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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR ADVANCED SMART HOME IMPLEMENTATION

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ABSTRACT: Smart-home concept has been around for many years and played a very important part in the design and implementation of future houses. Early research focus on the control of home appliances but current trends are moving into a creation of self-thinking home. In the recent years many research projects were performed utilizing artificial intelligence tools and techniques. This article highlights research projects employing multi-agent system, 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. This article provides platform for future relative studies between different algorithms, architectures and serves as a reference point for developing more cutting edge smart home technologies.
KEYWORDS: Smart home, multi-agent system, action prediction, artificial neural network, fuzzy logic, reinforcement learning

INTRODUCTION

In the early years, smart home 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. This provide convenient interface for homeowner to remotely switch appliances on or off, arm a home security system, control temperature gauges, control lighting, program an entertainment system or home theater, and carry out other related tasks [1].

The current research projects focus more on the creation of intelligent home, a home that is able to control and make decision on its own, which follow the guidelines set by occupants directly and indirectly. Due to this trend, the artificial intelligence (AI) is greatly used in the recent smart-home research. AI is the ability of a computer to perform tasks such as reasoning and learning that human intelligence is capable of doing.

In this article we will give a detailed illustration of how AI techniques are being used in the latest smart home projects.

MULTIAGENT SYSTEMS FOR SMART HOME

A multiagent system (MAS) is a system composed of several agents, capable of speedy mutual interaction between them [2, 3]. This can be message passing or generating changes in their common environment. The agents can be autonomous entities e.g. robots or software agents. MAS can consist of human agents as well. MAS allows the sub problems of a constraint satisfaction problem to be subcontracted to different problem solving agents with their own interests and goals. Each agent in MAS has a set of goals and capabilities. The agent also consists of an intelligent and reasoning unit. The responsibility of this particular unit is to implement a plan on how to use these capabilities in order to achieve the given goals.

A multiagent architecture was developed by Jae Chul Moon and Soon in 2000, for intelligent home network services, which organize heterogeneous and distributed home devices effectively [4].

The architecture consists of several agent spaces that are interconnected to each other with very powerful and flexible model known as Tuple model, was proposed by Carriero and Gelertner in 1980's, for supporting extremely dynamic communication and coordination patterns [5].

An agent autonomously handles a specific home device, a room-net or several other agents using the agent spaces and the space interconnect, in which status of all devices can be transparently accessed despite of the location of the agent. Due to the location transparency, an agent or a newly attached home device can easily get the information of another agent by taking or reading the information from the agent space as shown in Figure 1. The multi-agent architecture of Jae and Soon is very novel since it provides flexible communication between the agents with asynchronous stream channel of IEEE1394 using event-driven middleware. It supports data transfer rates of up to 400Mbps and 800Mbps in 1394a and 1394b respectively.

The only limitation is that the architecture does not support mobility of agent, which is actually the limitation of the Tuple model.

In 2002, Cheng-Fa Tsai and Hang-Chang Wu (2002) came out with another multiagent architecture for home network services named as MASSIHN [6]. The architecture uses Java as its programming language

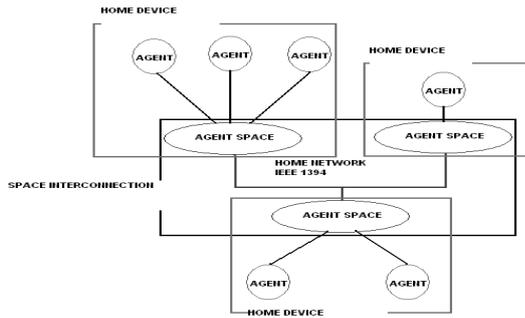which solves the problem of mobile agent in the previous architecture of Jae and Soon (2000) [4].

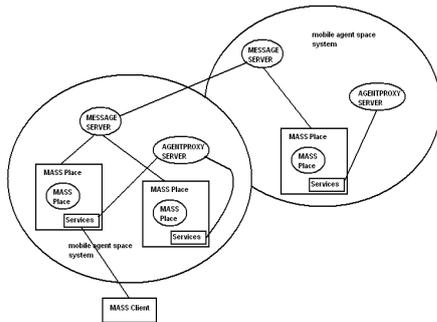*Figure 1. Overview of Jae and Soon System Architecture*

Figure 2. MASS System Architecture Overview

The proposed architecture uses Extensive Markup Language (XML) as a control language. The MASSIHN of Cheng-Fa and Hang-Chang has six major components: message server, MAS space, proxy server, services, agents and MAS clients. These components perform various operations in the system. The mobile agent space system architecture and their relationships are illustrated in Figure 2. Particularly, each space in MASS can be considered as a distributed computing group. A message to the MASS can be sent by the message server. If they want to join the space, all of the MASS Places have to register at the message server. Experimental results showed that this design is much more efficient than the previous architecture of Jae and Soon (2000) [4]. In 2010, a multiagent system to track the user for task isolation was proposed by Alam et al [7]. The algorithm clusters the smart home events by isolating opposite status of home appliance [7].

ACTION PREDICTION FOR SMART HOME

To adapt to the occupants and meet the goals of comfort and efficiency, an intelligent environment should be able to acquire and apply the knowledge about its occupants. These capabilities are based upon the effective prediction algorithms. Prediction is based on observations, experience, and scientific reasoning. Given the smart-home device usage pattern data, we can use this data to train the prediction algorithm to forecast the future action that a home inhabitant might perform.

In 2003, Diane J. Cook, Michael Youngblood, Manfred Huber and Karthik Gopalratnam developed two learning algorithms as a part of the MAVHome smart home project [8]. The first algorithm predicts actions that the occupant will take in the home. The second one learns a policy to control the home. Given a prediction of inhabitant activities, MAVHome can decide whether or not to automate the daily activities, which includes switching on or off

particular device or activating the security system when the inhabitants are not in the house or improve the activity to meet the house goals. The smart-home inhabitants repeated usage of various devices in their daily activities leads to conclude that the sequence can be modeled as a stationary stochastic process. Diane et. al. used the Markov predictors based on LZ78 family of comparison in their algorithm. For prediction, the algorithm computes the probability of each action in the parsed sequence, and predicts the action with highest probability. The experimental results show that the algorithm predicts inhabitant's actions very well. However, it is slow and it is limited to handle single inhabitant's action prediction.

Edwin O. Heierman and Diane J. Cook developed another prediction algorithm in 2003, based on a novel data-mining algorithm Episode Discovery (ED) [9]. Within a sequential data stream, the ED discovers behavior patterns. To improve home automation, a prediction algorithm of decision learner is provided by the corresponding filtered data and pattern knowledge. Additionally, incremental interactions are processed by the framework. This can be used in a real-time system also. By processing each event occurrence incrementally, maximal episodes are generated by the algorithm from the input sequence. The occurrences are maintained by an episode window. It is pruned when an occurrence is beyond the allowable window time frame for addition of a new event occurrence. Prior to pruning, the window contents are maximal for that particular window instance. To generate a maximal episode, the contents are used. Next, the algorithm constructs an initial collection of item sets, one for each maximal episode. For significance, additional item sets are generated so that the episode subsets of the maximal episodes can be evaluated. While ensuring item sets leading to significant episodes are retained, ED must prune the complete set of potential item sets in a tractable manner to avoid generating the power set of each maximal episode item set. This algorithm is very efficient and fast. ED can be utilized to improve the predictive accurateness of a home agent and to comprehend the nature of the activities occurring.

In 2003, Sira Panduranga Rao and Diane J. Cook used Hidden Markov Model (HMM) for action prediction [10]. Hidden Markov models have been extensively used in various environments which include the location of the devices, device identifiers and speech recognition cluster. Traditional machine learning techniques such as memory-based learners, decision trees etc have difficulty in using historic information that is employed for classification to make sequential predictions. A portion of the history which is implicitly encoded by Markov models, offers an alternative representation.

The algorithm identifies the activity which includes a set of actions. Using unsupervised learning, it discovers these tasks. Dividing the action sequence into subsequences is the first step. These are expected to be a part of the similar task. Given the different groups from the partitioning process, the algorithm clusters similar groups together as the first

step to form abstract task classes. Then it extracts meta-features describing the group as a whole. Information like the starting time and time duration of the group, the number of actions in the group, the locations visited and devices acted upon can be collected from each group. The information is kept as a partition and supplied to the clustering algorithm. In a HMM, the clusters attained from the clustering step as hidden states.

Thus, the hidden states contain the similar features as the clusters. These are the number of actions in the cluster, time duration of set of actions in cluster, start time of actions in cluster, location of devices and device identifiers. Having this information the algorithm then precedes to HMM prediction process. The results show that this approach is very efficient in terms of speed and flexibility compared to other approaches.

Another system was developed in 2004 by Lucian Vintan and Arpad Gellert, in which the system predicts the next movement of the home inhabitants using neural predictors [11]. The aim of the system is to improve the quality of ubiquitous systems through enhancing the context awareness of home appliances. The architecture of the system is based on multi-layer perception with back-propagation learning algorithm and a hidden layer as shown in Figure 3. To save computing cost, the rooms and the persons are binary codified. This is of particular interest for fast moving (real-time restrictions) applications or mobile (energy restrictions). Therefore, as a substitute of one-room-one-neuron encoding with complexity N, the system uses bit encoding with complexity $log_2 N$. The system can be trained statically and dynamically. In static training, the predictor is trained based on room history patterns which belong to the previous presented benchmarks (person room movements) before effective run-time prediction process. In dynamic training, the system learns online from the actual user activities. This system improves the quality of ubiquitous computing applications. They used two types of predictors: the local and global predictors. The local predictor monitors a single inhabitant that has a higher accuracy compared to the global predictor, which monitors more than one user.
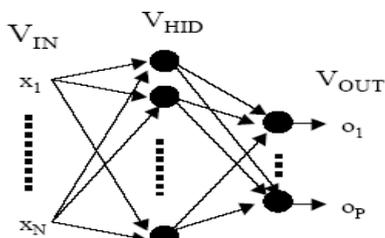

Figure 3. The Multilayer perception used by the system of Lucian Vintan and Arpad Gellert

NEURAL NETWORK FOR SMART HOME

A neural network is defined as an interconnected group of artificial or biological neurons. Artificial neural networks (ANN) refer to mechanical, electrical or computational simulations or models of biological neural networks [12]. The requirement for 'smart' devices in consumer electronics is growing for the last few years. The reason is the extensive utilization of low-cost embedded electronics. This is also motivated by the requirement for systems which understand users to design an easy interface. Thus, it is enviable that electronic devices are able to deliberately sense, comprehend surroundings and adapt services according to contexts. Several works had been performed to implement ANN in smart home.

In 1995, Marie Chan et al. developed a smart-home automation system for disabled and elderly people [13]. The system is developed using a smart multi-sensor system based on advanced telecommunication. To learn the home inhabitant's behavior, the system uses ANN. The system monitors the inhabitants of the home using the smart sensors in real time. Figure 4 illustrates the concept used to model the system. It includes learning the habits of the old person and relies on it to arrive at a diagnosis in case of a change in his behavior.
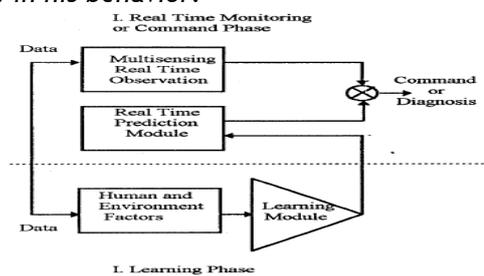

Figure 4. The principle used to model the system

In 1995, Michael C. Mozer used artificial neural networks to develop a home. This programs itself by monitoring the desires and lifestyle of the occupants, learning to accommodate and anticipate their requirements [14]. The system is equipped with sensors that monitor the environment and generate a report at any given time. For each control domain lighting, air and water ventilation and heating, this architecture is replicated. The instant environmental state is supplied through a state transformation which computes statistics such as variances, maxima, minima and averages in a given temporal window. A state representation is the result which provides more information about the environment than the instantaneous values. The instantaneous state is also provided to an occupancy model. This determines whether or not it is occupied for each zone of the house usually corresponding to a room. Although, the occupancy model depends on motion detector signals, but includes rules that say "a zone remains occupied, even when there is no motion, unless there is motion in an adjacent zone that was previous unoccupied." Thus, even when there is no motion, the occupancy model maintains occupancy status. Figure 5 illustrates the system architecture. The evaluation results show that the system is dynamic and very suitable for complex environment.

The most recent system was developed in 2005 by Fei Zuo and Peter H. N. where a face recognition module is embedded into home devices such as music players, televisions and video. The system always observes its surroundings and captures active user presence [15]. Home devices tailor services such as selection of favorite music or TV programs for the individual user by automatic face identification.
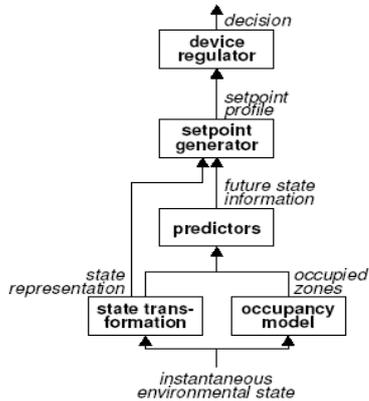
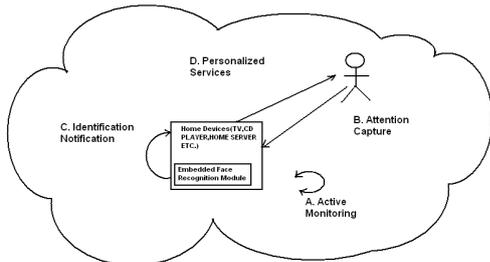*Figure 5. Diagram illustrating the system architecture*

Figure 6. The Face Recognition System Operation Illustration

A conceptual description of the prototype is given in figure 6. The system functions on live-feed video from embedded cameras. It performs the recognition close to real time. It can detect existing faces and tracks the located motions of faces from same user form a smooth trajectory for each frame. The detection of a 'break' of this trajectory can easily identify a new user. For accommodating varying face scale, pose, and position, the rest face images are selected for further processing as key samples. For normalization purposes, an accurate extraction of significant facial features is needed. The final face identification looks for a database of the reference faces and the 'best-match' is returned. The result of the proposed face recognition system has a comparatively unhindered operation environment. It also offers high processing effectiveness by utilizing low-cost hardware.

FUZZY SYSTEM FOR SMART HOME

Fuzzy Logic (FL) is a problem-solving control system methodology which lends it to implementing in systems starting from small, simple, embedded micro-controllers to large, networked, multi-channel workstation or PC based data acquisition and control systems. FL provides a conclusion based on imprecise, ambiguous, vague, noisy or missing input information.

The main aim of home automation is to provide a convenient and efficient integration and inter-operation within the household appliances. The definition of linguistic rules is a suitable programming method for home automation systems that can be processed by a fuzzy-system. Based on this idea, in 1998 Harald J. Zainzinger developed a neuru- fuzzy controller [16]. The inhabitants are watched by the system at controlling their devices. The home system detects every action related to the correct appliance such as increasing the room temperature by switching on the heater. This event

changes the value of the existing control and is kept in a database that is user-specific. This gives the training-data for the neuro-fuzzy network optimization. The system is a hybrid neuro-fuzzy controller which is based on a generic fuzzy-perception [17]. By a reinforcement-learning algorithm, the system can learn fuzzy rules and sets. The adaptability of this system is the benefit of this implementation. This system also can be used to control other non-time critical applications, and not only limited to smart environment.

In 2002, Hani Hagras, Graham Clarke, Martin Colley and Victor Callaghan proposed a smart-home automation system using a fuzzy Incremental Synchronous Learning (ISL) technique [18]. The aim of the system is to provide a non-intrusive, life-long, online method for learning personalized behavior and anticipatory adaptive control for physical environments. The nature of the envisaged target environments are short "initialization" and long "life-long" learning. Generally, a learning process would be non-intrusive within a building. The agent is an augmented behavior based architecture that utilizes a set of parallel Fuzzy Logic Controllers (FLC), each forming a behavior. The behaviors are fixed for an Intelligent Building (IB) which includes the Economy, Emergency and Safety behaviors. It can be dynamic and adjustable such as, Comfort behaviors (i.e. behaviors tailored to inhabitant's real behavior). Each dynamic FLC has a parameter which can be changed with the Rule Base (RB) for each behavior. Each behavior is implemented as a FLC. It uses a singleton fuzzifier, max-product composition, product inference, height defuzzification and triangular membership functions. The system consists of two modes: initialization mode and control mode. During the initialization mode the system needs to monitor the inhabitant's behavior. After the initialization period, the ISL enters to a Control mode. In this mode, to guide its control of the room's effectors, the rules learnt during the initialization period are used. Whenever the behavior of the user changes, there is a requirement to delete, add or modify rules in the rule base. ISL suspends environmental control and returns briefly to non-intrusive monitoring cycle during this event. It infers rule base changes essential to find out the new preferences of the users. This is transparent to the user, short cycled and distributed for the duration of the environment use. As such, it forms a life-long learning phase. Compare to other offline method, especially Mendel-Wang ANFIS approach, this method shows comparably better result [19]. However, this has got added benefits adaptation to new users, online and is able to particularize rather than generalize.

In 2005, Faiyaz Doctor and Hani Hagras developed a life-long novel learning approach for intelligent agents which are embedded in intelligent environments [20]. The agents aim to implement vision of ambient intelligence in an intelligent inhabited environment (IIE). This was accomplished by providing ubiquitous computing intelligence in environment supporting the actions of users. Ambient

intelligence is a new information paradigm. In this paradigm, people are empowered through a digital environment which is "aware" of their context and presence, and is responsive, sensitive and adaptive to their needs. The proposed technique, which is termed as AOFIS, is an unsupervised data-driven one-pass approach for membership functions and extracting fuzzy rules from data to learn a fuzzy controller which will model behaviors of user. Over a time period, the data is collected by observing the user in the environment. AOFIS system is shown in figure 7. The experimental results show that the system learns the user particularized behavior and adjusted online for any changes in life-long learning mode in non-intrusive way. The system is very transparent and therefore, the user was not aware of the intelligently invisible responsive infrastructure of the environment.
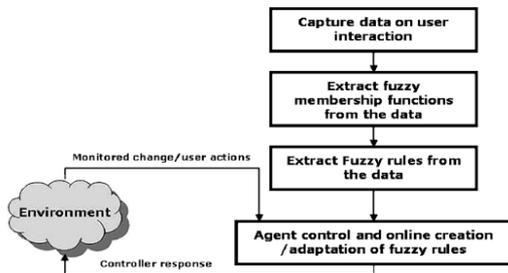

Figure 7. A flow diagram of the five phases of AOFIS

REINFORCEMENT LEARNING FOR SMART HOME

In machine learning, Reinforcement Learning is a class of problems in machine learning that postulate an agent exploring an environment where the agent perceives its current state and takes actions. The environment provides a reward in return which can be negative or positive. Over the course of the problem, reinforcement learning algorithms attempt to find a policy for maximizing cumulative reward for the agent. The concept of reinforcement learning generated interests of researchers in behavioral architecture design and its implementations.

In 2002 Y. Wang, D. J. Cook, V. N. Papudesi and M. Huber, developed a user-guided reinforcement learning of robot assistive tasks for an intelligent environment [21]. A method of achieving variable autonomy was introduced by the system. This was accomplished by integrating autonomous control policies and user input in a Semi-Markov Decision Process (SMDP) model which is made on hybrid control architecture. From a set of reactive behavioral elements, overall behavior is derived which address local perturbations autonomously.
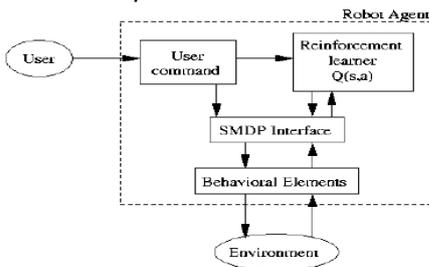

Figure 8. Overview of the control system

The system also employed Q-learning algorithm to serve as a method of training the robot. The training data is obtained from the user commands as shown in

figure 8. The experimental results show that this approach enables person assistive task robots to be used by general end-users. The control and interface approach of the system provide the robots of variable modes of autonomy.

In 2004 Diane J. Cook, Sajal Das and Karthik Gopalratnam used reinforcement learning technique to develop a health monitoring system to be used for smart-home environment [22]. The goal of the system is to assist the individuals and elderly with disabilities by giving home capabilities to monitor health trends and assist in the occupant's day-to-day activities at their homes. Predication techniques and reinforcement learning are both used to develop the system. The prediction portion of the system I used future forecasting of the inhabitants next actions sequence. On the other hand reinforcement learning technique is implemented using Q-learning algorithm that is used for decision-making process. The testing results show that the system successfully watches the inhabitant's health and provide reminders concerned with the home inhabitant's health.

Another approach for home automation using reinforcement learning was achieved in 2004. C. Gatzoulis, W. Tang and T.R. Wan developed a virtual servant robot to serve a virtual human (the residence of the house) by doing everyday household works [23]. The robot is set to have no prior knowledge of its actual task initially. It will perform its actions arbitrarily. As such, the learning will be from the experience of doing the tasks. Actions which are suitable for the sub-states of the agent are designed in agent control architecture. A state value associated with each state indicates the performance of the learning of the robot. The robot gets positive reward for proper action through a reinforcement mechanism. It gets negative when the selected action does not improve the value of the state. By issuing orders and commands the virtual human interacts with the robot. The system architecture in figure 9 shows the modules and system architecture.
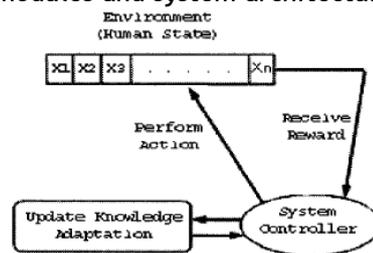

Figure 9. Overview of C. Gatzoulis, W. Tang and T.R. Wan System Architecture

The human state is the vector with the sub-states' fuzzy values. Based on received reward, system control decides actions to be done. The system controller parameters are modified to improve performance by the update knowledge adaptation module. The system has been tested with two reinforcement learning algorithms based on Q-Learning (QL) [24] and ZLCS [25] with Fuzzy Inference Systems (FIS). Both the algorithms are derived from analogue computation and natural. Gatzoulis et. al. (2000) system uses fuzzy variables to depict an infinite number of diverse likely states of changeable level of importance [23].

CONCLUSIONS

Based on the discussed research works we can conclude that the need for flexible communication between the agents is very important, especially when there is a shared resource to be used by the agents. We also realized that when designing such systems, a friendly user interface to control the system would be in the favor of the home inhabitants because these systems are very complex.

From the illustration of the given works we can conclude that predicting future inhabitant's device interaction is needed for home automation. On the other hand, since the prediction algorithms do not always provide 100% accuracy it should not be used alone for home automation. To avoid wrong prediction we can combine both prediction algorithms and reasoning techniques such as reinforcement-learning, this way we can make sure that unnecessary prediction outcomes are avoided.

We can conclude from the discussed research work that the use of neural-networks significantly increases the automation of home appliances as well as a very user-friendly solution. We further think that such a user interface is very helpful; especially when it comes to people with disabilities, because there is not need for direct interaction with the system and also it is automatically configurable.

We can conclude that FL is very suitable for heterogeneous home appliances, because fuzzy logic is very robust in headlining computing problems where we have many rules and devices to be addressed.

We conclude that reinforcement learning is very straightforward to implement in smart-home automation application. The simplicity and robustness makes this method very desirable especially when dealing with situation where the agent may not be used.

We suggest that future work could be to use a hardware prototype of multi-agent system to manage the smart-home environment. Hardware prototyping using FPGA has been used effectively in many areas and showed a great result. We believe that a multi-agent hardware prototype could be very useful for home automation, as it could provide faster speed and more efficient power consumption than software based.

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