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Multiagent System for Home Automation

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Abstract: - Smart-home conception has emerged in recent years and played a very important part in the formation of future houses. Since the beginning of the smart-home era, home automation benefits have never overshadowed the cost of such systems. One of these costs is that there is always the need for home inhabitants to program the system to perform daily tasks. In this paper we present prototype of a system that overcomes this problem by giving the home enough intelligence to adapt to its inhabitants life style without the need for the inhabitants to exercise authority. The system makes use of multi-agent and prediction techniques to provide intelligent smart-home appliances automation. Results indicate that the technique applied in this research not only makes the system very fast and accurate but also makes it portable and cost effective.

Key-Words: - Smart-Home, Multiagent, FPGA, Prediction.

1 Introduction

A Smart-home or building is a home or building that is equipped with special structured wiring to enable occupants to remotely control or program an array of automated home electronic devices by entering a single command. Nippon Homes Corporation and other fifty companies in Japan first started smart-home concept in 1988. The project was named “Tron Smart House” which was fully automated consisting 380 computers, costing 1 billion Yen. After that many research groups such as IBM, Microsoft, MIT etc. are working in this area. Quite a reasonable number of smart home test beds have been setup for research, such as the MAVHOME [1].

The Artificial Intelligence (AI) designation; is the ability of a computer to perform rational tasks, such as reasoning and learning similar to human intelligence [2]. Unlimited AI related applications can be defined where concepts of human intelligence can be used. One such application is the smart-home appliances automation. The idea of smart-home appliances automation is to give the home appliances individually or as a group, enough intelligence to be self-controlled.

During the past years, AI, communication technologies and human machine interface have a great effect in representing the future living environment. Many research districts contributed to smart-homes. For instance many protocols, algorithms and appliances were invented to make present houses technologically more enhanced [3, 4, 5]. Smart home has advantages over ordinary living environment, since it provides safe and comfortable living environment. The benefit of this technology is even greater for elderly living people or disabled person. Smart home technology is also used to minimize disabling obstacles.

Although previous systems achieve the required home mechanization needs but most of the previous systems are software based and expensive to be implemented. Commercialization is probably the main reason why the general public did not use previous systems. In this paper we present a portable, low cost and fast hardware prototype of a multi-agent system that is designed to provide home automation without needing to be programmed. In this research, Field Programmable Gate Array (FPGA) will be used for the hardware prototyping.

In the next section we will look into the detail of the techniques used in the proposed system. The paper will illustrate the expected performance of the system. Furthermore future works will be discussed.

2 Research Methodology

One of the main goals of the system is to achieve low cost and portability with speed and efficiency. To achieve these goals this research decided to implement the system on hardware rather than software. The design target of this research is to have the smart-home divided into separate sections or rooms such as living room, bed rooms etc. consisting many agents. Each agent will be responsible to automatically adapt the inhabitant's life style and automate the appliances usage. The agents are homogeneous and non-communicative. The only communication that the agents can perform is to share the overall environment state of the whole smart-home so that better predictions and device automations can be made.

To communicate with the outside world the system can translate X10 protocol packets and generate X10 packets to send commands to a home appliance. The X10 "receive module" is used to receive and decode the X10 packet. It receives the 13 bit parallel data of the packet and based on the information contained in the packet, the unit generates a message to each agent environment state maintainer. When the device state maintainer receives the message it updates the local view of the agent devices state.

The system is triggered by events. The events are time driven and controlled by a system clock. Home inhabitants can choose the time frame for the event to be triggered. Each time an event trigger is generated the agents will issue a device command based on their learned knowledge that were gathered by monitoring the user's everyday device interactions.

The main agent units are the prediction unit, decision unit and communication unit. The "prediction unit" is modeled using the "Active-Lezi" algorithm" [6]. The unit is responsible for predicting the future environment state based on the current environment state. The "decision unit" is modeled using techniques of "Reinforcement learning" where the algorithm used for modeling is Q-Learning [7].

The use of "prediction unit" with the "decision unit" increases the system performance since it is sometimes undesirable to directly predict and operate a particular home appliance. The reinforcement learning techniques is needed so that the agent learns from previous experience not letting the "prediction unit" performs unnecessary action.

The "communication unit" is responsible to handle communication between the agents. Since the agents are homogeneous, thus they share the same implementation and goals. Therefore the information one agent needs to share with the other agents is the environment state of the whole home as illustrated in Fig.1.

Before plugging the system to a particular home environment the system needs to be trained offline. Collecting sample devices interaction pattern data of a particular home does the training. The "training unit" is responsible for performing this kind of training. The training is very important because better home automation is achieved through the increase of trainings. For detailed system superficial overview, refer to Fig. 2.

2.1 Decision Unit

The "decision unit" of the system is modeled using Q-Learning algorithm. Q-Learning is a reinforcement learning technique that works by learning an action-value function that gives the expected utility of a given action in a given state.

Given the environment devices states as [S], and the device actions taken on a given environment state as [A], the Q value array of reinforcement learning can be shown in equation 1.

$$Q = S \times A \tag{1}$$

According to Q-Learning algorithm the Q value array is used to store rewards the agent has received by performing a particular action at a given environment state. Each time the agent makes a correct decision, the agent is given a positive reward or a negative reward. The reward is calculated based on user feedback to the agents performed action, which can be sensed by the system through monitoring the devices state constantly.

The Q value function is calculated as shown in equation 2.

$$Q^*(x,a) = (1-\alpha)Q^*(x,a) + \alpha(r + \gamma V^*(y)) \tag{2}$$

where Q^* is the Q-learning value function, x is the environment states, a is the action that can be taken, α is the learning rate, γ is the value of future reinforcement and V* is the future Q-learning value function.

2.2 Prediction Unit

The "prediction unit" is modeled using the Active-Lezi algorithm [6]. Active-Lezi is an online predictor that can be used to predict the future environment state and supply the decision unit with possible actions that can be taken for a particular state.

Active-LeZi algorithm is an enhancement of both "LZ78" and "LeZi-Update" algorithms. It incorporates a sliding window approach to address the drawbacks of both "LZ78" and "LeZi-Update". This approach demonstrates various other desirable characteristics as given below.

- The core model of Active-Lezi algorithm is "Growing-Order-Markov" model based on "LZ78" algorithm, therefore Active-Lezi accomplish optimal predictability.

- Active-Lezi stores more information, which implies that as the input sequence (the experience) grows, the algorithm performs better. This is a desirable characteristic of any learning algorithm.

After simulating Active-Lezi algorithm by using input data pattern with high noise shows that the simulation is very desirable since the algorithm achieves prediction of 100%. The simulation result is shown in Fig. 3 [6].

3 Results and Discussion

The aim of the research is to implement the multiagent system for home automation. The system is still under development, and so far it is being tested at the early stages using synthetic data generator.

Device usage patterns need to be generated to test the system for a particular home. The data is generated randomly to stimulate the device usage scenarios of a particular home. The scenario includes the time, the event occurred, and the action performed by the user for a particular device. Sample synthetic data is shown in Table 1.

According to the results it is observed that the system can achieve more accurate automation based on the number of patterns that is used to train the system. Fig. 4 illustrates the accuracy of the system using nine months of training data patterns. By looking at the graph it is demonstrated that at the early stages of the testing the accuracy is low, due to the fact that the system did not learn the inhabitants life style. To increase the accuracy of the system more data need to be fed to the system. From the graph it is shown that when supplying the system with nine months of device usage patterns, the system performs better and the accuracy is increased.

Comparing the proposed system to other smart-home projects such as the MAVHOME and "The Neural Network House" [8, 9], it is observed that this system is faster due to the fact that it is hardware based. Also the system is very accurate according to the results obtained. Another point that needs to be mentioned is that since the system is based on multi-agent, it is able to adapt to more than one inhabitant's life style.

4 Conclusion

The aim of this research is to give an overview of smart-home multiagent system for home automation and to illustrate the methodology that is being used for implementing the system for hardware prototyping. The simulation result is promising and shows sufficient and higher performance than existing methods. The design is now be modeled using VHDL and synthesized. Later it will be downloaded in FPGA for further testing and analysis, which will be the actual hardware prototype of the device. Since the system is hardware based and also makes use of multiagent techniques, therefore this research expects the system to be portable, cost effective, and fast.

References:

[1] M. Coen., Design principles for Intelligent Environments, AAAI Spring Symposium, Stanford, pp. 36-43, 23rd - 25th March, 1998.

[2] Edwin Heierman, Diane Cook, Improving Home Automation by Discovering Regularly Occurring Device Usage Patterns, ICDM Third IEEE International Conference on Data Mining, Florida, USA, pp. 537- 540, 19-22 Nov. 2003,

[3] R. Hamabe, M. Murata, and 1. Namekawa, Home Bus System (HBS) Interface LSI and its Standard Protocol Example, IEEE Trans. Consumer Electronics. vol. 36, no. 4, pp. 949-953, November 1990

[4] Kashiwamura. H. Koga, and Y. Murakami, Telecommunications Aspects of Intelligent Building, IEEE Commun. Mag., vol. 29, no. 4, pp. 28-40, April 1991

[5] CK Lim, PL So, E Gunawan, S Chen, TT Lie, YL Guan, Development of A Test Bed for High- Speed Power Line Communications, Int'l. Conf. Power Sys. Tech., Perth, WA, Australia, vol. 1, pp. 451–56, 4th –7th December 2000

[6] Karthik Gopalratnam, Diane J. Cook, Active LeZi: An Incremental Parsing Algorithm for Sequential Prediction, FLAIRS Conference, St. Augustine, Florida, USA, pp. 38-42, 12th –14th May 2003.

[7] Reinforcement Learning An Introduction, The MIT Press, ISBN 0262193981

[8] Cook, Youngblood, Heierman, MavHome: an agent-based smart home, Proceedings of the First IEEE International Conference, Fort Worth, Texas, USA, pp. 521-524, 23-26 March 2003.

[9] M. Mozer, The Neural Network House: An Environment that Adapts to Its Inhabitants, Proc. AAAI Spring Symp. Intelligent Environments, tech. report SS-98-02, AAAI Press, Menlo Park, Calif., pp. 110–114, 1998.

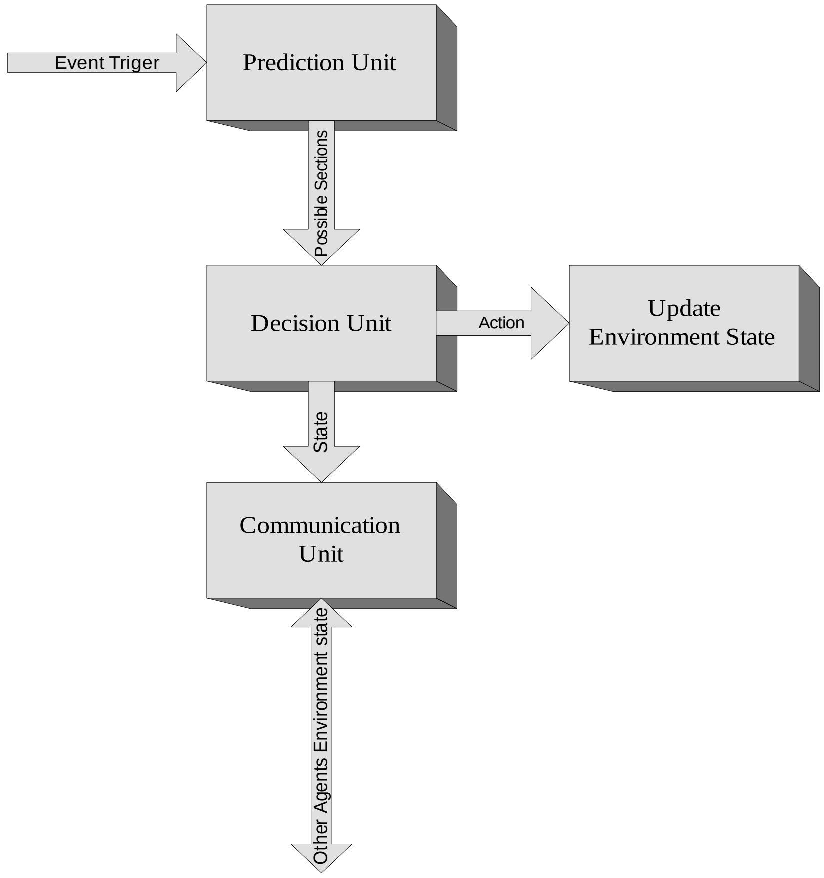

Fig. 1 The agent illustration diagram.

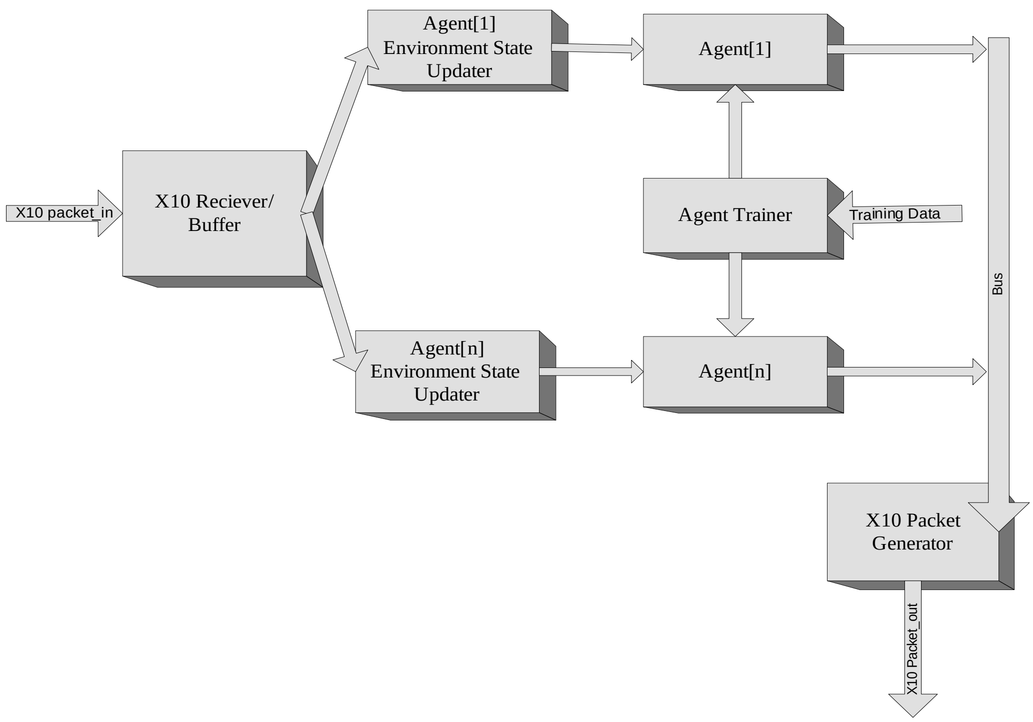

Fig. 2 Superficial illustration diagram of the system.

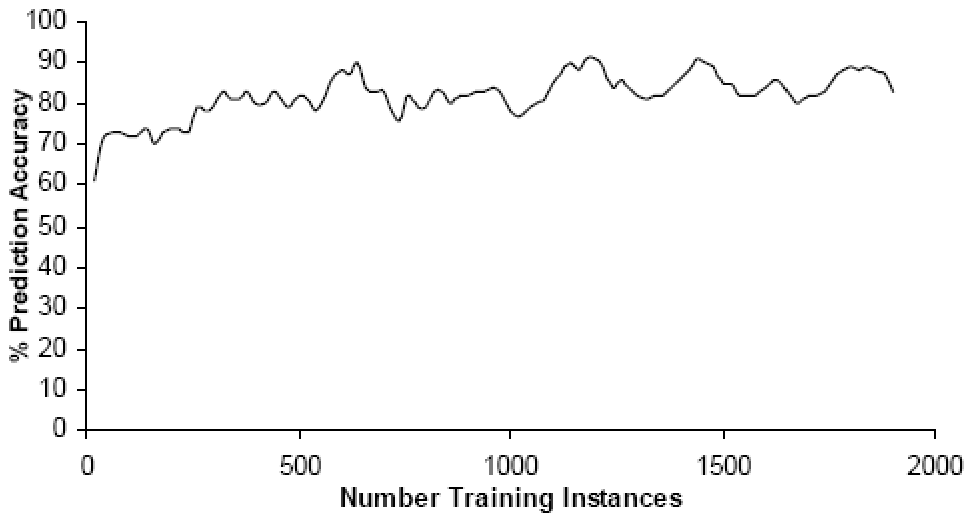

Fig. 3 Graph showing the prediction accuracy of Active-lezi.

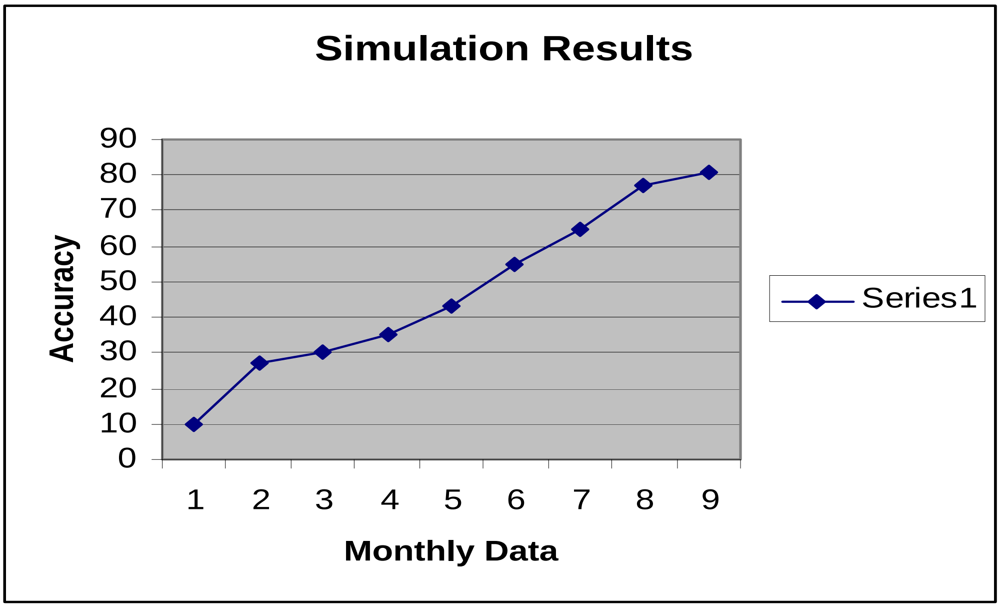

Fig. 4 Graph illustration of the simulation results.

Table 1 Sample synthetic data used to train the multiagent system.

Date and Time	**Action**	**Device**	**Location**
2006-03-03 / 09:21	On	Lamp1	Living Room
2006-03-03 / 10:26	Off	Fan1	Bedroom
2006-03-03 / 10:29	On	Tv1	Living Room
2006-03-03 / 18:21	Off	Lamp1	Living Room
2006-03-03 / 20:22	Off	Tv2	Bedroom