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Machine Learning Based Adaptive Context-Aware System for Smart Home Environment

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Abstract

Context-awareness is the key element for building a smart home environment. The goal of a smart home is to predict the demand of home users and proactively provides the proper services by considering the user's context information. Several methods are used in context-aware system to provide services. Machine learning based approaches are capable to make better prediction and adaptation than others. In this paper, we present 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. This approach indicates better adaptation for context-aware service due to the low error rate.

***Keywords**: Back propagation Neural Network, Context-awareness, Smart home, Temporal Difference class Reinforcement learning*

1. Introduction

Context-aware system in smart home provides the services that maximize the user's comfort and safety while minimizing the user's explicit interaction with the environment. In general, a set of rules have to be specified for the possible contextual configurations and each rule is assigned to a specific service in context-aware system. This is a common problem to determine and limit the set of possible context configurations. Instead of rule base approach we use machine learning to predict all possible and meaningful context configurations. This machine learning approach can use previous choice about the service and can adapt itself by new choice about service from user feedback information. ACHE (Adaptive Control of Home Environments) is an adaptive house that controls the comfort systems of a home such as lighting, ventilation, and air and water heating [1]. The objectives of ACHE are the prediction of inhabitant actions and the decrease of energy consumption. It tries to decrease the need for manual control of the systems by anticipating the need to adjust them. The MavHome (Managing an Intelligent Versatile Home) project uses multi-agent systems (MAS) and machine learning techniques to create a home environment that is able to act as a rational agent [2]. The Essex intelligent Dormitory (iDorm) is a test-bed for ambient intelligence and ubiquitous computing experiments [3]. The iDorm embedded agent contains the most intelligence in the dormitory. It receives the sensor values, computes appropriate actions using the learnt behavior of the user as a reference and sends the actions through the network to the actuators. Mahalanobis distance based K nearest neighbors classifier technique is proposed in [4]. Our aim is to use different techniques of machine learning approach to develop the context-aware application. This context-aware application can provide service proactively by using two different types of learning algorithm in real smart home environment [5]. One of the most

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famous and interesting learning algorithm, back propagation neural network, is used in the service selection module of context-aware application section. The sets of predefined context configurations are served as the training set to the back propagation neural network. The user preferences (choice for services) may change over time, so we propose an adaptive learning algorithm in adaptation module of context-aware application section. Adaptation module uses Temporal Differential (TD) class of reinforcement learning algorithm. The benefit of this algorithm is that it does not need predefined models of the environment and it can learn the model from user's feedback to the service provided by the system.

The organization of this paper is as follows. In Section 2 we describe our proposed method in details. Section 3 presents the implementation environment followed by conclusion in Section 4.

2. Proposed Method

We have followed three layers architecture for the context-aware system [6]. These layers are sensor layer, middleware layer and application layer. In sensor layer various types of sensors are installed to collect environmental information. The middleware layer plays a vital role for context-aware system. The middleware is responsible for context modeling, context reasoning and controlling the sensors, appliances and devices based on the decision from context-aware application layer. In this paper, we will focus on context-aware application layer and use machine learning technique for making the context-aware system adaptive. The context-aware application layer consists of several modules for specific task as shown in Figure 1. The context-aware application layer provides different types of services such as Morning call service, Dinning service, Entertainment service, Sleeping service and Guarding service according to the current contexts.

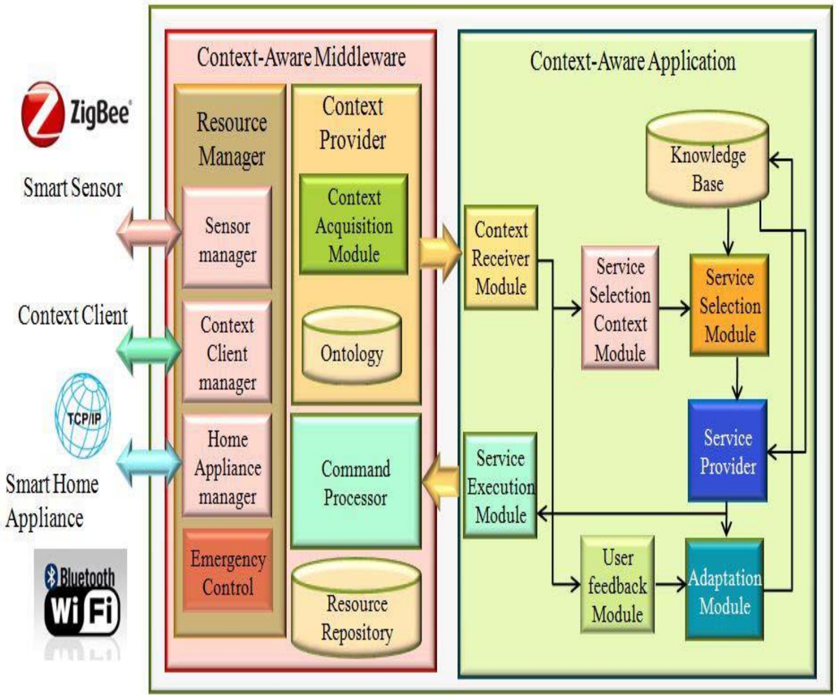

Figure 1. Block Diagram of Machine Learning Based Adaptive Context-aware System

2.1. Context Receiver Module

Context receiver module receives predefined context information from context provider. Context information is classified into service-selection information and user feedback. Some context information (Person ID, Location, Time, Day and Activity) those are used for selecting services are called service-selection information. After providing the service by the application, user's satisfaction can be explicitly or implicitly obtained by user feedback information. A details explanation of user feedback is added in the user feedback module and adaptation module sections. Service-selection context module detects service-selection information element and sends it to service selection module.

2.2. Service Selection Context Module

We have chosen five information elements: person ID, location, time, day and activity as service selection information. Context elements are specified by a set of values as shown in Table 1.

Table 1. Context Elements with Values

Context elements	Context elements values
Person ID	Father, Mother, Son, Daughter, Grandmother, Grandfather
Day	Workday, Holiday
Time	Morning, Noon, Afternoon, Evening, Night, Late night
Location	Outside, Bedroom, Living room, Toilet, Kitchen, Hallway
Activity	Standing, Sitting, Walking, Reading, Lying

Context elements can be defined as $E=\{E_1,E_2,E_3,\ldots.. \; E_n\}$, where $E_1=\{x_{11},x_{12},\ldots.x_{1last}\},\ldots\ldots. \; E_n=\{x_{n1},x_{n2},\ldots.x_{nlast}\}$,$x_{ij}$ represents j th value of i th context elements. We can define each context configurations by a set of 5-tuples i.e $C_i=\{x_{1i},x_{2i}\ldots\ldots\ldots..x_{ni}\}$. Examples of some context configurations are as C_1={Father, Holiday, Morning, Bedroom, Lying}, C_2={Daughter, Workday, Evening, Living room, Reading }, C_3={Mother, Workday, Night, Kitchen, Sitting}.

2.3. Service Selection Module

We need to map each service-selection context configuration to the appropriate service depend on the values of context elements. For examples, C_1={Father, Holiday, Morning, Bedroom, Lying}>> Morning Call service, C_2={Daughter, Workday, Evening, Living room, sitting }>> Entertainment service, C_3={Mother, workday, Night, Kitchen, Sitting}>> Dinning service. This context configuration will serve as a training data set to a supervised learning algorithm. Back propagation neural network is used in this paper. Architecture and characteristics of back propagation neural network are shown in Table 2. For training set, we consider 28 context configuration sets of service-selection information.

Table 2. Architecture and Characteristics of the Back Propagation Neural Network

No of Inputs	Five neurons (person ID, location, time, day, activity)
No of Outputs	Five neurons (Sleeping service, Morning call service, Dinning service, Entertainment service and Guarding service)
No of Hidden Layers	3
Activation function	Sigmoid Function
Training Algorithm	Back propagation supervised learning
Learning Rate	0.7
Training Set	28
Test set	144
Training Time	1000
Mean Absolute Error	0.012

Whenever a new service-selection context is available then it will send to service selection module. Service selection module will provide decision based on the trained model.

2.4. Service Provider Module

Service provider module is responsible to describe the services as selected by the service selection module. Service provider uses knowledge base to get the description of the services. Service provider checks the service-selection context and determines the form of the services. Figure 2 shows the description of each service.

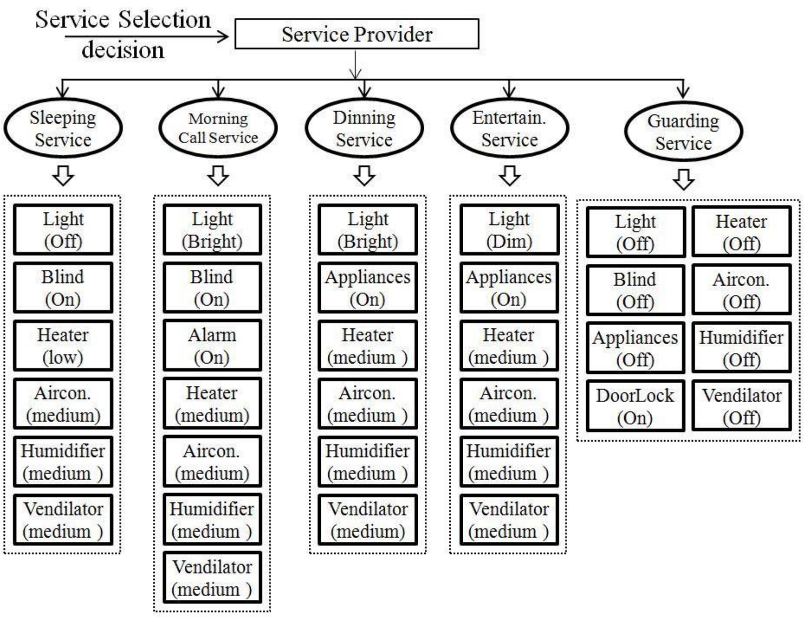

Figure 2. Description of Each Service Generated by Service Provider Module

2.5. Service Execution Module

Service execution module is an interface between middleware and context-aware application layer. It sends the information to command processor module in middleware architecture for execution.

2.6. User Feedback Module

This module receives implicit feedback and generates positive or negative reward values for explicit feedback. This explicit feedback is send to adaptation module. If users do not response for predefined time then it will calculate the feedback with the following equation

$$Feedback = \frac{User\ Stay\ time\ with\ service}{Total\ time\ for\ service} - 1$$

2.7. Adaptation Module

One challenge for the learning algorithm is that the user may change his behavior over time. Consider an inhabitant that used to turn on the TV every day at 7:30 p.m. but later changes his habit and turns it on at 6:30 p.m. So, it is not always practical to learn the user's behavior off-line instead an adaptive learning algorithm is needed [7]. We apply temporal differential class of reinforcement learning (RL) as an unsupervised algorithm in adaptation module. RL does not need predefined models of the environment and can learn the model from user's feedback to the service the system provides [8]. If the user is not satisfied with the service made by the system, (s)he is more likely to return to the previous service or to switch to a completely new one. There are two types of feedback, positive feedback and negative feedback. These feedbacks can be received by explicit input from the user or estimated implicitly. If Q(s,a) reaches a certain threshold value then the corresponding context and service is added as train data for neural network.

Adaptation module receives explicit or implicit user's feedback with every change in the service. Adaptation module records relative rate of negative feedback with service taken in every state for different state-action pairs and is updated according to algorithm 1 [9, 10].

Algorithm 1. Temporal Class of Reinforcement Learning

Variable a and a' denote actions taken by the algorithm in states *s* and s', *r* represents reward values (0 or -1), *Q(s,a)* represents the value of satisfaction with action *a* taken given state *s* for different state-action pairs.

1. Initialize *Q(s,a)* arbitrarily
2. Do forever:
3. Take action a, observe *r* and s'
4. Choose either the action a' with height $Q(s',a')$
5. $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma . Q(s',a') - Q(s,a)]$
6. $a \leftarrow a'$, $s \leftarrow s'$

2.8. Knowledge Base

Knowledge base stores the training sets of context configurations with service label. It also holds the description of services. When adaptation module makes any training sets of context configuration with service label then it is updated in knowledge base.

3. The Implementation Environment

Our test-bed is constructed in a 93.73 square meter apartment with 2 bed rooms, 1 living room, 1 toilet, 1 kitchen, 1 storage room and hallway. All rooms are equipped with sensors (temperature, humidity, CO2, illuminance, pressure sensor, and camera) smart device (door lock, blind, smart phone) and smart appliances (TV, refrigerator, washing machine, air conditioner, microwave oven, room heater, etc.). All sensors, smart devices and smart appliances are connected to a residential gateway. The role of the home gateway is to communicate among sensors, smart device, appliances and the control system. We have used Pallet OWL reasoner, OWL API and Java platform for implementation of our proposed application within this test-bed [11]. After running our program, we have made a manual verification of the selected service. We have noticed that there were only two errors in selection out of 144 context configurations. This low error rate satisfies that proposed approach is better suited for context-aware service adaptation.

4. Conclusion

It is challenging to control the complex and dynamic environment in smart home. A control system based on machine learning approach is necessary to achieve adaptive control in smart home environment. Rule-based approaches rely on rules for making any decision. If current condition does not satisfied the rules then rule-based approach will not provide any decision. In this paper, we have introduced learning mechanism to make the context-aware system adaptive. Machine learning approach ensures better mapping each context configuration to the appropriate service. Moreover low error rate indicates better adaptation for context-aware service. In future, we will try to include probabilistic approach with machine learning.

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