although relevant could not be placed within the scope of our research goals and could not meet the set requirements. These results include:

- Home Activity and Sensors Datasets [7] that were collected and reported also related to the CHI 2009 Workshop on Developing Shared Home Behavior Datasets to Advance HCI and Ubiquitous Computing Research. This collection of home activity datasets includes mainly instrumented living environments recorded data that are somewhat irrelevant to our research aims since we are not dealing with in house user behavior.
- the Ambient Intelligence Datasets [1] which contains links to smart home datasets, as well as data gathered from wearable sensors.
- the Smart* Data Set [31] that deals with energy consumption and continuously gathers a wide variety of data in three real homes, including electrical (usage and generation), environmental (e.g., temperature and humidity), and operational (e.g., wall switch events).
- the HomeData [19] which is a collection of publicly available datasets recorded from different homes for use in research on Load Disaggregation, Smart Homes, and Ambient Assisted Living.
- a common repository [11] for context recognition data sets initiated during Pervasive 2004 Workshop on Benchmarks and a Database for Context Recognition.
- the ContextPhone [12] dataset on mobile context and communication.
- Nodobo [26] containing data gathered during a study of the mobile phone usage of high-school students, from September 2010 to February 2011.

[4] `http://www.smartsantander.eu/` SmartSantander is a city-scale experimental research facility in support of typical applications and services for smart cities.

Finally, we contacted various recipients within the FIRE or related frameworks aiming to disseminate our quest for publicly available datasets that would prove useful to user and context modeling as well as usage information that could simulate the respective adaptation process. Initially, we contacted the FIRE facilities that will be utilized during SandS large scale validation. Crew [13], OpenLab [28] and SmartSantander were contacted but this communication did not produce any results although a number of contact redirections were performed. In the following we widened the scope of our research and contacted the European Network of Living Labs [15], OneLab [27] and PlanetLab [29] both centrally as well as individually. None of our attempts proved successful but important conclusions were drawn. Initially, we feel that on the one hand FIRE facilities neither monitor closely the projects implemented on them nor they followup on the obtained results and on the other hand frameworks and networks of labs such as ENoLL do not centrally manage interchangeable information that would be of common interest to the participating institutions and to the research community as a whole similar to the one encountered in the areas discussed above. We feel that the user aspect within this research area is largely ignored although individual institutions have highlighted this need. We could not summarize this better that to use a quote from one of our interlocutors "We'd love to know who our users are but actually have no idea!".

7 Conclusions and Future Work

In this paper the pervasive Future Internet, and namely the SandS paradigm, has been discussed from the human centered perspective. The research questions investigated were: a) how users can be modeled through a number of fuzzy knowledge formalism based on stereotypical user profiles and b) how context can be modeled and integrated in modeling in computing systems and especially in the SandS smart home paradigm. 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 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. Finally, moving forward from existing, conventional context modeling approaches relying on data of the physical environment, we address the issue of incorporating contextual information characterizing the entire system's entities state and interaction, usage information and social activity derived information.

Ongoing, the progress relying heavily on the issues raised in section 6, and future work includes 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.

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