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A Hybrid Modular Context-Aware Services Adaptation for a Smart Living Room

Moeiz Miraoui[a], Sherif El-Etriby[b], Chakib Tadj[c] and Abdulbasit Zaid Abid[a]

[a]College of Computer at Al-leeth, University of Umm Al-Qura, Makkah, Kingdom of Saudi Arabia; [b]Faculty of Computers and Information, Menoufia University, Menoufia, Egypt; [c]Ecole de Technologie Superieure, University of Quebec, Montreal, Canada

ABSTRACT

Smart spaces have attracted considerable amount of interest over the past few years. The introduction of sensor networks, powerful electronics and communication infrastructures have helped a lot in the realization of smart homes. The main objective of smart homes is the automation of tasks that might be complex or tedious for inhabitants by distracting them from concentrating on setting and configuring home appliances. Such automation could improve comfort, energy savings, security, and tremendous benefits for elderly persons living alone or persons with disabilities. Context awareness is a key enabling feature for development of smart homes. It allows the automation task to be done pro-actively according to the inhabitant's current context and in an unobtrusive and seamlessly manner. Although there are several works conducted for the development of smart homes with various technologies, in most cases, robust. However, the context-awareness aspect of services adaptation was not based on clear steps for context elements extraction (resp. clear definition of context). In this paper, we use the divide and conquer approach to master the complexity of automation task by proposing a hybrid modular system for context-aware services adaptation in a smart living room. We propose to use for the context-aware adaptation three techniques of machine learning, namely Naïve Bayes, fuzzy logic and case-based reasoning techniques according to their convenience.

KEYWORDS

Smart space; context-aware; service; adaptation; naïve bayes; case-based reasoning

1. Introduction

Smart spaces in general and smart homes in particular are sub-fields of ubiquitous and pervasive computing where everyday objects communicate and collaborate to provide adapted services to users according to their current contexts. The Smart Home vision has become technically feasible with the spread of the recent developments in sensor networks, communication technologies and devices with computing ability especially home appliances. So far, there is no explicit or common definition of smart spaces, which are also known as Ambient Intelligence, home automation or Ambient Assisted Living. In the literature, there are several definitions of smart spaces and smart home. The most useful definition of such spaces is the one proposed by Cook & Das (2004); "Smart space is able to acquire and apply knowledge about its environment and to adapt to its inhabitants in order to improve their experience in that environment". Another interesting definition proposed by Satpathy (2006):

> A home, which is smart enough to assist the inhabitants to live independently and comfortably with the help of technology, is termed as smart home. In a smart home, all the mechanical and digital devices are interconnected to form a network, which can communicate with each other and with the user to create an interactive space.

Devices and appliances in a smart space should be capable of interacting with people in order to provide intelligent services to users for improved comfort (i.e., quality of life), energy saving, safety and security, and increase the level of autonomy for both elderly people living alone or persons with disabilities. There are mainly two major requirements for development of smart homes; context-awareness and pro-activity. The latter promotes intelligence and autonomy by unobtrusively anticipating inhabitant actions, which minimize his intervention. The former allows the smart space to provide the accurate service according to the current context.

A lot of research has been conducted in the field of intelligent spaces (resp. Smart homes) in order to automate services in such spaces. The overwhelming majority of previous works have been based on machine learning techniques. However, they assumed a static learned model, which cannot change over the time once deployed. Moreover, only a few of them dealt with flexibility of the adaptation system.

Another major shortcoming of previous approaches are that they either not context-aware or do not deal in depth with context-awareness, which is a key feature in such spaces by using an incomplete set of context knowledge. In addition, smart home environments are complex and dynamic and most of the proposed approaches for dynamic services did not provide strategies to master such complexity. Our aim is to propose a hybrid approach for context-aware services adaptation in a smart living room based on Naïve Bayes, fuzzy logic and case-based reasoning. We tackle in depth the context-awareness aspect by focusing on context definition and context gathering. The proposed approach is enough modularity, which enhances its flexibility and extensibility.

The remainder of this paper is structured as follows: Section 2 surveys related work. Section 3 presents a description of an exemplary living room. Section 4 describes context in the smart living room and how it can be achieved. Section 5 introduces our context-aware services adaptation approach. Finally, Section 6 concludes this article by summarizing our work.

CONTACT Moeiz Miraoui mfmiraoui@uqu.edu.sa, azabid@uqu.edi.sa

2. Related Work

Plenty of research has been conducted for the automatic execution of tasks in a smart home and considerable effort has been spent for enabling home automation. Several techniques and approaches were used, among them the case-based reasoning technique used by Ni, Zhou, Zhang, Miao, & Fu (2009) for services adaptation in a smart home or used by Ma, Kim, Ma, Tang, & Zhou (2005) to adapt the behavior of smart homes to user preferences. Leake, Maguitman, & Reichherzer (2006) have shown how to use CBR as context awareness solution in smart home. Kofod-Petersen (2006) has identified and analyzed four main challenges in the light of their experiences from developing an ambient intelligent system utilizing case-based reasoning. Sohn, Jeong, & Lee (2014) have proposed a framework for PersonAlized Service disCovery Using FuZZY-based CBR and Context Ontology (PASCUZZY). Li, Sun, & Hu (2012) developed a context-aware lightning control system for smart meeting rooms. They used an ontology-based context modeling approach and a rule based system for context reasoning. Madkour, Benhaddou, Khalil, Burriello, & Cline (2015) used a Weighted Case Based Reasoning (WCBR) for enabling context awareness. They illustrated the elaboration of an adaptive and autonomous control of HVAC (Heating Ventilation and Air Conditioning). Case Ontology is used to represent knowledge of different cases and a group of experts establish the ideal weights for the context attributes and the action rate that ideal control strategy should have. They used the Evenshtein distance to calculate similarity between cases. Zehnder, Wache, Witschel, Zanatta, & Rodriguez (2015) proposed a recommender system that can be used to save energy in smart homes. They proposed an algorithm, which applies machine learning to suggest actions for inhabitants to reduce the energy consumption of their homes. Their work was based on a rule-based system. Chahuara, Portet, & Vacher (2013) presented an audio-controlled smart home based on a framework composed of knowledge representation module using a two-level ontology, a situation recognition module based on the SWRL logic reasoner and a decision-making module based on the markov logic network (using weighted logic rules) to deal with uncertainty and imprecision of context information. Vainio, Valtonen, & Vanhala (2006) used a context sensitive and proactive fuzzy control system for controlling the home environment. Their implementation consists of a lighting control system that is implemented into a smart home, which learned its rule table without any predefined information and didn't need any training prior to use. Inhabitants' actions would have to be monitored, and system would have to learn through these observations. The learning process would need to be continuous, because our habits and routines change over time. The used fuzzy values are; time, outdoor light and person activity (present, absent). Rasch (2014) proposed a smart home recommender system by continuously interpreting the user's current situation and recommending services that fit the user's habits. The proposed method extracts these temporal relationships between user actions from a user's smart home history. They used the Dempster-Shafer theory of evidence for classification, which is a generalization of the naive bayes classifier. Cavone, De Carolis, Ferilli, & Novielli (2011) proposed an agent-based approach for controlling the behavior of a Smart Home Environment that, based on the recognized situation and user goal, selects a suitable workflow for combining services of the environment. The adaptation is based on user's behavior learning using Inductive Logic Programming, which provides a continuous adaptation and refinement of the available knowledge. Rashidi & Cook (2008) introduced CASAS, an adaptive smart home system that discovers and adapts to changes in the resident's preferences in order to generate satisfactory automation policies. In their work, they considered automation of sequential complex activities that adapts to the user's preference data is mined by their mining algorithm called FPAM to discover activity patterns of interest for automation; and later these patterns are modeled by their Hierarchal Activity Model (HAM) to further utilize the underlying temporal and structural preferences. To achieve preference adaptation, the Preference Adaptation Miner (PAM) algorithm adapts to any changes in those patterns and responds to user guidance. Venturini, Carbó, & Molina (2008) described an algorithm for prediction of user preferences through making use of the Heuristic Genetic Algorithm. Badlani & Bhanot (2011) proposed an adaptive smart home system for optimal utilization of power, through Artificial Neural Network (ANN). Kumar, Fensel, & Froehlich (2013) presented a semantic policy adaptation technique and its applications in the context of smart building setups. Dixit & Naik (2014) proposed the use of Active LeZi Prediction Algorithm in logical implementation of a Smart Home. The Active LeZi Prediction Algorithm is then introduced to overcome the drawbacks of LZ78 and helps in effective prediction of probable next event. Khalili, Wu, & Aghagn (2009) used temporal differential class of reinforcement learning, which is an unsupervised learning method to learn preferred music and lighting service settings of the user in presence of different states of the user. The system created a user-centric methodology for adaptation of system services based on accumulated knowledge about the user preferences. These preferences are learned through user's explicit or implicit feedback to the system when the user opts to react to the provided service. The system adapts to provide the most satisfactory music and ambient lighting to the user. Fahad, Ali, & Rajarajan (2013) identified the change in the daily routine of a person by long term monitoring of the everyday performed activities. Useful features are extracted from the pre-segmented activities. They used the learning algorithm probabilistic neural network for activity recognition. The recognized activities are then utilized to group the days in which a person follows a different routine from normal. They used K-means clustering algorithm for grouping. Nazerfard & Cook (2013) proposed an activity prediction approach using Bayesian networks. They proposed a novel two-step inference process to predict the next activity features and then to predict the next activity label. Rasch (2014) proposed smart home recommender system, which continuously interpret the user's current situation and recommending services that fit the user's habits. The proposed system learns which actions the user typically performs in a given situation. The training is unsupervised. After the training phase, the system continuously interprets the user's current situation and generates personalized recommendations. Kabir et al. (2015a) presented a context-aware application, which can provide service according to predefined choice of user. It uses Mahalanobis distance based k nearest neighbor's classifier technique for inference of predefined service. They combined the features of supervised and unsupervised machine learning in the proposed application. This application can also adapt itself when the choice of user is changed by using Q-learning reinforcement learning algorithm. Kabir et al. (2015b) presented a machine learning based context-aware system, which can provide service according to the trained model. Two effective learning algorithms: Back propagation Neural Network, and Temporal Differential (TD) class of reinforcement learning are used for prediction and adaptation respectively. Aztiria, Izaguirre, Basagoiti, & Augusto (2009) proposed a system, which learns user's patterns of behavior and an interaction system, based on speech recognition, which facilitates the use of such patterns in real applications. Wang, Luo1, Li, & Zhao (2016) proposed a new habit pattern learning scheme in smart home by recording the operations on each electric appliance in the form of time series, they firstly showed that the habit can be classified into fixed-length habit and timing habit. Then, proposed habit extraction methods based on the corresponding activity probability and calculation formulas of the habit strength. Finally, Reaz (2013) highlighted research projects employing multi-agent systems, action prediction, artificial neural network, fuzzy logic and reinforcement learning. It is found that the combination of tools and techniques are crucial for successful implementation. Francillette, Gaboury, Bouzouane, & Bouchard (2016) proposed an approach for building adaptive smart home based on a generic model of smart home behavior, an object-oriented model of context and an adaptation strategy. They used behavior trees as simpler way to develop the behaviors of smart homes. In their approach the system could adapt the behavior tree according to the current context. Vlachostergiou, Stratogiannis, Caridakis, Siolas, & Mylonas (2016) proposed a rule-based system for services adaptation by providing a novel semantic representation of the home rules expressed using the Semantic Web Rule Language (SWRL) that continuously adapts home environment conditions to the user's actions and preferences. They proposed to restrict user-related context to the smart home environment.

As mentioned before most of the previous work did not deal in depth with context-awareness either by being not context-aware or by not providing a clear and concise method for establishing context elements. Some of them were based on machine learning techniques for the services adaptation that assumed a static learned model that cannot change over the time once deployed, which affect their flexibility. In addition, most of them tackle the adaptation task without presenting a strategy to master the complexity of the task by designing a modular system, which helps a lot to master the complexity and a lot of benefits for extensibility and maintenance.

3. Smart Living Room Description

A typical smart living room is basically composed of four systems: Light system, which is composed of window blinds and a set of light bulbs, entertainment system, which may include a smart TV with satellite receiver, home theater and a radio/music player, heating, cooling, & an air quality system, which is composed of a heater, air conditioner and air purifier and finally the telecommunication system, which can be composed of the land-line phone or the user's mobile phone and may also include the intercom system. In this paper, we focus only on the first three systems and keep the communication system for future work. All these systems should provide a set of services through different forms (or modes) to the inhabitant of the smart living room (Figure 1). These services should take into account the user's preferences and should be triggered (resp. changed) according to the current context of the smart living room. Contextual information is gathered from different

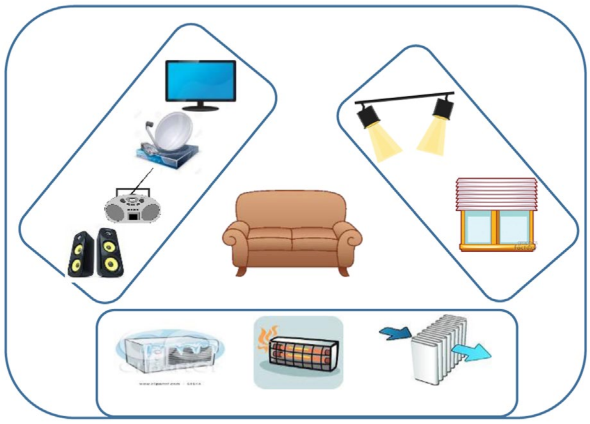


Figure 1. Components of a Typical Smart Living Room.

physical sensors installed in the living room in addition to some logical sensors.

In the initial state of the living room (empty), everything is off (TV, radio/music player, light, air conditioning, heater, window blinds closed, etc.). Upon the entrance of the user and detection of his presence, the lighting system composed of the window blinds and light bulbs starts first to adjust the light to the preferences of the user and the current context. Then, the climate system composed of an air cooler, heater, and air purifier starts to adjust the room temperature and air condition to the user's preference and according to the current context. The former system will trigger only if the system perceives at least one user seated on the sofa to avoid wasting energy if the user makes a simple entry and exit from the living room without the intention of staying. After a small period of time (δT), the multimedia system then starts to turn on the TV or radio/music player and home cinema depending on the preferences of the user if he is alone or surrounded by other people.

There are two main states of the smart living room; empty and occupied. In the first state (i.e., initial and final state), the network sensors perceive that there is no one in the living room, so all the equipment should be off. As soon as the network sensors perceives the presence of one or more users, the smart living room moves to the second state, which in turn contains three sub-states that describe the preferred order of system booting. The light system will start first (occupied 0), and after perceiving at least one user seated on the sofa, the climate system (occupied 1) will start. Then, after a small period of time (δT), the multimedia system will start. At any time during the occupied state of the smart living room, if the network sensors perceive that there is nobody in the room (presence=0), the smart living room will transit directly to the empty state. The dynamic aspect of the smart living room could be modelled using a simple timed automaton as shown in Figure 2.

4. Context Identification and Acquisition

Context-awareness constitutes a major challenge for developers of pervasive and ubiquitous computing systems as well as smart environments. Such technology has the ability to minimize users' interventions and maximize functional autonomy of systems by adapting services to the current context without explicit user intervention. The first step to providing more effective ambient intelligence in smart spaces is to identify context elements and establish its components in clear and

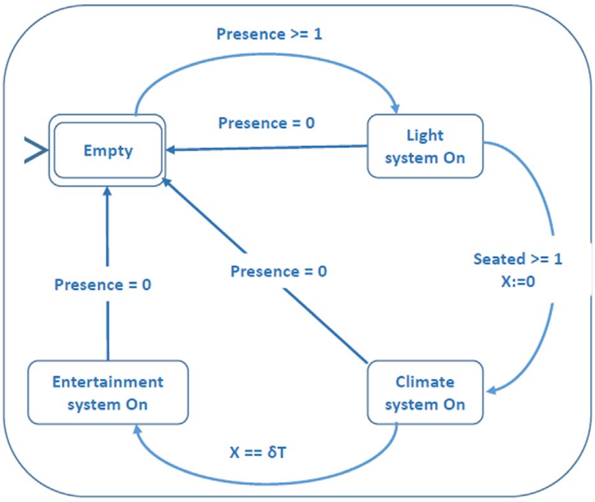


Figure 2. The Dynamic Aspect Model of the Smart Living Room.

Table 1. Service Triggering Information.

Device	Provide service	Triggering information
Window blinds	Lighting	User's presence
Light bulbs	Lighting	User's presence
TV/Satellite receiver	Entertainment	Seated user
Home theatre	Entertainment	Seated user
Radio/Music player	Entertainment	Seated user
Cooler	Cooling	Seated user
Heater	Heating	Seated user
Air purifier	Air conditioning	Seated user

concise manner. In the literature, several definitions of context were proposed, and some of them were based on enumerating contextual information (localization, nearby people, time, date, etc.) like those proposed by Brown, Bovey, & Xian Chen (1997); Ryan, Pascoe, & Morse (1997); Schilit & Theimer (1994). Others were based on providing more formal definitions in order to abstract the term, like the one proposed by Dey (2001). However, most of these definitions were specific to a particular domain, such as human-computer interaction and localization systems. In our previous work (Miraoui & Tadj, 2007; Miraoui, Tadj, & Amar, 2008), we made a survey of existing definitions of context and proposed a service-oriented definition of context for pervasive and ubiquitous computing environments as follows: "Any information that triggers a service or changes the quality (form or mode) of a service if its value changes." This definition is sufficiently abstract and helps to limit the set of contextual information. We believe that this definition is more expressive, because it is simple, clear, and complete; in addition, it covers all aspects of context. The first step in establishing context elements of the smart living room consists of specifying for each equipment, the provided service and the set of information that could trigger the service (Table 1). The second step consists of specifying for each service the set of forms through which the services can be provided. We should also specify for each form of service the set of information whose change will change the form of a service (Table 2). The last step consists of making the union of the two previous sets to get the final list of contextual information and define the set of possible values for each context element (Table 3). This information will compose the global context.

5. Context-Aware Services Adaptation

5.1. The Light System

The light system of the smart living room is composed of two sub systems; a) light bulbs set and b) window blinds. It is triggered when the smart living room perceives the presence (resp. entrance) of at least one user. When triggered the light system starts to adjust the luminosity level inside the smart living room according to the current context, which composed of the following elements:

(indoor light, outdoor light, motion, day type, time, nearby)

The light service could be provided by the two sub systems through different forms (classes) based mainly on the indoor light and outdoor light which summarized by Table 4.

The light system should react to some specific contexts such as when the user is making a nap or sleeping, which requires the light system to reduce the luminosity of the smart living room in order to improve the user's comfort. Another interesting context consists of recommending the user to go to sleep by reducing the smart living room luminosity when it is late night and the day type is work day. These contexts are presented by the following vectors (Table 5).

By changing the "?" symbol by the corresponding possible values of each context element, we obtain forty (40) additional values for each row in Table 4. The total real configuration of light system will be then 640 possible configurations of the light bulbs set and window blinds. We should also change some rows of them according to special cases given by Table 5 e.g. from the forty rows generated from row 1 of Table 4, the ones containing motion=no motion, time=afternoon and nearby=alone should be changed window blinds=mostly closed and light bulbs=off instead of window blinds=totally closed and light bulbs=high.

The resulting set will form the training set for a naïve Bayes classifier chosen as a machine learning technique for light

Table 2. Service Forms Changing Information.

Device	Service forms					Form changing information
Window Blinds	closed	mostly closed	half opened	mostly opened	totally opened	user's presence, indoor and outdoor light
Light bulbs	off	on low	on average	on high		user's presence, indoor and outdoor light
TV/Satellite receiver	off	on preferred	on other			user's preferences, day of the week, time, motion, nearby
Radio/Music player	off	on preferred song	on preferred radio station	on other		user's preferences, day of the week, time, nearby
Home theatre	off	on low	on average	on high		time, day of the week, motion, nearby
Heater	off	on preferred	on other			indoor temperature
Cooler	off	on preferred	on other			indoor temperature
Air purifier	off	on low	on average	on high		air quality

Table 3. Context Values.

Context	Values						
User's presence	0	1	several				
Seated user	yes	No					
Indoor light	dark	low	average			high	very high
Outdoor light	dark	low	average			high	very high
Indoor temperature	very low	low	almost low	average	almost high	high	very high
Air quality (pollution level)	clean	low	average	high			
Day type	work day	week-end					
Motion	yes	No motion					
Time	morning	afternoon	evening	night	late night		
Nearby	alone	not alone					

Table 4. Light Service Forms.

Indoor light	Outdoor light	Motion	Day type	Time	Nearby	Blinds	Light bulbs	Form
dark	dark	?	?	?	?	totally closed	high	1
dark	low	?	?	?	?	totally opened	average	2
dark	average	?	?	?	?	totally opened	low	3
dark	high	?	?	?	?	totally opened	off	4
low	dark	?	?	?	?	totally closed	average	5
low	low	?	?	?	?	totally opened	low	6
low	average	?	?	?	?	totally opened	off	7
low	high	?	?	?	?	mostly opened	off	8
average	dark	?	?	?	?	totally closed	low	9
average	low	?	?	?	?	totally opened	off	10
average	average	?	?	?	?	mostly opened	off	11
average	high	?	?	?	?	half opened	off	12
high	dark	?	?	?	?	totally closed	off	13
high	low	?	?	?	?	mostly opened	off	14
high	average	?	?	?	?	mostly closed	off	15
high	high	?	?	?	?	totally closed	off	16

The symbol "?" means whatever value.

Table 5. Light Service Forms.

Indoor light	Outdoor light	Motion	Day type	Time	Nearby	Blinds	Light bulbs	Form
?	?	No motion	?	Afternoon	Alone	mostly closed	off	17
?	?	No motion	?	Night	Alone	totally closed	low	18
?	?	No motion	?	Late night	Alone	totally closed	low	19
?	?	?	work day	Late night	?	totally closed	low	20

service adaptation. The Bayesian Classification represents a supervised learning method as well as a statistical method for classification. For each new sample, they provide a probability that the sample belongs to a class. Training is very easy and fast, no need for complicated training process as in neural networks. Naïve Bayes is fast and space efficient. It can provide an optimal decision-making system even in presence of violating independence assumption. We have used the free machine learning tool WEKA (Waikato Environment for Knowledge Analysis) (WEKA tool web site, 2016) to implement the light adaptation system. We have made several tests on the light system and the obtained results are very encouraging with acceptance rate of 96%.

5.2. The Climate System

The climate system of the smart living room is composed of three devices; (a) heater, (b) cooler and (c) air purifier. The latter is mainly used to remove impurities such as CO2 from air. It is triggered when the smart living room perceives at least one seated user on the sofa. In addition, it is triggered compulsory after the light system. When triggered the climate system, starts to adjust the temperature inside the smart living room according to the current context which composed of the following elements; current temperature and air quality inside the smart living room.

Table 6. Possible configuration of the climate system.

Indoor Temperature	Cooler	Heater
very low	off	high
low	off	average
almost low	off	low
medium	off	off
almost high	low	off
high	average	off
very high	high	off

The operation of the cooler and heater depends on only one context information namely current temperature. The set of possible configuration is very limited and shown in Table 6.

In the same manner, the air purifier operation depends on only one context information namely the air quality inside the living room. The possible configurations are also limited and shown in Table 7.

For the implementation of the adaptation mechanism of the climate system we have used the fuzzy logic technique. Fuzzy systems are well suited for dealing with imprecise quantities used by humans. Fuzzy logic is often used to help make human-like decisions. Control systems using fuzzy logic are generally fast, user friendly, cheap and they don't need much memory (Wang, 1997). As an implementation tool, we have used the fuzzylite, which is a free and open-source fuzzy logic control

Table 7. Possible Configurations of the Air Purifier.

Air quality (pollution level)	Air purifier
clean	off
very good	very low
good	low
average	medium
bad	high
very bad	very high

library (www.fuzzylite.com). Figure 3 shows the implementation of the cooler/heater controller using the fuzzylite tool. The implementation of the air purifier control is alike.

5.3. The Entertainment System

The entertainment system is composed of three devices: a) TV/satellite receive, b) radio/music player and c) home theater. It is triggered after a certain period of time just after the operation of the climate system. The adaptation procedure is based on learning a user's habits for a period of time, which is fixed to one week, because user's habits can be weekly repetitive tasks. However, user's habits often change over time, because human behavior is not predictable and it keeps on changing day by day. A common learning algorithm, which assumes a static learned model, i.e., once the resident's activity preference patterns have been learned, no changes are applied to maintain the model over time. Such learning algorithms could not solve this problem, because a training set will not contain examples of appropriate decisions for all possible contextual situations. In this case, we require an incremental learning system. We have chosen the case based reasoning (CBR) technique to achieve adaptation for the entertainment system. CBR is such a problem-solving technique that reuses previous cases and experiences to find a solution for current problems. It does not need an explicit model of the domain. CBR not only reuses previous cases, but also store new cases for future reference.

A case-based reasoning system is typically made up of four steps (Figure 4) (Aamodt & Plaza, 1994).

(1) Retrieve: In this step the most similar case or cases to a certain problem are retrieved.
(2) Reuse: The solutions of the retrieved cases are used to solve the problem at hand.
(3) Revise: The proposed solution is revised based on feedback.
(4) Retain: The revised case or a new case is stored in the case base to be used for future problem solving

5.3.1. Case Base

The first step in providing personalized services consists of recording user's preferences. We have recorded the usage of the devices composing the entertainment system namely TV, radio, music player and home theater during a period of one week, because most user's tasks are repetitive each week. For each day, the time vector is divided into a twenty-four (24) time slot. For every slot of time of each day of the week, the system will record for each device its usage (only its operation state); increment the field of the volume level (low, medium or high) used of the home theater. A particular field called frequency, which consists of the global sum of usage time will be filled automatically. The data structure used for implementing the case base is shown in Figure 5.

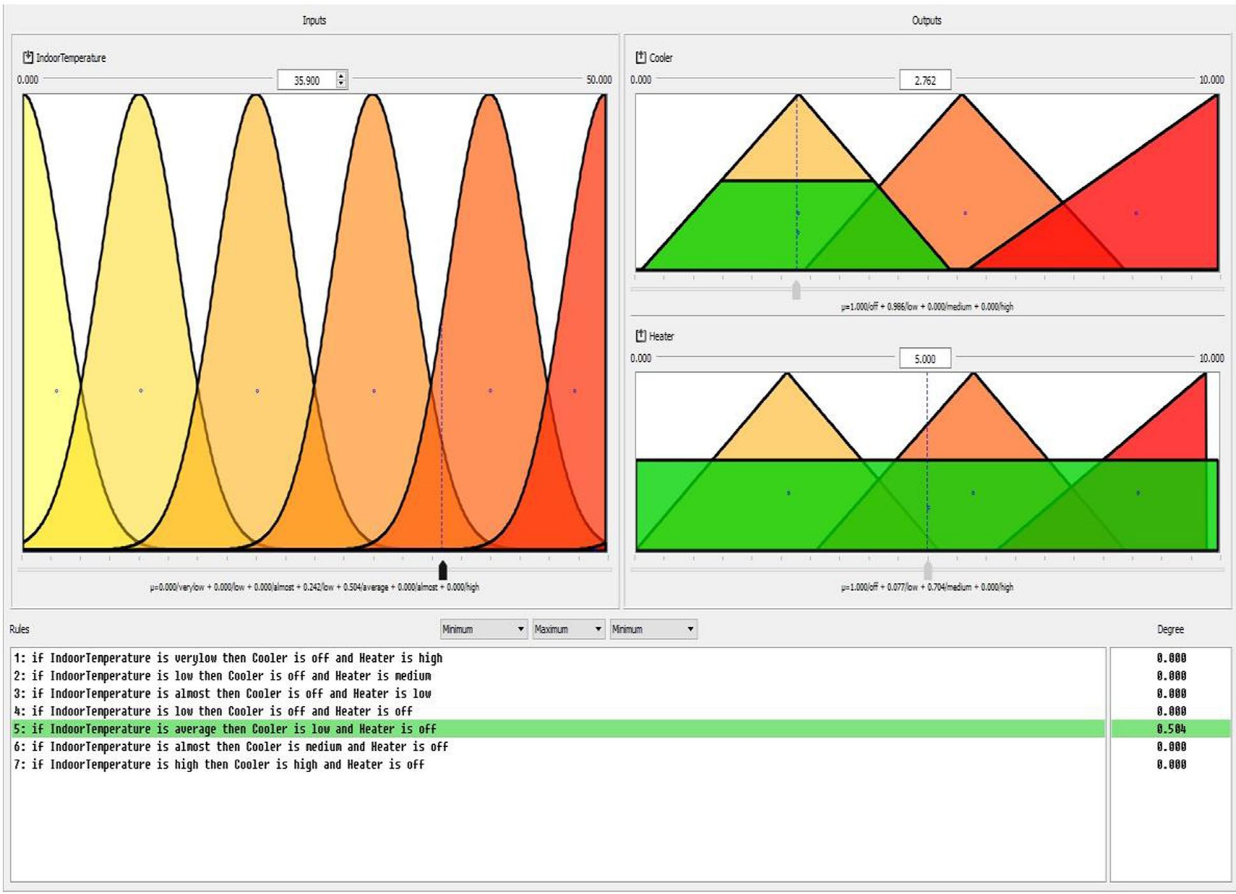


Figure 3. Implementation of the Cooler/heater System Using Fuzzylite.

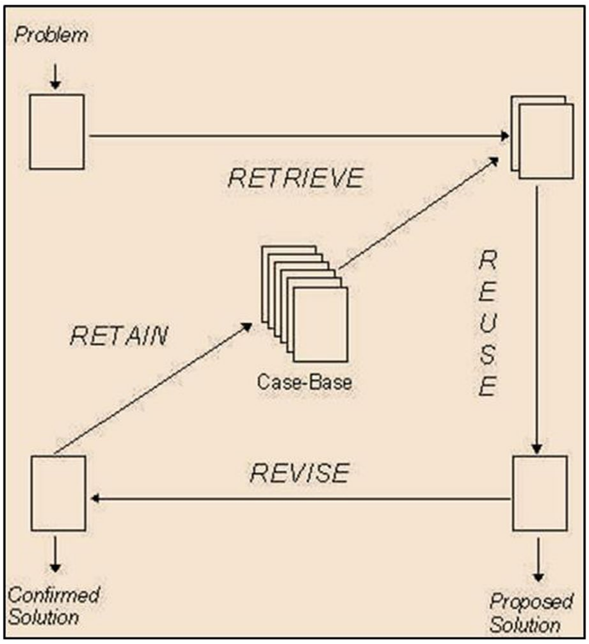
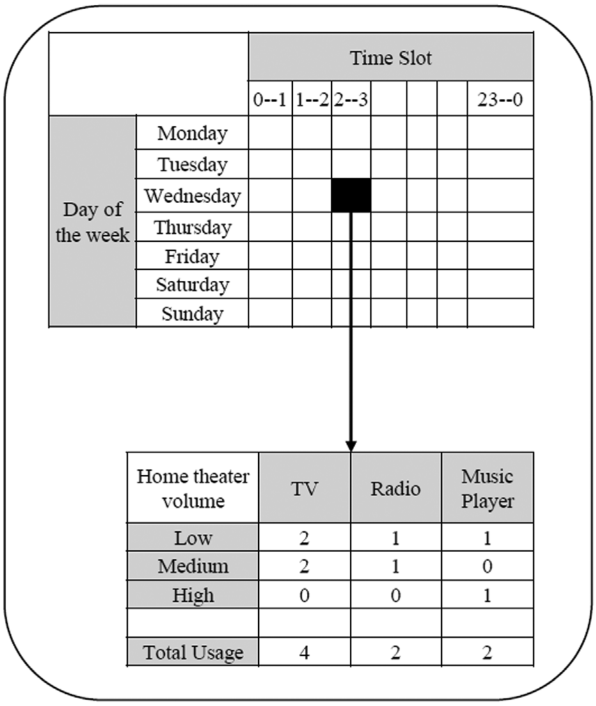


Figure 4. The CBR Cycle (Aamodt & Plaza, 1994).



		Time Slot						
		0--1	1--2	2--3				23--0
Day of the week	Monday							
	Tuesday							
	Wednesday							
	Thursday							
	Friday							
	Saturday							
	Sunday							

Home theater volume	TV	Radio	Music Player
Low	2	1	1
Medium	2	1	0
High	0	0	1
Total Usage	4	2	2

Figure 5. The Data Structure used for Implementing the Case Base.

5.3.2. Case Retrieval

Each time the system confronts a new case, it will search the similar one in the case base based on the day of the week and the time slot. In a case based reasoning system, it's often necessary to use a similarity measure based on a certain type of distance in order to retrieve the most similar case or cases. However, in our system there is no real need for that, because it is easy to retrieve the accurate similar case based on day of the week and the time slot.

5.3.3. Case Reuse

The aim of this step consists of adapting the new case to its similar case retrieved previously. The adaptations process consists of choosing the most frequently used device based on the field total usage. If there are more than one device having the same usage frequency (equal total usage) then the system will choose one of them randomly. After that the system will choose the most frequently used volume level of the home theater. As previously if there is more than volume level having the same usage frequency then the system will choose one randomly.

5.3.4. Case Revise

During this step the system will wait for user feedback to the adopted case from previous step. The system will mainly record weather the user is satisfied or not.

5.3.5. Case Retain

This is the final step of the process, which depends on the previous step. If the system receives a positive feedback from the user i.e. he did not change the proposed device operation configuration, then the presented case will be saved in the case base by just incrementing both the total usage field of the selected device and the corresponding volume level of the home theater. Otherwise if the user refuse the proposed case and choose another device configuration then the system will record his choice by updating the necessary fields in the case base.

We have performed several tests on the implemented system and we have got satisfactory results and have noticed the incremental aspect of the learning system.

On one hand, the usage of different machine learning tools has improved enormously the quality of provided services and on the other hand the decomposition of the device set into almost independent sub-systems has promoted the complexity mastery of the design and implementation of the smart living room. In addition, the usage of our approach for context identification facilitated the integration of the context-awareness aspect in the services adaptation. The context identification approach is based on clear definition of context and simple steps. We have made several tests on the implemented system and we have obtained encouraging and acceptable results.

6. Conclusion

Smart spaces are based on the vision of ubiquitous and pervasive computing where everyday objects communicate and collaborate to provide adapted services to users according to the current context and in an unobtrusive manner. The aim of such spaces is to increase comfort, aid elderly and disabled people, and help inhabitants save energy in addition to automating inhabitant's routines. In this paper, we have presented an approach for building a smart living room, which takes into consideration the current context for the service adaptation. We have decomposed the set of devices into three independent modules in order to master the complexity and enhance both extensibility and maintenance of the system. We have used for each sub-system the most convenient technique of machine learning for the context-aware services adaptation. The obtained results are very encouraging and makes our approach clear. The future work consists of making the adaptation task for more than one inhabitant and taking into consideration the preferences of each inhabitant.

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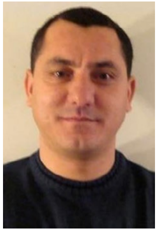
Notes on contributors



Moeiz Miraoui is an assistant professor at Umm Al-Qura University, Makkah, Saudi Arabia. He received a BSc in Computer Science from University of Tunis, Tunisia in 1999, an MSc degree in Computer Science from University of Sfax, Tunisia in 2003 and a Ph.D. degree in Computer Science from the École de Technologie Supérieure (University of Quebec, Canada) in 2009. His research interests include pervasive and ubiquitous computing, context-aware systems and smart spaces.

Sherif El-etriby is an associate professor at Umm Al-Qura University. He received BSc and MSc degrees in Computer science from Menoufia University, Egypt in 1999 and a Ph.D. in Computer science (Computer Vision) from Institute for Electronics, Signal Processing and Communications (IESK), Otto-von-Guericke-University Magdeburg, Germany in 2008. His research interests are image processing, pattern recognition, computer vision and artificial intelligent.

Chakib Tadj is a professor at École de Technologie Supérieure, University of Quebec at Montreal (Canada). He received a Ph.D. degree from ENST Paris in 1995. He is a member of Laboratory of Information Processing and Signals at ETS. His main research interests are ubiquitous computing, multimodal systems, automatic recognition of speech and voice mark.

Abdulbasit Zaid Abid received a BSc degree in Electrical and Computer Engineering from Umm Al-Qura University, Makkah, Saudi Arabia, and a Master's degree in Computer Engineering from the University of Essex, Colchester, United Kingdom and a Ph.D. degree in Computer Engineering from John Moores University, Liverpool, United Kingdom. He is currently with the Department of Computer Engineering, Umm Al-Qura University, Makkah, Saudi Arabia. His current research interest include image processing, computer vision and artificial intelligence.

ORCID

Moeiz Miraoui http://orcid.org/0000-0003-2220-8673
Chakib Tadj http://orcid.org/0000-0002-3322-4882

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