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A Dual-Layer User Model based Cognitive System for User-Adaptive Service Robots

Seong-Yong Koo, Kiru Park, Hyun Kim, and Dong-Soo Kwon, *Member, IEEE*

Abstract— **This paper proposes a dual-layer user model to generate descriptive service recommendations for user-adaptive service robots. The user model represents user preferences as the associative memory in the bottom-layer and association rules in the top-layer. The learning and inference processes in the two layers, and the bottom-up rule extraction process, are explained. The proposed user model was applied to a user-adaptive coffee menu recommendation system, and the quantitative and qualitative performances of the user-adaptive and descriptive recommendation system were evaluated by comparison with non-descriptive and random recommendation methods.**

I. Introduction

THE cognitive process is a key component for many social robots, allowing them to perform proper actions in a dynamic human environment. The robots should generate certain knowledge to achieve a specific goal by observing human actions, which are formed by complex mental states such as goals, intentions, and emotions. One of the approaches to implementing cognitive systems in robots is to mimic the human cognitive processes that allow humans to interact with environments [1-2]. Although this subject has not been fully explored in the cognitive and brain science areas yet, some applicable cognitive architectures have been proposed to simulate a human cognitive process or for implementation as artificial cognitive agents [3-4].

As accessibility to personal history information has increased through many internet-based systems, user-adaptive service robots are promising in terms of providing personalized services to users according to their interaction history rather than simply responding to the user requests [5]. In order for the cognitive capability of user adaptation, the system should have a user knowledge model which is capable of inferring user preferences in the environmental context, learning by interaction, and allowing to plan robot actions based on the knowledge.

This paper proposes an adaptive dual-layer user model representing personal preferences for services in an environmental context, and a descriptive service recommendation system for user-adaptive service robots based on the user model. The qualitative and quantitative evaluations of the system were performed with a coffee recommendation service robot scenario. The remainder of this work is organized into the related work in Section II; a dual-layer user preference model in Section III; simulation and results in Section IV; and conclusion in Section V.

II. Related Works

One of the personalized services based on the user model is Internet service [6]. [7] proposed an item recommendation system for an online book store (Amazon.com), and [8-9] utilized corrected user web search history to generate conversational recommendations to the user. The way of constructing a user model is categorized as content-based filtering [10], collaborative filtering [11], and combined filtering [12-13]. Content-based filtering is the investigating of attributes of an item in order to recommend a new item that has the same

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S. Koo is with the Department of Mechanical Engineering and Human-Robot Interaction Center, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea (e-mail: koosy@robot.kaist.ac.kr).

K. Park was with the Department of Mechanical Engineering and Human-Robot Interaction Center, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea. He is now with the Hyundai Motor Company (e-mail: kirupark@hyundai.com).

H. Kim is with the Network Robot Research Team, Electronics and Telecommunication Research Institute (ETRI), Daejeon, Korea (e-mail: hyunkim@robot.kaist.ac.kr).

D. Kwon is with the Department of Mechanical Engineering and Human-Robot Interaction Center, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea (corresponding author to provide phone: 82-42-350-3042; fax: 82-42-350-8240; e-mail: kwonds@robot.kaist.ac.kr).

attributes, while collaborative filtering is using the history of others who selected the same item [14].

However, these methods for the web-based applications are limited for the dynamic adaptation to the user, and the learning should take place online in the human-robot interaction. The adaptive user model in this work is used to personalize user knowledge of services by interacting with a human. In order to handle the knowledge of both associations of attributes and symbolic rules between services and contexts, a dual-layer user model is proposed.

III. A DUAL-LAYER USER PREFERENCE MODEL

A. Architecture of User Preference Model

One of the approaches to describe the human cognitive process is a dichotomy of implicit and explicit knowledge [15]. Implicit knowledge is inaccessible, imprecise and subsymbolic, while explicit knowledge is publicly accessible, precise and symbolic.

To represent human knowledge by interaction, the explicit knowledge process has to handle symbolic data for human knowledge, which is a set of rules consisting of condition-conclusion pairs. This is useful for symbolic processes such as dialog managers, task planners and rule-based programming, which can be applied to various service applications. The implicit knowledge process means understanding the relation between environmental contexts and human states by the connection of their attributes, which are perceived as unit sensor data or characteristics of the symbols.

Fig 3 shows the dual-layer user preference model with descriptive recommendation and learning processes.

A context consisting of several attributes is an input of top and bottom layers of the user preference model. The bottom layer is a probabilistic associative memory that is a set of networks between attributes of context and services. The probabilities of services associated with the context produces a ranked service list. Some salient

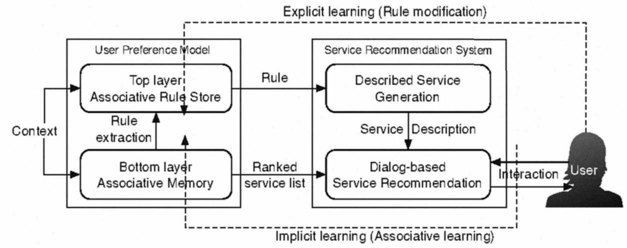

Fig.3. A dual-layer user preference model

associations of contexts and services are extracted to the associative rule store in the top layer. The rules are explicitly accessible and a distinct service corresponding to a context input is produced according to the rules. The rules are used to generate a description of the service recommendation. If the rule exists in the context input, the service recommendation system recommends the produced service to the user with a dialog-based description; otherwise, the ranked service list, which is the output of the bottom layer, is provided to the user. This dual-layer user preference model can be learned explicitly and implicitly by the interaction with a user. Explicit learning means the user can access the rule store and modify the rules directly, while implicit learning is the process of associative learning in the bottom layer.

B. Bottom-Layer: Probabilistic User Model

The implicit user model in the bottom layer is a form of associative memory neural network, as in Fig 4 [16].

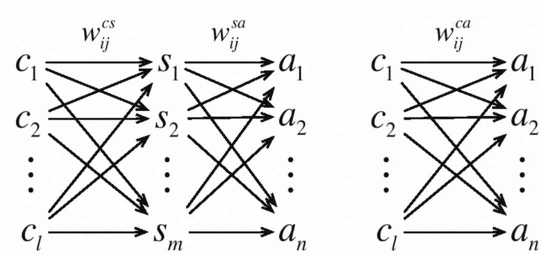

Fig.4.Associative memory in the bottom layer

The input nodes of the network are attributes of input context C, each of which is a dimension-value pair.

$$C = \{c_1, c_2, ..., c_l\} \quad (1)$$

S is a hierarchical set of services, s_i, which is a node of the network. An attribute of the services, a_i, is also a dimension-value pair.

$$S = \{s_1, s_2, ..., s_m\},\ A = \{a_1, a_2, ..., a_n\} \quad (2)$$

The association between a service and a service attribute is expressed by the weight w_{ij}^{sa}, which has a value of one or zero; these values are predefined in the service-modeling step. The associations between a context attribute c_i and services, S, or service attributes, A, are expressed by the normalized weights.

$$w_{ij}^{cs}, w_{ij}^{ca} \in [0,1],\ \sum_j w_{ij}^{cs} = \sum_j w_{ij}^{ca} = 1 \quad (3)$$

In the implicit learning step, inputs are context attributes and service, c_k, s_t, activated simultaneously. The weights, w_{ij}^{cs}, w_{ij}^{ca}, are learned by the delta rule of associative learning.

$$\Delta w_{kj}^{cs} = \gamma_{cs} P(c_k)(d_j - w_{kj}^{cs}),\ d_j = \begin{cases} 1 & if\ j = t \\ 0 & otherwise \end{cases} \quad (4)$$
$$\Delta w_{kj}^{ca} = \gamma_{ca} P(c_k)(d_j w_{tj}^{sa} - w_{kj}^{ca})$$

The inference step of the bottom layer is used to calculate the probabilities of service and attribute preferences of the user for the given context C, as in (5) and (6). w_i^c is the normalized weight of the context attributes.

$$P(s_j \mid C) = \sum_{i \in input} w_i^c P(c_i) w_{ij}^{cs} \quad (5)$$

$$P(a_j \mid C) = \sum_{i \in input} w_i^c P(c_i) w_{ij}^{ca} \quad (6)$$

In order to extend (5) to the hierarchical service, the child service preference probability is calculated as in (7). λ is a normalized factor to make the sum of probabilities in the same level equal to one.

$$P(s_j \mid C) = \lambda \prod_{k \in parents} P(s_k \mid C) \sum_{i \in input} w_i^c P(c_i) w_{ij}^{cs} \quad (7)$$

C. Top-Layer: Rule-based User Model

The top-layer is an association rule store consisting of condition-conclusion pairs. This rule is extracted from one association in the bottom-layer, which means that a condition is a context attribute and a conclusion is a service or a service attribute. Each rule has two additional values, confidence cnf and support spt, which define the certainty of the rule [17].

$$cnd_i \rightarrow cnc_j(cnf_{ij}, spt_{ij})$$
$$cnf_{ij} = \frac{n(i \cap j)}{n(i)},\ spt_{ij} = \frac{n(i \cap j)}{n(total)} \quad (8)$$

The confidence value stands for the certainty of occurrence of j when i appears. The support value means the maturity of the rule because it is the frequency of the rule in the total cases.

The process of rule extraction is used to construct a rule from the salient associations in the bottom-layer. Because the entropy represents the degree of energy distribution of a group, the entropy of a group k for the context attribute i is used to define the saliency of the group.

$$S_{ik} = \frac{\sum_{j \in group\ k} -w_{ij} \log_2 w_{ij}}{\log_2 n(j \in group\ k)} \quad (9)$$

A group can be a set of services in the same category or a set of service attributes having the same dimensions. The association of the highest probabilities in the group k is extracted to the new rule when the S_{ik} is less than a threshold value.

$$if\ S_{ik} < th_S,\ \begin{cases} cnd_i = \operatorname*{argmax}_{c_i} P(s_j \mid c_i) \\ cnc_j = \operatorname*{argmax}_{s_i} P(s_j \mid c_i) \end{cases} \quad (10)$$

If a group k is the attribute group, s_j is replaced with a_j.

The extracted rules are stored in the hypothesis rule store to be tested as to the validity of the rule by the confidence and support values. The role of this hypothesis region is to maintain the independence of the top-layer and bottom-layer in the explicit and implicit learning step. Fig. 5 shows the inter-layer implicit learning step.

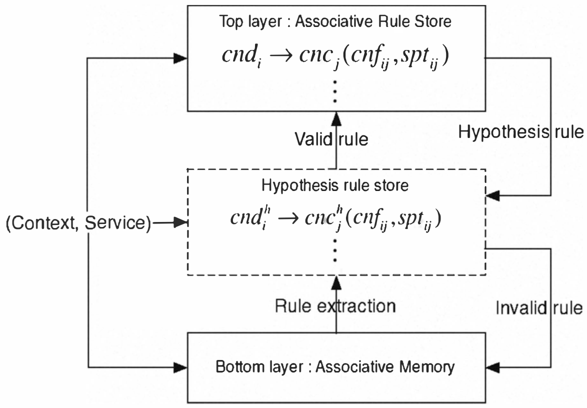

Fig.5.Rule extraction and hypothesis rule test process

When a context and service are activated, the association is learned in the bottom-layer, and if there is the rule, the confidence and support values are also updated in the hypothesis region and top-layer. The updated rules are tested as shown in Fig. 6; valid rules are stored in the top-layer, hypothesis rules are in the hypothesis rule store, and invalid rules are released in the bottom layer.

In the explicit learning case, a user removes or generates a rule explicitly. The hypothesis region plays the role of a buffer to update the associations in the bottom-layer. Because the bottom-layer stands for the history of the user, the explicit learning should not affect the history directly, but if the modification is true, the bottom-layer would be learned by the future history.

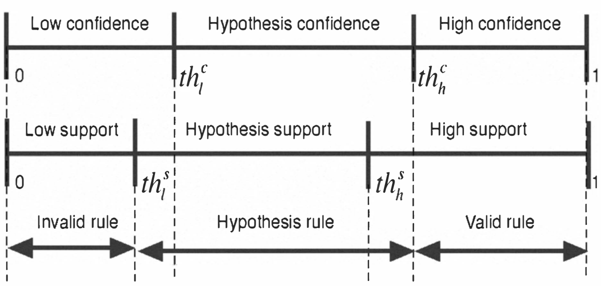

Fig.6.Hypothesis rule test

In the associative rule store, the generalization and specification processes update rules. The rule generalization is used to combine conditions having the same conclusion. If the combined conditions cover all values in a dimension, the corresponding conclusion is always true regardless of the condition of the dimension; this is a general rule. The specification process is used to specify the service in the hierarchy having the same conditions. These processes make rules more practical to the user.

D. *Descriptive Service Recommendation*

One of the advantages of the top-layer associative rules of user knowledge is the possibility of describing the reasoning process explicitly. The proposed system recommends a service to the user with a dialog-based description in order to explain the reason of the recommendation. Fig 7 shows the processing flow of the descriptive recommendation.

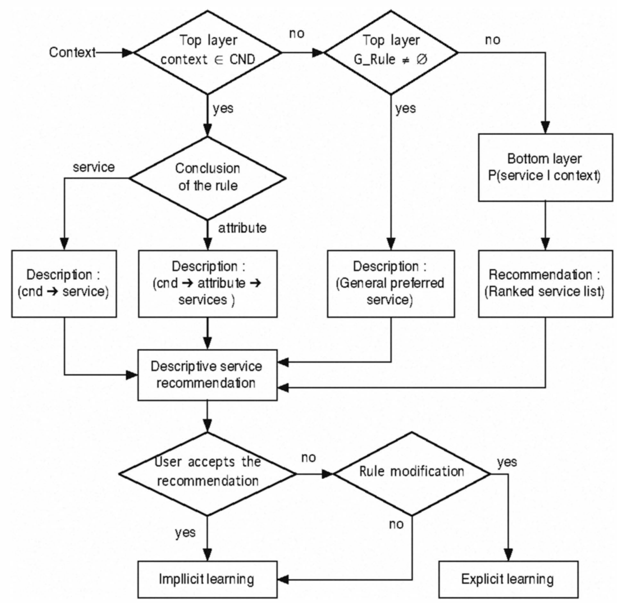

Fig.7. A flow chart of descriptive recommendation generation

When there is a specific rule for the input context, the description is used to explain the condition and the conclusion, such as 'You prefer the *conclusion* normally in this *context*.' If there is a general rule, the description is used to explain the user's general preference, such as 'You prefer the *conclusion* usually.' In the case in which the conclusion is a service attribute, the description can recommend several services associated with the attribute, such as 'You would prefer the *services* related with the *conclusion* in this *context.'* These descriptions are provided to the user with service recommendations.

On the other hand, if there is no rule, the system can provide only a ranked service list generated from the bottom-layer without any certain description.

The implicit learning is performed by the user's acceptance or rejection of the recommendation. If the user rejects the recommendation and wants to modify the preference rules, explicit learning is executed.

IV. Simulation and Results

A. Coffee Recommendation Robot Scenario

In order to simulate and validate the proposed user preference model, the model was applied to a coffee recommendation system. The objectives of the simulation are to find the user's qualitative and quantitative evaluations of the user-adaptive descriptive recommendation system. The context, service and attributes of the coffee recommendation scenario are modeled under the assumption that the time, temperature, and brand can affect the preference of coffee selection, as shown in Fig. 8.

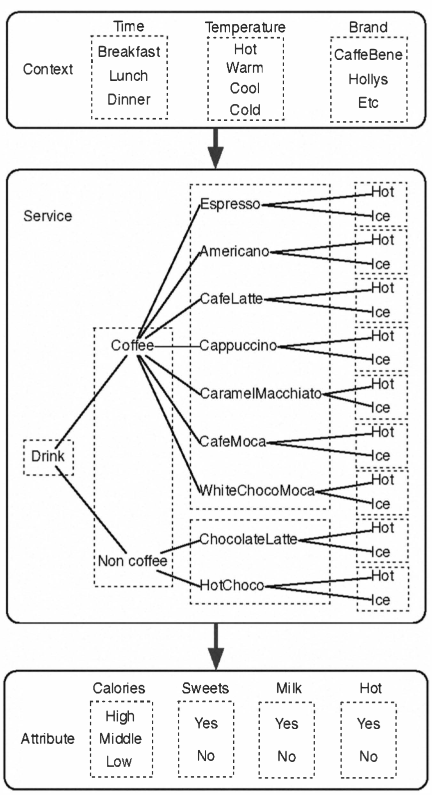

Fig.8.Context-service-attribute model for coffee menu scenario

This model is represented in XML format, and the recommendation system is configured by the model. The recommendation system is prodeced as software with a Graphic User Interface (GUI) for menu and text display, a robot agent and user menu selection, and Text to speech (TTS) device for dialog-based descriptive recommendations.

B. Result

In order to evaluate the proposed system, the performances of three recommendation methods were investigated and compared: recommendation with a dialog-based description, display result only, and random recommendation. The quantitative performance is measured by the acceptance rate of the recommendations, and the qualitative performance is measured by a survey given to the user about the degree of friendliness, satisfaction, reliability and persuasiveness to the system. The subjects were 9 people (8 men, 1 woman) ranging from 20 to 30 years old, who used to drink more than a cup of coffee a day. They performed 36 recommendation episodes of randomly selected all contexts for each of the methods. The dialog-based descriptive recommendation method adapted to the user during an episode and recommended the service with a description through TTS. The result-only method also adapted to the user and displayed the recommended services through GUI. The random recommendation method did not adapt to the user and suggested a randomly generated service.

The questionnaire items were 12, three different items for one question for reliability. Table I shows the significant results of ANOVA tests for the five evaluations. The acceptance rate is the percentage of the frequency of user acceptance of the recommended service in an episode. The user-adapted recommendation was significantly higher than the random recommendation because it reflected the user's preference via the learning processes.

TABLE I
ANOVA USER TEST RESULTS FOR THE PROPOSED SYSTEM

Evaluation	Method	Mean	STD	p-value
Acceptance rate [%]	Descriptive	90.98	4.53	0.00000423
	Result only	91.35	2.08	
	Random	37.96	5.74	
Friendliness [point]	Descriptive	5.52	0.84	0.00000115
	Result only	4.52	1.15	
	Random	2.3	0.92	
Satisfaction [point]	Descriptive	6.15	0.91	0.00000231
	Result only	4.70	1.38	
	Random	2.37	1.20	
Reliability [point]	Descriptive	6.11	0.87	0.00000011
	Result only	4.85	1.25	
	Random	2.67	0.37	
Persuasiveness [point]	Descriptive	5.85	0.73	0.0009
	Result only	4.74	0.98	
	Random	3.44	1.62	

The four qualitative evaluations were measured by 7-point scale questionnaires. The descriptive recommendation methods significantly make users feel welcome and satisfied, and seem like reliable and persuasive methods for the system, especially more so than other methods.

V. CONCLUSION

In this paper, we proposed a dual-layer user preference model for a descriptive recommendation system. The probabilistic associative memory in the bottom-layer implicitly represents associations of user preference between attributes of context and services; the association rule store in the top-layer has explicit user preference rules between contexts and services. The two layers can be learned by implicit interaction or by explicit user feedback, which is a process of user adaptation. The rule extraction from the bottom-layer to the top-layer is performed by the concept of entropy. The rules can be utilized to generate a dialog-based description of the recommendation for the user.

The concept of a dual-layer user model and the hypothesis rule test contributed to generate a user-adaptive service recommendation with a dialog-based description; this is applicable not only to improving recommendation performance, but also to improving user mental satisfaction concerning the system. However, the system was tested only in simulation software, and the situation was given to the user by text. The proposed system will be applied to service robots, and other related problems for user-adaptive services will be issued, such as user identification and long-term interaction, in further works.

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