CLASSIFICATION AND DETECTION OF INTELLIGENT HOUSE RESIDENT ACTIVITIES USING MULTIAGENT

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ABSTRACT. The intelligent home research requires understanding of the human behavior and recognizing patterns of activities of daily living (ADL). However instead of understand the psychosomatic nature of human early projects in this area simply employed intelligence to the household appliance. This paper proposed an algorithm for detecting ADL. The proposed method is based on two opposite state entity extraction. The method reflects on the common data flow of smart home event sequence. The developed algorithm clusters the smart home events by isolating opposite status of home appliance. Result shows that, the algorithm can successfully identify 135 unique tasks of different lengths. This algorithm is surely being an alternate way of pattern recognition in intelligent home.

Keywords: Smart home, pattern recognition, activities of daily living (ADL), activity classification, multiagent system

INTRODUCTION

The Smart home research requires understanding of the human behavior and recognizing patterns of activities of daily living (ADL). Early projects in this area hardly try to understand psychosomatic nature of human. Those projects simply employed intelligence to the household appliance without considering psychological understanding (Vainio et al., 2008 and Das et al., 2002). The algorithms were not very effective and the architectures were not strong enough to achieve desired progress. Bayesian Method, statistical inferential algorithms (Virone et. al., 2008), Neural Network (Zheng et. al., 2008) and Fuzzy logic (Vainio et. al. 2008) are some of the major algorithms that can resolve the problems. Latest algorithm that has been used in smart homes is multiagent system (MAS). Researchers also realized that the study of human behavior should be the initial step to conduct smart home research.

Current trends show that most of the recent projects are involved in identification of ADL. The House_n group at MIT developed PlaceLab to study human activities in ubiquitous environment (Intille et. al., 2005). To acquire user information, the house is occupied with numerous wire, light, pressure, temperature, water, gas sensors. The project used video and audio retrieval devices to create vast amount of real life data. Isoda et al. (2004) applied C4.5 algorithm to build spatiotemporal context of the user. The system used sensors and RFID tag to define task models and user behavioral pattern at any moment that is matched with the recently detected states. De Silva et al. (2007) utilized multimedia technology to implement an audiovisual retrieval and summarization system. They used a large number of cameras to create personalized video clips by hierarchical audio clustering and video handover. The system can track people, extract key frame, localize sound source and detect lighting change. Zheng et al. (2008) used self-adaptive neural network to classify activities of daily living. For the purpose, they proposed a growing self-organizing map (GSOM) based on Kohonen self-organizing map with adaptive architecture. Virone et al. (2008) applied statistical predictive algorithms to model circadian activity rhythms (CARs) and their deviation. Park et al. (2008) combined computer vision and RFID sensors to recognize ADL at multiple levels of detail. The system builds a dynamic Bayesian network and can identify coarse-level and fine-level ADL.

The major problem related to data classification algorithm is deciding the exact starting and ending point. Researchers try to solve the problem by using period. However, there is a chance to count noisy information because the period does not consider actual data flow. Others try to implement LZ78 data compression rule but it also has the same short fall. Many of the researchers in recent years proposed multiagent architecture considering various realization features. Higher-level software based multiagent model for smart homes are described in Sterling et al. (2005).On the other hand hardware realization of a multiagent system is proposed by Reaz et al. (2006). Service based orientation of agent structure which is known as MAHAS (Multi-Agent Home Automation System) is used in multiagent system by Abras et al. (2008). Services like heating, washing, cooking, vacuuming etc. are organized by the MAHAS agents. Moreover, the system also has energy source controlling agents and the load based agents. Simulation results showed that energy management of smart home could be done using this system. Task based modeling is another approach to put into practice multiagent system. A task-oriented infrastructure is proposed by Hannon et al. (2005). The model specifies each of the agents according to functionalities like entertainment, appliance control, inhabitant tracking etc. Managing an Adaptive Versatile Home, which is better known as MavHome, consists of cooperating agents that are distributed along with location and electrical devices (Cook et. al. 2006). Layered approach was considered to model each of the agents for data acquisition, communication and information processing and decision-making.

In this research an intelligent home architecture is proposed using multiagent. This multiagent is designed based on tasks. The proposed algorithm solely considers appliance states, which is based on sequences characteristics and can accurately identify ADL of the resident. The location of user along with temporal information and the sequence of events are monitored by entity agents for forecasting the actions of resident as well as his behavior.

METHODOLOGY

The behavior of human can be defined as a pattern of tasks (Marufuzzaman et. al. 2013). Reading books or watching TV, making coffee even some cooking sequences can be treated as tasks. However, some tasks can be contained long patterns such as using toilet or kitchen etc. Building a sustainable smart home largely depends on the event and tasks classification in relation to temporal and location information.

In order to isolate the tasks precise clustering of distinctive episodes are essential. The starting and ending point of a task need to be defined properly. In this research an algorithm is developed based on opposite state modeling such as, identify kitchen activities. The activity may be started with the turning ON the light. Then the user might switch ON the micro oven. After heating the food for a while user might turned it OFF. Finally the activity is finished while the user turns OFF the kitchen light. Hence, the starting point and ending point of the kitchen activity is defined properly by turning the kitchen light ON and OFF respectively. If we think cooking activities, the starting point will be turning ON the cooker as well as the end point is defined as OFF states of the cooker. In this way, any activities can be classified in a home just by considering ON-OFF states of its appliances.

The pseudo code is shown in figure 1. Depending on the sequences, this algorithm employed a window to track the events. The window length that is defined by the programmer is depending on the episode length and it is fixed. In order to determine the pattern current event is compared to the first event of the window. The whole window will be added only if the current event is in opposite state of the first event for the same entity. Later, that window is added in *episode_database*. If the episode exists the frequency count will be updated. Finally, from this *episode_database* the classified episodes and their rate of recurrence are obtained.

```
initialize episode_database:= null
initialize window:= null
initialize window_length:= desired_episode_length

loop
    wait for the next event e
    add e to the window
    if length(window) = window_length
        If window[1]= on state and window[window_length]=opposite state of window[1] event
                add window to the episode_database or update frequency count
        remove window[1] and update window index
forever
```

Figure 1. Pseudo code of the proposed algorithm

The Multiagent System

The overall architecture of the multiagent system is shown in figure 2. Four interconnected agents are existed in a multiagent system. These are event prediction agent, temporal prediction agent, location aware agent and supervisor agent.

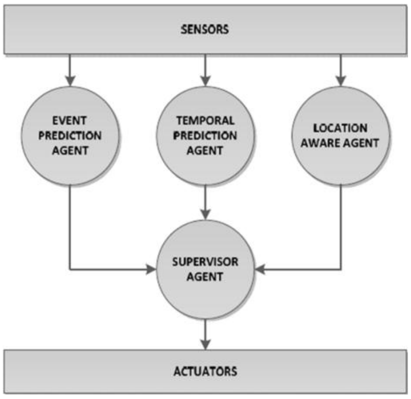

Figure 2. Architecture of the Multiagent System

Classification of event progression is predicted by event prediction agent. Temporal prediction agent is extracted temporal characteristics of the events and the location aware agent classifies the sequence derived from the user location.

The agent architecture follows a layered approach. Figure 3 illustrates the common bottom up hierarchy of an agent. Data acquisition layer (DAL) is responsible to perceive sensory information from the home appliances or other cooperating agents. Information processing layer (IPL) constructs a knowledge base according to the agent functionality. Decision layer (DL) processes the stored knowledge of IPL to provide anticipated solution. The processed decision is shared with other agent or applied to the home appliances through data transmission layer (DTL).

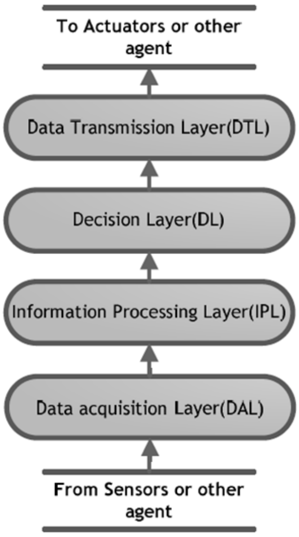

Figure 3. Common Agent Architecture

Smart home user activity is a collection of events that consecutively occur inside the home. The agents that are used in smart home are described as follows:

Event Prediction Agent: The event prediction agent scrutinizes the progression of incident via DAL. The information is processed by IPL and accumulated in a data structure. For predicting the next event, DL is operated the IPL information. The verdict is broadcasted to the supervisor agent using DTL.

Temporal Prediction Agent: The time of the next event occurrence is predicted by temporal prediction agent. The agent monitored absolute time and relative time of the events with the help of DAL. Absolute time is the sum of seconds' starts from 12AM whereas, the difference between two consecutive events is known as relative time. After processing the information, it is being stored in IPL. The time of the next event is predicted by the DL. Like other agents, the prediction is shared with the supervisor agent via DTL.

Location Aware Agent: Location aware agent is pursued the inhabitant through DAL. A virtual map is made of the user route in its IPL. DL is predicted next location then the supervisor agent is collected the user existing location information from DL via DTL.

Supervisor Agent: The supervisor agent is the main course of action architect and managing agents. Unlike other agents, the supervisor agent is received processed information from agents via DAL. The agent also discovers the user location, next event and time for storing in IPL. DL of this agent decides the ultimate prediction of the smart home event. By using the DTL, the decision is applied to the home appliances.

The overall data flow and agent activity diagram of the system is shown in figure 4. The information of the sensors is processed by all the agents at a time. Their DAL is responsible to do this job. According to agent characteristics in IPL, every agent processes the information. The partial decision that takes in DL is passed to the DAL of supervisor agent through DTL of these agents. According to figure 4, it is being also shown that based on the inferential engines, DAL of supervisor agents is integrates the knowledge of cooperation agents and operates the actuators.

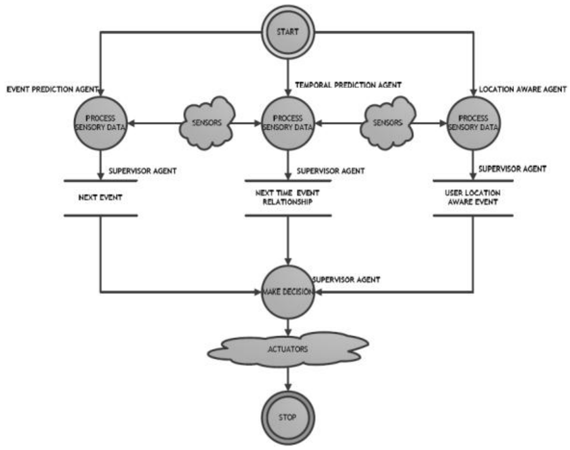

Figure 4. Activity diagram of the proposed multiagent system

RESULTS AND DISCUSSION

In order to evaluate the algorithm, a huge practical set of data is required. This research is used data from a practical smart home name as MavHome project (Das et. al. 2002). In MavHome architecture, more than 60 X10 based appliances were used. All these X10 appliances are divided into 16 zones and each zone hold a unique id (Das et. al. 2002). The extracted information from the X10 devices is used as input of the proposed algorithm. The proposed algorithm is identified 135 tasks successfully. The identified patterns of different length tasks are shown in figure 5. The higher pattern length indicates complex tasks while lower pattern length means simple tasks.

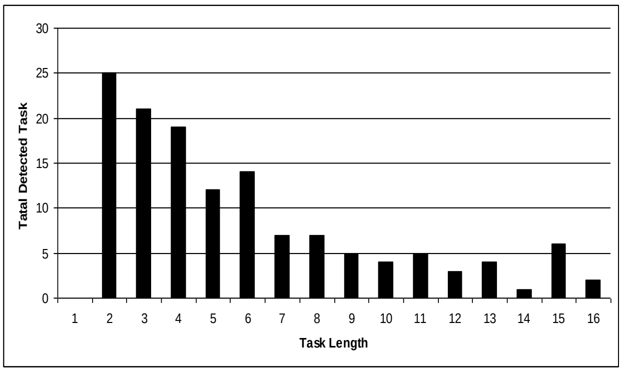

Figure 5. Total number of activities according to episode length

According to the figure it is being shown that for lower length episodes like 2, 3, 4, 5, and 6 the proposed algorithm can identified 25,21,19,12 and 14 distinct tasks respectively. On the other hand total tasks are reduced to 4 while the episode consists of 10 events. Thus, the algorithm can identify different length of activity pattern employing the opposite state episode boundary. The task-oriented approach of multiagent system provides an adaptive environment to accommodate new appliances. Design complexity is reduced by hierarchical organization of agent components. Moreover, the supervisor agent provides a cumulative efficiency.

CONCLUSION

In smart home development, user activity detection plays an important role. This research is presented the approach for detecting daily living tasks. The proposed method is based on two opposite state entity extraction. The method reflects on the common data flow of smart home event sequence. Result proves that, it can effectively categorize 135 actions of different lengths. This algorithm is surely being an alternate way of pattern recognition in smart home.

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REFERENCES

Abras, S., Pesty, S., Ploix, S., & Jacomino, M. (2008). An Anticipation Mechanism for Power Management in a Smart Home using Multi-Agent Systems. *Proc. 3rd Int. Conf. on Information and Communication Technologies: From Theory to Applications,* 1-6.

Cook, D. J., Youngblood, M., & Das, S. K. (2006). A multi-agent approach to controlling a smart environment, *Designing Smart Homes,* Heidelberg, Berlin: Springer Verlag, 165-182.

Das, S.K., Cook, D.J., Battacharya, A., Heierman III, E.O., & Tze-Yun Lin (2002). The role of prediction algorithms in the MavHome smart home architecture, *IEEE Wireless Comm.,* 9(6), 77-84.

De Silva, G.C., Yamasaki, T., & Aizawa, K. (2007). An Interactive Multimedia Diary for the Home, *Computer,* 40(5), 52-59.

Hannon, C. & Burnell, L. (2005). A distributed multi-agent framework for intelligent environments, *Journal on Systemic, Cybernetics and Informatics,* 3(1), 1-6.

Intille, S. S., Larson, K., Beaudin, J. S., Nawyn, J., Munguia Tapia, E. & Kaushik, P. (2005). A living laboratory for the design and evaluation of ubiquitous computing interfaces, *Proc. on Extended Abstracts of the 2005 Conference on Human Factors in Computing Systems,* 1941-1944.

Isoda, Y., Kurakake S. & Nakano, H. (2004). Ubiquitous sensors based human behavior modeling and recognition using a spatio-temporal representation of user states, *18th Int. Conf. on Advanced Information Networking and Application,* 512-517.

Marufuzzaman, M. & Reaz, M.B.I. (2013). Hardware Simulation of Pattern Matching and Reinforcement Learning to Predict the User next Action of Smart Home Device Usage, *World Applied Sciences Journal,* 22(9), 1302–1309

Park, S. & Kautz, H. (2008). Hierarchical recognition of activities of daily living using multi-scale, multi-perspective vision and RFID, *Proc. IET 4th Int. Conf. on Intelligent Environments,* 1-4.

Reaz, M. B. I., Assim, A., Choong, F., Hussain, M. S. & Mohd-Yasin, F. (2006). Prototyping of Smart Home: A Multiagent Approach, *WSEAS Transactions on Signal Processing,* 2(5), 805-810.

Sterling, L. & Juan, T. (2005). The software engineering of agent-based intelligent adaptive systems, *Proc. 27th Int. Conf. on Software Engineering,* 704-705.

Vainio, A.-M., Valtonen, M., & Vanhala, J. (2008). Proactive Fuzzy Control and Adaptation Methods for Smart Homes, *IEEE International System,* 23(2), 42-49.

Virone, G., Alwan, M., Dalal, S., Kell, S.W., Turner, B., Stankovic, J.A. & Felder, R. (2008) Behavioural Patterns of Older Adults in Assisted Living, *IEEE Trans. Inf. Technol. Biomedicine,* 12(3), 387-398.

Zheng, H., Wang, H. & Black, N. (2008). Human Activity Detection in Smart Home Environment with Self-Adaptive Neural Networks, *Proc. IEEE Int. Conf. on Networking, Sensing and Control (ICNSC),* Sanya, China, 1505-1510.