

# Context-Aware Implementation based on CBR for Smart Home

Tinghuai Ma, Yong-Deak Kim, Qiang Ma, Meili Tang, Weican Zhou

**Abstract**—Context awareness is emphasized in order to provide automatic services in smart home. This paper uses case based reasoning as the reasoning method which solves the problem “In the first phase, we don’t know exactly about the key processes and their interdependencies in smart home’s context”. The context’s contents in smart home are described in this paper. Also, case representation, case storage and similarity calculation are discussed in smart home’s context awareness. We propose a framework of context aware based on CBR, and discuss the case adaptation in detail.

**Index Terms**—case base reasoning, context aware, smart home

## I. INTRODUCTION

MARK Weiser has described us an environment named Ubiquitous computing, which aims to “Enhance computer use by making many computers available throughout the physical environment, but making them effectively invisible to the user” [1]. Ubiquitous computing allows users to access varieties of services at any time and any place. Accordingly, pervasive computing also provides a variety of applications throughout our living and working spaces. These devices and network services coordinate with each other to assist people in completing their tasks without disturbance and notice. Smart home has been always considered as an important part of the ubiquitous computing.

The home system will effectively integrate communication and computing networks among the previously separated equipments in home and incorporate core tenets of ubiquitous computing. If the home system wants to dynamically adapt its behaviors according to the user’s activities and environments, awareness of the user’s activities and environment are required. Many researchers have focused on context-aware architecture and context-aware applications [2, 3]. Automatically collecting the context information and reacting in ways that fit in with the

Tinghuai Ma is with the Computer Science Department, NanJing University of Information Science & Technology, China (e-mail: ma\_tinghuai@msn.com)

Yong-Deak Kim is with the Electrical and Computer Engineering Department, College of Information Technology, Ajou University, Korea (e-mail: yongdkim@ajou.ac.kr)

Qiang Ma is with the Electrical and Computer Engineering Department, College of Information Technology, Ajou University, Korea (e-mail: qiang@ajou.ac.kr)

Meili Tang is with the Public Administration Department, NanJing University of Information Science & Technology, China (e-mail: meilitg@163.net)

Weichan Zhou is with the Mathematics Department, NanJing University of Information Science & Technology, China

environment are the main design goals of the context-aware system. Machine learning, data mining, and intelligent decision algorithm with context information are the key technologies to implement context-aware in home environment.

CBR (case based reasoning) is an approach targeting problem resolution in domains where little information is known about the key processes and their interdependencies. For context aware in smart home, at the beginning, we don’t know the interdependency among appliances and services. And also, there is no theory to identify the context situation. But awareness can be obtained by retrieving and adapting the solutions to previous scenarios.

In this paper, we show how to use CBR as context awareness solution in smart home. The context contents and case’s organization format are discussed respectively. Related table is chosen to store the cases. For case retrieving, multi-level similarity is suggested. From bottom to top, attribute similarity, table similarity and global similarity are defined. The framework of context aware based on CBR has been developed. According to different action, different solution of case adaptation is defined. In smart home, a specific solution for case revising is suggested.

The remainder of this paper is organized as follows. Related work about context-aware is summarized in section II. In section III, the context contents in smart home are discussed. Context-aware based on CBR, including case representation, case storage, similarity calculation and the whole framework, is described in section IV. Conclusions are given in section V.

## II. RELATED WORKS

### A. Contexts aware

Nowadays, a lot of smart home projects have been initiated by many research institutes such as Georgia Tech Aware Home [4], MIT Intelligent Room [5] and Neural Network House [6] at the University Of Colorado Boulder. Context-aware is one of the primary characteristics of smart home. Collecting information from sensors, reasoning from known database, and thus adopting corresponding activities are the main steps of context-aware applications. Much work has been done on how to use reasoning algorithms to achieve context aware.

W.Y. Lum et, al. use decision trees to decide the optimal content version for presentation, base on the specific context, such as intended target device capabilities, network conditions, and user preferences [7]. A. Ranganathan et, al. propose a

context model based on first order predicate calculus [8]. They use first order model to express complex rules, which involves contexts. This knowledge expression enables automated inductive and deductive reasoning to be easily done on contextual information. H. Chen et, al. use ontology models to express basic concepts of people, agents, places, and presentation events in an intelligent meeting room environment [9]. It's convenient to integrate the agents that employing knowledge. It's also convenient to reason to understand the local context. M. Wallace et, al. develop a context aware clustering algorithm to mining user's consumption interests of multimedia documents, based on use history [10].

### B. Case based reasoning

CBR is such a problem solving technique that reuses previous cases and experiences to find a solution for current problems. L.D. Xu et, al. discuss the CBR's advantages and the process of the CBR and provide an application that uses CBR to judge the AIDS [11]. W.C. Chen et, al discuss the features that can delegate the case [12]. They propose a framework to mining the features by using machine learning methods. W. J. Yin et, al. use the joint of genetic learning approach and case-based learning, solving job-shop scheduling problems [13]. The similarity calculation is defined based on DNA matching. D. Grosser et, al. use case-based reasoning (CBR) to predict the object oriented software's stability [14]. K. Li et, al. introduce time function as the adjustable factors in similarity measuring [15].

## III. CONTEXT IN SMART HOME

### A. Scenarios

Smart home sometimes means automated home. Some used cases are as follows:

“At noon, Mr. Lee enters the living room; the room temperature is 30 °C, the air condition will automatically turn on to decrease the temperature. At the same time, the TV is turned on and the news report channel is tuned.”

“At 23:00, Mrs. Park leaves living room and enters bedroom, the air condition and TV in the living room are turned off. The light in bedroom is turn on, and just the brightness to low.”

Although the above scenarios seem to be relatively simple, it would be challenging to achieve these “simple” scenarios in the real home environment. The purpose of context aware is “right situations do right things”. The basic of the commonsense reasoning and context awareness is the understanding of current state. But there are many situations TV, AC and light might encounter.

For adjusting TV channel: some persons like news, some like sports. Sometime TV stations provide comedy, sometime TV stations provide sitcom. And some program fits living room, and some program fits bed room, and so on.

For switching the AC: some like warm or cool, some like turn on AC while sleep or not, some like wind, and so on.

It almost means impossible for the system designer to envision all possible contexts before the system deployment.

The home system will sometimes perform in unexpected and undesirable ways inevitably and thus disappoint the home occupant. A common learning algorithm also can't solve this problem because a training set will not contain examples of appropriate decisions for all possible contextual situations.

### B. Content of context

Context is usually classified into three categories: environment, user's activity, and user's physiological states [16]. Each category has its own subcategories.

In the beginning, our context information model will be simple and idiographic. We don't deal with abstract concepts. We assume that context information can be simplified into a collection of discrete facts and events with numeric parameters.

According to the above analysis, there may be different TV programs at different time and different devices in different rooms. Occupants' habits are also different. So, the context in smart home can be classified into three dimensions: (1) time, (2) environment, and (3) person. In each category, there are several entities as shown in Table 1.

As occupants deal with a large amount of information, context information is modeled hierarchically.

TABLE 1  
CONTEXT CATEGORIES AND ENTITIES IN SMART HOME

CONTEXT CATEGORIES AND ENTITIES IN SMART HOME		
Time	time	second/Minute/Hour/Day/Week/Month/Season
	Time sequences	Event occurring Sequence
Environment	location	Bedroom/Bathroom/Kitchen/Dining room/Living room
	status	Leaving/Staying/Entering
	temperature	Environment's temperature
Person	ID	Person's ID
	Profile	Name/Gender/Age
	Habit	Sports/News/Warm/...

## IV. CONTEXT-AWARE BASED CBR

As discussed in section III, the system designer can't envision all situations the users will encounter even for a simple scenario. Designing a complete rule based system is almost impossible. CBR not only reuses previous cases, but also store new cases for future reference. If no rule in database matches the new case, CBR system will store the new case as a rule. Since the system designer can't consider all situations in smart home in advance, CBR may be the best reasoning approach to implement context-aware in home environment.

In the context of CBR, four important issues need to be addressed: case representation, similarity measurement, case retrieval and solution reuse.

### A. Case representation

Knowledge representation is rather important for artificial intelligence. At the same time, case representation is related not only to knowledge storage but also to knowledge reasoning. We use frame to represent case for storage and indexing.

Fig.1 shows us a representation of context in frame form.

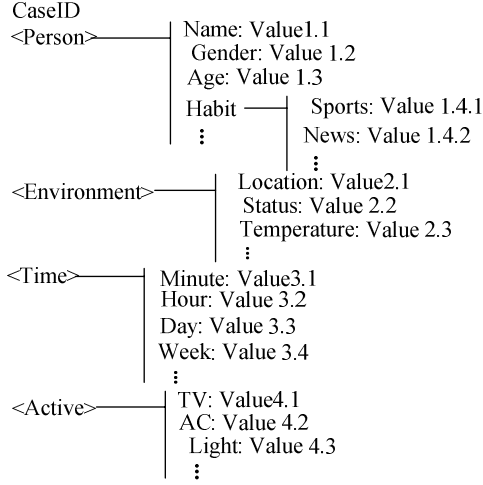


Fig. 1. Representation of context in frame form

In the initial stage, we use database to store the case. The database consists of five tables: case table, person table, habit table, environment table and active table. The case table is the main table and can be expressed as follows:

$case = (caseID, personID, habitID,$

$environmentID, activeID, time)$   
 personID, habitID, environmentID, activeID are primary keys of person table, habit table, environment table, active table respectively and foreign keys of case table at the same time. By joining the main table and related tables, a new table that contains all attributes of those tables can be obtained.

### B. Similarity calculation

Since the case representation is organized as two levels: main table and related tables such as environment table and active table, the similarity is defined on two levels: local similarity and global similarity accordingly. The generalized distance can be used to estimate similarity.

**Attribute similarity.** Local similarities include related tables' (person table, habit table, environment table, and active table) similarities. In those tables, there are many types of attribute values (according to entities in table 1), such as string, numerical value and Boolean. Each kind of values has its own similarity calculation method, which can be expressed in a general form:

$$dis(A_j(c), A_j(c')) = \frac{|A_j(c) - A_j(c')|}{dom(A_j)} \quad (1)$$

where  $c, c'$  mean two different cases,  $A_j(c)$  means the case's attribute  $A_j$ 's value and  $dom(A_j)$  means the maximal difference of two values  $v_1, v_2$ . Obviously, for any pair of cases  $c$  and  $c'$ , the value  $dis(A_j(c), A_j(c'))$  is within  $[0, 1]$ .

**Table similarity.** The related tables represent frame's slots correspondingly as shown in Fig. 1. The slot's similarity calculation can be replaced by calculating the table's similarity. The table's similarity is the combination of all attributes' similarity of table. Considering different attribute has different

contribution to the table's similarity, the attribute weight is used in table's similarity. The table's similarity can be evaluated as follows:

$$dis(T_i(c), T_i(c')) = \sum_j \xi_j dis(A_j(c), A_j(c')) \quad (2)$$

where  $\sum_j \xi_j = 1$ . For example, we

assign  $\xi_1 = \xi_2 = \dots = \xi_p = 1/p, \forall_j = \{1, 2, \dots, p\}$

Time slot's similarity calculation is done on minute level and described as follows:

$$dis(T(c), T(c')) = \frac{|T(c) - T(c')|}{60 \times 24} \quad (3)$$

where the time's unit is minute.

**Global similarity.** Global similarity is the case's similarity. It is the combination of relation tables' similarity and time's similarity. We can treat related tables and time attribute as case's complex attributes. Thus, the case's similarity can be expressed as follow:

$$dis(c, c') = \sum_i \omega_i dis(T_i(c), T_i(c')) \quad (4)$$

In different scenarios, for case's similarity, the same table's contribution is not equal. So, the tables' weight  $\omega_i$  is different and  $\sum_{i=1} \omega_i = 1$ . The range of  $dis(c, c')$  is  $[0, 1]$ , 0 meaning perfect match and 1 meaning severe mismatch.

### C. Solution adaptation

The adaptation means developing a solution to find a best match set from the existent cases. In CBR, the best match sometimes is not a single case, but a combination of cases. Simply, the best match is the first nearest neighbor of the current case. If high precision is required, the best match is a combination of the solutions, which represents a similarity trade off between the current case and previous cases. The majority choice is usually used for Boolean variables whereas linear combinations are chose for continuous variables.

We use various strategies in the adaptation. For TV action, the first nearest neighbor, which call 1-NN, is choosing as the best match solution. This is because for channel, there are only two choices, on or off. For AC and light action, the temperature and brightness can be continuous varying. So, K-NN is used for combination as best match solution. Empirically, K was chosen as five or ten. The solution may be expressed as follows:

$$\begin{aligned} < AC \text{ action}, \text{ light brightness} > \\ &= sim(c, c_1) * < AC \text{ action}_1, \text{ light brightness}_1 > \\ &+ sim(c, c_2) * < AC \text{ action}_2, \text{ light brightness}_2 > \\ &+ \dots \\ &+ sim(c, c_K) * < AC \text{ action}_K, \text{ light brightness}_K > \end{aligned} \quad (5)$$

where  $c$  means current case,  $(c_1, c_2 \dots c_K)$  means K-NN set and  $K = 5$  or  $10$ .

### D. System Framework

As an analogical reasoning system, CBR bases itself on the

“similar problems have similar solutions” and gets a solution from previous cases and does necessary modification to adapt new circumstance.

In CBR system, database is used to store cases. Case is organized into related tables. As classical CBR system, there are phases from case retrieving, to case reusing and to case storage. The original data is generated by sensors. After sensor data is structured, similarity can be calculated. The best match set is retrieved from case database. Using 1-NN or K-NN strategies, new solution is gained.

For smart home, the users have no interface to modify the solution. Smart home system uses one of the candidate solutions to set the TV channel, AC temperature and light brightness. If users adjust TV channel, AC temperature and light brightness, the case will adopt the input values as users’ revising. In Fig 2, users’ modifications are expressed as AC action, lamp action and TV action. Thus, case adaptation is achieved.

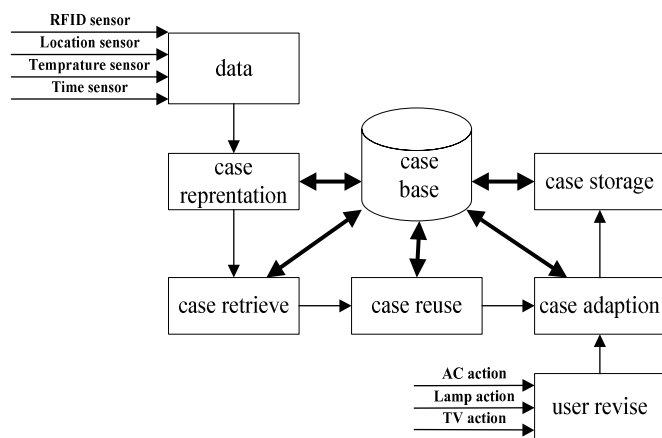


Fig. 2. CBR System Framework in smart home

## V. CONCLUSION

Smart home is the prototype of ubiquitous network. The intelligence is the core of smart home. Context-aware plays an important role for smart home’s intelligence. With context-aware, systems can decide what services should be provided. Building a case based expert system is a feasible solution. Firstly, smart home is a complexity system; present study can’t prove the interdependencies and key features clearly. Secondly, it’s impossible to enumerate all scenarios that may appear before the context awareness system is deployed. Thus CBR is a suitable solution in context aware.

This is the first phase of context awareness in smart home. Within the system framework, the case representation adopts related tables, case retrieving adopts multi-level similarity, and case adaptation adopts with users’ modification. There are a lot of context contents in home environment and the rest work is to add more case features into case tables within this framework.

## REFERENCES

- [1]. M. Weiser, “Some Computer Science Issues in Ubiquitous Computing. Communication,” *Communications of the ACM*, vol. 36, no. 7, pp. 75–84, July 1993.
- [2]. S.H. Lee and T.C. Chung, “System Architecture for Context-Aware Home Application,” in *Proc. of the 2<sup>nd</sup> IEEE Workshop Software Technologies for Future Embedded and Ubiquitous Systems (WSTFEUS’04)*, Vienna Austria, 2004, pp. 149–156.
- [3]. G.D. Abowd, M. Ebling, G. Hunt, H. Lei, and H.W. Gellersen, “Context-Aware Computing,” *PERVASIVE computing*, JULY–SEPTEMBER 2002, pp. 22–23.
- [4]. S. Helal, B. Winkler, and C.H. Lee, “Enabling Location-Aware Pervasive Computing Applications for the Elderly,” in *Proc. of 1<sup>st</sup> IEEE Int. Conf. Pervasive Computing and Communications (PerCom’03)*, pp. 531–538.
- [5]. A. Roy, “Location Aware Resource Management in Smart Homes,” in *Proc. of 1<sup>st</sup> IEEE Int. Conf. Pervasive Computing and Communications (PerCom’03)*, pp. 481–488.
- [6]. D. J. Cook, “MavHome: An Agent-Based Smart Home,” in *Proc. of 1<sup>st</sup> IEEE Int. Conf. Pervasive Computing and Communications (PerCom’03)*, pp. 521–524.
- [7]. W.Y. Lum, “A Context-Aware Decision Engine for Content Adaptation” *PERVASIVE computing*, JULY–SEPTEMBER 2002, pp. 41–49.
- [8]. A. Ranganathan and R. H. Campbell, “An infrastructure for context-awareness based on first order logic,” *Personal & Ubiquitous Computing*, 2003, vol. 7, no. 6, pp. 353–364.
- [9]. H. Chen, T. Finin, and Anupam, “An Ontology for Context-Aware Pervasive Computing Environments. Special Issue on Ontologies for Distributed Systems,” *Knowledge Engineering Review*, Cambridge University Press (2004), pp. 197–207.
- [10]. M. Wallace and G. Stamou, “Towards a context aware mining of user interests for consumption of multimedia documents” in *2002 Proc. IEEE Multimedia and Expo*, vol. 1, pp. 733–736.
- [11]. L. D. Xu, “Case based reasoning for AIDS Initial Assessment,” in *Proc. of the 1993. IEEE Int. Conf. Systems science and systems engineering*.
- [12]. W.C. Chen, “A framework of features selection for the case based reasoning,” in *Proc. of IEEE Int. Conf. Systems, Man, and Cybernetics*, 2000.
- [13]. W.J. Yin and M. Liu, “A genetic learning approach with case based memory for job-shop scheduling problems,” in *Proc. of the first Int. Conf. Machine learning and cybematics*, Beijing, 2002, pp. 1683–1687.
- [14]. D. Grosser, H. A. Sahraoui and P. Valtchev, “An analogy-based approach for predicting design stability of Java classes” in *Proc. of 9<sup>th</sup> Int. Software Metrics Symposium (METRICS’03)*, Sydney Australia, 2003, pp. 252–262.
- [15]. K. Li and Y.S. Liu, “Fuzzy case based reasoning: Weather Prediction,” in *Proc. of 1<sup>st</sup> Int. Conf. Machine learning and cybematics*, Beijing, 2002, pp. 107–110.