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ScienceDirect

Procedia Computer Science 00 (2021) 000–000

Procedia Computer Science

www.elsevier.com/locate/procedia

25th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

Leveraging commonsense reasoning towards a smarter Smart Home

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Abstract

The "smart" behaviour that characterises commercial Smart Home systems is due to the relations that users manually establish between devices and actions through automation rules. Therefore, the intelligence of these systems is entirely (or mostly) predefined by humans. To address this problem, several Artificial Intelligence techniques have been applied in this field to try to improve the smartness of Smart Home systems by enhancing features such as self-adaptation, self-evolution and self-awareness. This work in progress article presents an approach to provide smart homes with these features through a reasoning system able to deduce, define, monitor and update the automation rules that drive their behaviour, in an autonomous manner and with a knowledge management at different levels of abstraction. That is to say, the rules normally defined by humans are now created and modified automatically. The proposal is based in a commonsense knowledge model that represents how the world works and enables to infer what resources can be used to accomplish a specific objective. Automations are generated according to general, commonsense and context (topology, users, sensors, etc.) knowledge, and they are more or less sophisticated depending on the available devices. The set of behavioural rules is updated when any of these resources change. *Scone* is the high-performance and open-source knowledge base system where the knowledge model has been implemented. Finally, to evaluate and demonstrate the potential of the model, a set of automation rules is built for a concrete use case. Results are shown in a virtual smart home on the *Home Assistant* platform.

Keywords: Smart Home; Knowledge representation; Knowledge processing; Commonsense knowledge

1. Introduction

Several definitions of Smart Home (SH) can be found in the literature [23, 22]. In general, a SH is a residence where different hardware and software technologies are integrated into the environment with the aim of improving people's comfort and quality of life. Typically, communication between deployed sensors and actuators takes place through a central management device named gateway [43] that is connected to the Internet, creating an Internet of Things (IoT) network. The users utilize this gateway to control the network of devices and define how the system

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operates explicitly via automations: rules that determine the actions to perform when a specific set of events occur. As a result, the behaviour of these SH systems is predefined, and it is far from the intelligent functioning expected in this type of systems [27].

The SH paradigm emerged many years ago but, according to [17], it is still in an early stage and some requirements must be satisfied to transform SH into more mature systems. Facilitate communication between heterogeneous devices or sub-systems; make it possible to modify the device network in a simple and transparent way for the user, without any impact on the rest of the system; or improve usability, extensibility or the security and protection of the data are some of the purposes. But we can say one of these major requirements is the inclusion of intelligence, that "is becoming a basic ingredient to get automation smarter in SH and IoT technologies" [17] and is closely related with another area of interest for researchers in the field: context awareness [1].

Formally, SH systems are Cyber-Physical Systems (CPS) [11], and [27] also states that one of the features that could make them the next revolution in the information and communications technology (ICT) is a higher level of smartness. The system should be able to adapt its functionality in an autonomous manner, in real time, being aware of the context and without user intervention. Mekuria argues in [26] that this self-adaptation process is performed by "the brain of the SH", the reasoning system, and through an analysis of the Artificial Intelligence (AI) work that can be found in the literature with these purposes determines the desirable characteristics of a SH reasoning system: the ability to learn, predict or plan, even under uncertainty and incomplete knowledge, and taking into account situation and context information to enable a proactive self decision-making process.

The expected behaviour of these SH reasoning systems is intended to mimic some aspects of the humans thinking. To deduce what is happening around, our brain structures knowledge about how the world works, our senses capture and filter relevant stimulus from the environment, the data is analysed to reason about different possible situations that can be taking place (or that will happen or may have happened) and, when the most likely is chosen, an action according to the context is performed. Typically, humans make assumptions about the most plausible explanation for a given situation without measuring probabilities accurately. The evaluation of situations requires the same non-probabilistic basis for selecting the best option in the deductive process [21]. People make these kind of everyday decisions through commonsense reasoning, an area of study introduced in AI many years ago [14] that could be a powerful tool to achieve the desired smartness.

The "smart" behaviour that characterises commercial SH is due to the relations that users manually establish between available resources through automation rules, and therefore, the intelligence of these systems is entirely defined by the user. This work proposes an approach for SH systems with the features of self-awareness, self-adaptation and self-evolution through a goal driven strategy based in commonsense reasoning and inference processes. From global knowledge, that can be used in every deployment scenario, universal automation rules are deduced, defined, monitored and updated autonomously, without human intervention, taking into account context information. This is possible thanks to the processing and management of knowledge carried out at three different levels of abstraction:

- The global knowledge level, that refers to the general and commonsense knowledge that describes how the world works and how humans typically behave. It is defined by experts, but can be modified or extended by these experts or the system itself.
- The context level, in which knowledge of the first level is used to build knowledge about specific users and environments. Through this knowledge, a set of ad-hoc automation rules (and therefore the behaviour of the SH system) is defined for a given context.
- The live knowledge level, where events captured by the devices deployed in the environment produce facts that trigger the rules defined in the second level. These rules can generate other facts or have an action as a consequent.

This article is organised as follows. First, Section 2 reviews the literature of the SH paradigm, paying special attention to reasoning systems. Section 3 presents the three levels of abstraction of the knowledge considered for the reasoning system model that have been described above. Section 4 addresses the commonsense knowledge model proposed, the automation rule generation process and the use case designed to show and test the results. Finally, Section 5 summarizes the main ideas withdrawn from this paper.

2. Related Work

SH systems have been studied in the literature for years. A large number of review and survey papers can be found covering different SH issues [37, 23, 43, 31, 38, 1], and these works make it possible to know what are the main interests in the research area. Energy saving and management [39, 13]; health care [4, 3], especially for elderly people [10, 16]; or comfort services [8, 2] are some of the primary purposes of SH systems. Also, other research works pretend to enhance SH features from a more general point of view: the capability to interconnect heterogeneous devices [29, 42, 12], the extensibility to allow the scale of the network or the addition of new technologies [15], or security and privacy protection [18, 33], among others. But concretely the study of the intelligent processes that can be used to improve the smartness of the system is considered an important task.

Some recent review papers like [26] and [25] summarise the extensive research that concerns the SH reasoning systems domain. According to these works, most of the contributions in the field are presented as knowledge-based systems and 55.5% of the research is conceptual. It is also discussed what are the fundamental requirements of a SH. Self-adaptation and learning are two of them but, although they are some of the most desirable characteristics in this type of systems [27], many of the approaches in the area don't address these features. In many cases the functioning of the system is based in a set of predefined static rules without the ability of self-learning or self-adaptation, but the dynamic nature of this kind of systems makes difficult to obtain good results with a fixed behaviour [7, 32]. In [41] it is highlighted that SH are environments with a huge amount of entities, events and scenarios, with a vast number of action plans, reason why it is a need to provide SH with reasoning systems capable of adapting to several situations and contexts.

The aim of improving SH systems intelligence has its origins in the intention of people to achieve the best results (in different aspects) with a minimum level of interaction, requirements of configuration and effort. Basically, we want the system to know what we want and need without giving explicit instructions and, for that, the system should reason and infer as we do. Even so, there is no shortage of works with this objective that propose the use of AI techniques that are far from resembling the human thinking. In [19], for example, it is addressed the proposal of a system that applies machine learning to process explicit or implicit user's feedback and adapt the system behaviour, and [30] drives the learning process through the analysis of pattern occurrences.

Commonsense reasoning is an AI field that emerged sixty years ago pursuing to reproduce the human reasoning process, and one of its main challenges is the representation of the knowledge to enable commonsense inference. E. Davis states in [9] that "commonsense knowledge" means "what a typical seven year old knows about the world, including fundamental categories like time and space, and specific domains such as physical objects and substances; plants, animals, and other natural entities; humans, their psychology, and their interactions; and society at large". Several SH proposals based on commonsense reasoning and knowledge can be found in the literature [6, 34]. In [20], i. e., commonsense is applied to generate a smarter behaviour when the user interacts with the environment and the device states change, and [35] proposes a planning strategy based in commonsense reasoning for service composition. According to the idea presented in these works, this article is intended to leverage commonsense reasoning to build the automation rules normally used in SH systems and produce a smarter behaviour.

3. A three-layered knowledge management system

The behaviour of SH systems is based in feedback control loops that use physical devices to collect data, the computational part to analyse and process that data, and again the physical part to perform specific actions. The interaction with the environment is in the nature of these systems, so their capabilities are clearly limited by the devices at their disposal: sensors, that determine what kind of information is possible to collect, and services or actuators, that establish the decisions or actions that can be made or performed. For this reason, the improvement of the system intelligence requires a reasoning system capable of handling the raw data the deployed devices receive and send. Also, as is stated in [40], general, spatial-temporal or commonsense knowledge resources are essential to enable a real smart behaviour, but this knowledge represents more complex information than that used by the physical part of the system. This leads to the need for the reasoning system to also be able to operate with complex knowledge and, therefore, with information at different levels of abstraction. To find a method for the representation of all this heterogeneous knowledge is a requirement too.

Symbolic systems have been used for years to represent knowledge. In the review made in [26], for example, the 51% of the reasoning approaches considered use symbolic AI techniques with different purposes. Based in the semantics of the language, these systems relate simple concepts and entities to build more complex ideas or information, and in our work this is the method employed to define the behaviour of the SH. General and commonsense knowledge together with context knowledge about the deployment scenario is modelled with symbols and used to automatically generate a set of automation rules that drives the functionality of the system. When an event that occurs in the environment is captured it is considered a fact, and it can trigger a rule or be used to generate more sophisticated facts (knowledge with a higher level of complexity). The generated knowledge could be utilized to improve the knowledge models used in the rule generation process. All this results in a reasoning system that operates with more or less abstract knowledge in every stage of the SH feedback control loop. Thus, the SH system proposed is divided in three layers: the Knowledge layer, the Autonomous Automation layer and the Facts layer (KAAF), where knowledge, rules and the facts that trigger the rules are managed. All these elements are considered different types of knowledge about the way in which the world operates, how the system should behave and about what is happening around, respectively.

3.1. The knowledge layer

The reasoning process takes place at the same time the SH system runs its feedback control loop, participating in each of its steps. The reasoning system makes inferences to feed with the results other parts of the SH system, and information extracted from different resources in these parts can be utilized to extend the available knowledge too in an autonomous way. But almost a basic version of the knowledge to be used must be modelled before the life cycle of the SH begins. Various types of knowledge models are required in the knowledge base:

- General knowledge models with knowledge about how the world works. These models represent facts like *fire burns*, *fish live in water* or the space or time knowledge units necessary to reason that, for example, if a person moves from the bedroom to the kitchen through a corridor, he or she will be located first in the bedroom, afterwards in the corridor and finally in the kitchen.
- Commonsense knowledge models to enable the kind of inference processes that happen in our everyday thinking. Mueller says in [28] this knowledge "is essential to intelligent behaviour and thought. It allows us to fill in the blanks, to reconstruct missing portions of a scenario, to figure out what happened, and to predict what might happen next". Following the previous example, if the system detects motion in the bedroom and later in the kitchen but not in the corridor previously, this knowledge allows to deduce that perhaps someone else is in the house (the first person has not passed through the corridor yet) but also, with less likely, that maybe there is a problem with the sensors of the corridor or kitchen.
- Specific knowledge models, if needed, defining measurement units, material properties or other type of concrete values that can be related with commonsense and general knowledge.

These basic models are defined by human experts, but once the SH system is deployed and its life cycle begins, the available knowledge should be able to be modified or improved by humans or by the system itself, at run time and without disrupting other system functionalities. As have been mentioned before, the data collected from the environment can be analysed and processed with, for example, Big Data techniques to produce new knowledge. This transforms the knowledge base in a kind of "global dynamic knowledge base" always up to date with general people habits that can be utilized in every scenario (a good candidate for a cloud service). Of course, it is important to consider that human habits and cultural aspects change over the years, or depending on the location or the season.

3.2. The automation layer

Although the knowledge in which the reasoning system bases its inferences is mainly global, the deployment scenarios where this knowledge is used have location specific characteristics and features. SH systems must be functional in a wide variety of situations and contexts, reason why they must also be aware of the environment all the time.

In the same way some knowledge models are necessary at deployment time, a specification of the environment is also required before the life cycle of the SH system starts. It is essential to know the devices available, where are they located, how are these locations related (topological knowledge), what is the normal usage of the spaces or who are the regular users of the SH. With this information and the global knowledge that can be applied to every deployment scenario, a set of automation rules can be built autonomously, ad-hoc to the context and in a transparent manner to the user. These rules are based in universal knowledge about user habits. For example: it is a common sense fact that people need light to perform most of the activities, so if there is not enough light in the room where one person is located and in that space it is common the performing of that activities, the lights available in the space must be turned on (even with a specific brightness). This automation rule can be created without the explicit intervention of the user, in contrast to the normal operation of this type of systems that was mentioned at the beginning of the article. The resulting set of generated rules could be modified later to adjust the SH behaviour to user preferences.

The automation rules that determine the behaviour of the SH system can also be modified at run-time. Any device can be removed from the system (or it may stop working momentarily or permanently), limiting some functionalities, or added, opening a new range of possibilities. In any case, automation rules must be reconstructed/adjusted/disabled/etc. As explained in the previous section, it is possible to modify or extend the knowledge at run-time too, updating the behaviour of SH systems even when context information remains unchanged. That is to say, the set of automation rules generated for a given scenario is adjusted when the sate of global or context knowledge is altered, providing the system with the capabilities of self-adaptation and self-evolution.

3.3. The facts layer

As is discussed in [28], to automate commonsense reasoning it is necessary knowledge about time, space, objects and agents and their common properties, and the events or actions that can take place. Context knowledge allows to apply this general knowledge in a given scenario by representing the identity of specific objects and agents, and the existing relations between them. Together, these types of knowledge enable to build the way in which the process of inference is performed and to construct the automation rules that determine the behaviour of the SH system. But, in addition, if this system pretends to face situations happening in a scenario in real time it must be fed with live knowledge: the information extracted from the events captured by the deployed devices in the environment in a concrete moment. This physical data is used in the following manner:

1. Events are processed to trigger the most basic behavioural rules built from general and context knowledge. The discrete data provided by sensors or by users, that have defined (implicitly or explicitly) their preferences, are transformed into facts to trigger rules that have as a consequent the generation of new knowledge for the SH reasoning system.
2. The knowledge generated by rules can be utilized (or not) with different purposes:

   a) Perform physical actions. The knowledge may contain information about how to accomplish an objective, a certain state of the scenario. Achieve this goal requires a decomposition of the semantic information of the action to construct the events and raw data expected by the devices that are going to perform the task. For example, from the fact *light is needed in the kitchen* it can be deduced which devices provide light in the kitchen (maybe a lamp), what is the state of this device that allows the device to produce the light (on) or the action that produces the change of the state (turn on).
   b) Form sophisticated facts. The fuzzy data represented by basic facts is transformed into more complex and abstract facts, even by combining a set of them. A set of temperature values provided by different temperature sensors could be used to deduce the temperature is high, low, falling, etc. in a space, only in a part of that space or similar.

3. In any case, the facts are introduced in a facts database that also serves as a log. Relevant information can be accessed later for other rules or reasoning processes.

This approach allows the interaction of the SH system with the environment in real time. Always the state of the environment changes, the system captures the events that represent the change to deduce what is happening and react consequently. All the possible situations that can occur (only the ones that can be handled by the available sensors, actuators or services) are considered in the set of automation rules. The information contained in events is turned into facts to trigger rules and determine the next task for the system.

4. Proof of concept

The requirement for the system to be able to cope with different situations in real time lead us to think the reasoning processes and inferences must be done in the moment in which those situations happen, but this need not necessarily be the case. The behaviour of the system is always predefined (the way in which it operates, not the tasks themselves), regardless of the AI technique applied: training algorithms, rule-based analytical processes, fuzzy logic or knowledge models, for example. As mentioned in previous sections, SH systems are limited by the resources at their disposal. Therefore, the whole behaviour (all the SH automation rules) can be built when these resources are known: once the system is deployed and a specification of the scenario is given.

This work in progress paper proposes a first version of the commonsense knowledge model that can be used to represent the functioning of the real world, the situations that can occur in a SH environment and the actions the system can perform based in the possibilities that would offer different resources at deployment time. Commonsense knowledge is modelled in terms of beliefs, intentions, abilities or wants, according to [24], so it is required a knowledge base (KB) able to support inference, search and reasoning processes over this kind of knowledge. In this work, Scone [36] has been used with this purpose, an open-source KB implemented in Common Lisp that provides the needed commonsense reasoning mechanisms.

In the following, the knowledge model is presented and applied in a concrete scenario. The use case is addressed through a detailed description of the available devices and the topology of the SH. Then, the rule generation process for that specific environment is explained, with emphasis on the knowledge utilized to obtain the abstract rules. Finally, the potential of this set of abstract rules and how it can be used to generate the rules expected in other systems or platforms, such as Home Assistant (HA), is discussed.

4.1. The reasoning system and the knowledge model

The knowledge model represents entities, properties and relations leveraging their semantics and the information of the concepts used to automate and delegate the automation rule generation to a computation system. Figure 1 illustrates, for example, that devices have been modelled considering two types of entities: transducers, to represent physical objects (like microphones or cameras), and services (lines 1-5). Transducers can be modelled as sensors or actuators too (lines 7-8). In this case, motion sensors and bulbs (actuators) have been included (lines 9-10).

```
1  (new-type {device} {thing})
2  (new-intersection-type {service}
3          '({device} {intangible}))
4  (new-intersection-type {transducer}
5          '({device} {physical object}))

7  (new-type {sensor} {transducer})
8  (new-type {actuator} {transducer})
9  (new-type {motion sensor} {sensor})
10 (new-type {bulb} {actuator})

11 (new-type {resource} {thing})
12 (new-is-a {information} {resource})

14 (new-type {light} {resource})
15 (new-indv {motion event} {information})
16 (new-type {occupied room} {information})
```

Fig. 1. Knowledge about devices (sensors and actuators), resources and information entities

Figure 1 also shows the definition of *resource* and *information* entities. *Resource* is the term employed to refer to anything that could be used by the system to feed a reasoning process, a rule, or to accomplish an objective and produce a specific situation (line 11).Accordingly, units of information are considered resources (line 12), and events and facts can be included to represent information in KAAF (lines 15-16). Entities such as *water*, *hot air* or *light* (line 14) are also resources representing a need, and they must be produced by concrete devices or actions.

User and context needs are modelled in Figure 2 as requirements (lines 6-9), and the resources that satisfy these requirements are considered provisions that can be supplied by certain providers (line 10). Of course, general knowledge about space is included in the model to reason and infer taking into account the spaces that conform the house (line 11). To define the meaning or implications of the most abstract information units the relation *indicate* has been added too (lines 1-4).

To illustrate the potential of this requirements/provisions-based model, knowledge to reason about light needs has been modelled. Concretely taking as a reference a simpler version of the example given in Section 3.2: people need light, so if there is not enough light in the room where one person is located, the lamps available in the space must be

```
(new-relation {indicate}
        :a-inst-of {information}
        :b-inst-of {information}
        :c-inst-of {location})

(new-relation {require}
        :a-inst-of {information}
        :b-inst-of {resource}
        :c-inst-of {location})
(new-type-role {provider} {thing} {thing})
(new-type-role {location} {thing} {room})
(new-type-role {status} {thing} {thing})
```

Fig. 2. *Indicate* and *require* relations, and the roles needed to define provisions

turned on. Figure 3 shows the knowledge defined to make this possible: motion sensors are providers of occupancy information and have a location (lines 1-2); when an occupancy event is captured by a motion sensor it indicates that there are people in the location of that event provider, and the status of the location is *occupied* (lines 3-47); finally, an occupied room requires light, and one of the light providers considered are bulbs (lines 8-10).

```
1  (x-is-the-y-of-z {motion sensor} {provider} {motion event})
2  (x-is-the-y-of-z {motion sensor:location} {location} {motion sensor})
3  (new-statement {motion event} {indicate} {occupied room}
4          :c (the-x-of-y {location} (the-x-role-of-y {provider} {motion event})))

6  (new-indv {occupied room:location} {location})
7  (x-is-the-y-of-z {occupied room} {status} {occupied room:location})
8  (new-statement {occupied room} {require} {light} :c {occupied room:location})

10 (x-is-the-y-of-z {bulb} {provider} {light})
```

Fig. 3. Knowledge modelling occupancy and light provisions

Figure 4 lists the sentences used to model *day* and *night* contexts (taking advance of the multiple-context mechanism supplied by Scone for the representation of different knowledge in distinct situations without leading to inconsistencies). In this case, windows are considered light sources during the day, but not at night.

```
(new-context {day} {general})
(in-context {day})
(x-is-the-y-of-z {window} {provider} {light})
(new-context {night} {general})
(in-context {night})
(x-is-not-the-y-of-z {window} {provider} {light})
```

Fig. 4. Day and night contexts, and knowledge about window providers.

All this knowledge has been modelled with the aim of allowing the generation of automation rules that enable to turn on lamps in a room when there is not enough light (without natural light sources, at night) and occupancy has been detected, as a proof of concept. Of course, the model can be extended and enhanced with new knowledge modules. As R. A. Brooks says in [5], in this type of AI systems "each module itself generates behaviour, and improvement in the competence of the system proceeds by adding new modules to the system".

4.2. Generating abstract rules

The knowledge model described in the previous section allows to leverage the commonsense knowledge to generate the automation rules based on the available devices, but these resources are not there to be utilized with a concrete purpose. All the SH components can be part of different services. The SH system is who is aware of the environment and who knows about the commonsense knowledge necessary to determine what kind of resources could be useful in each case and compose the rules, the ones that conform a lighting service in this example, more or less sophisticated depending on the deployment scenario and the system itself.

Although the approach presented in this article is in a very early stage of development, in this section it is addressed a basic case of use in which a set of lighting automation rules are generated. That rules are built as abstract rules that contain all the necessary information to represent them in any format. In this example, HA is the central control system for SH selected to verify the correctness of the behavioural rules generated, so finally the abstract rules are transformed into HA automations. The whole process can be seen in Figure 5, and relevant topology information

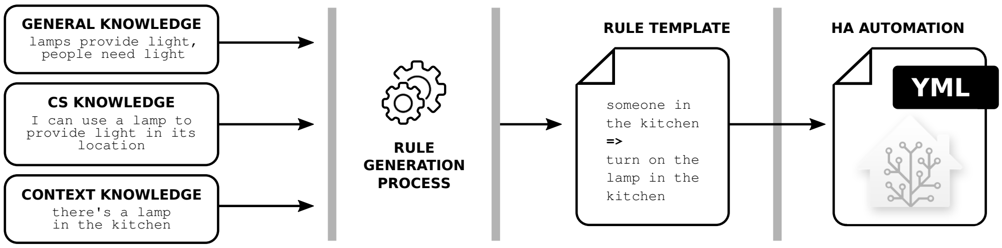

Fig. 5. The automation rule generation process. Concretely, to build HA automations.

about the SH considered is described in Table 1: smart light bulbs and motion sensors available and the list of rooms with natural light (rooms with a window).

Table 1. Case of use: scenario context knowledge

Room	Smart light bulb	Motion sensor	Natural light
Kitchen	✓	-	✓
Living room	✓	✓	✓
Bedroom	-	✓	✓
Bath	-	-	✓
Garage	✓	✓	-

The generation of abstract rules is possible thanks to an algorithm implemented in Python that makes the relevant queries to an instance of Scone in which the modelled knowledge has been loaded. The semantic information extracted from Scone inferences is used to determine the structure of two types of rule: a) rules that have as an antecedent facts formed with the raw data provided by sensors and that produce more abstract facts as a consequent, and b) rules that from abstract information (facts) trigger the performing of actions. For the use case addressed, the abstract rules generated are the following:

$$\begin{aligned}
r1 &: \quad occupancy_event_from(living_room_sensor) \rightarrow occupied_room(living_room)\\
r2 &: \quad occupied_room(living_room) \wedge night \rightarrow turn_on(living_room_bulb)\\
r3 &: \quad occupancy_event_from(bedroom_sensor) \rightarrow occupied_room(bedroom)\\
r4 &: \quad occupied_room(kitchen) \wedge night \rightarrow turn_on(kitchen_bulb)\\
r5 &: \quad occupancy_event_from(garage_sensor) \rightarrow occupied_room(garage)\\
r6 &: \quad occupied_room(garage) \rightarrow turn_on(garage_bulb)
\end{aligned}$$

As can be seen, the complexity of the information varies. In this case, the occupancy events sent by motion sensors are used to determine the occupancy status of the room where these sensors are located (*r1*, *r3* and *r5*). *Occupied room* is the state, the abstract fact extracted and built from the raw data. On the other hand, this abstract fact works as a trigger for the action of turning on the light bulb located in the room referred by the fact (*r2*, *r4* and *r6*). The existence of a window implies that there is natural light available during day hours, so the action rules that turn on the lamps are only triggered at night in these rooms. The action is always performed otherwise.

Rules are generated as objects that store the components of each rule (agents, objects, actions, locations, etc.) to be processed later and construct the rules in a concrete format. In this proof of concept final rules are transformed into HA automations. The SH is represented in this home automation platform through virtual devices, and the automations are loaded in HA to visualize the resulting behaviour. The example have been uploaded to this GitHub repository: *https://github.com/uclm-arco/kaaf-light-example*. Here, the knowledge model, the algorithm for the abstract rule generation and the translator to HA automations can be found. Run instructions are supplied in the repository's *README*.

5. Conclusions

This article proposes an approach to increase the smartness of actual SH. Based in a three-level knowledge management system, this work pretends to reduce the predefined behaviour that characterises commercial SH systems through the autonomous generation of the automations. With this purpose, a commonsense knowledge model has been designed to capture the semantics of devices, services, needs, goals and actions. The goal driven strategy used allows to build the rules according to the context information available, so the behaviour of the system is construct ad-hoc to the deployment scenario. To illustrate this, a use case is considered in which a set of rules is generated for a virtual SH deployed in the HA automation system.

Although the proof of concept of this work in progress only addresses the rule generation process, an overview of the complete knowledge management system to enhance the capabilities of the SH reasoning systems is given. This is the main contribution of the paper, the proposal to endow SH systems with features like self-adaptation, self-evolution and self-awareness. The knowledge model already improves the context-awareness of the system, and certain level of self-evolution and adaptation is achieved. But as a future work, the objective is the construction of SH systems capable of generating the automation rules for a wide variety of situations, monitor the system to update the rule set when any of the required resources (knowledge or scenario devices and services) change, and leverage all the information collected to finally enable the self-learning ability. It is also important to note that, apart from the generation of rules, other of the main goals of the requirements/provisions-based knowledge model designed is to allow to follow the traceability of different goals and needs to predict what is going to happen or to reason about past scenario states (to reconstruct the missing portions and fill in the blanks, as Mueller says in [28]). All the processes mentioned would, of course, be carried out in an unsupervised manner, making the SH system a real smart system.

Acknowledgements

This paper is partially supported by European Union's Horizon 2020 research and innovation programme under grant agreement no. 857159, project SHAPES (Smart & Healthy Ageing through People Engaging in Supportive Systems). It is also founded by the Ministry of Economy and Competitiveness (MINECO) of the Spanish Government (PLATINO project, no. TEC2017-86722-C4-4-R) and the Regional Government of Castilla-La Mancha under FEDER funding (SymbIoT project, no. SBPLY-17-180501-000334)

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