EVENT SEQUENCE RECOGNITION AND MULTIAGENT BASED TASK ISOLATION OF HUMAN ACTIVITIES

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ABSTRACT

People follow some specific patterns in their life style and recognition of human activity is thus a potential problem to develop an effective smart home. At the same time, inhabitant activity classification plays a vital role to predict smart home events. The paper proposed a novel algorithm to recognize activities of daily living of the resident by considering opposite entity states to extract the pattern of event sequence. Each extracted episodes represents a distinct task of the home user. The paper also proposed a multiagent system to track the user for task isolation. The system is composed of cooperative agents which works by sharing local views of individual agents. 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.

KEYWORDS

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

1 INTRODUCTION

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. Projects by Mozer [1], Vainio *et al.* [2], Adlam *et al.* [3], Das *et al.* [4] suffer from this types of drawback. Previous trends of smart home failed to achieve anticipated improvement. Ineffective algorithms and weak architecture are the main causes for its slow adoption. To overcome from the situation, advanced artificial intelligence algorithms are being developed using Bayesian Method [5, 6], statistical inferential algorithms [7], Neural Network [1, 8, 9, 10] and Fuzzy logic [2]. Recently, researchers are using Multiagent System (MAS) to solve this type of problem. Researchers also realized that the study of human behavior should be the initial step to conduct smart home research.

Smart home environment is monitored by ambient intelligence where the information perceiving and processing units remain invisible from the user to provide interactive computing services. It consists of numerous environmental parameters which can be subdivided into smaller problems to reduce complexity. To finalize the solution, smaller subdomains are integrated utilizing multiagent architecture.

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 [11]. 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. The goal of the project is to study human behavior, influence of technology on the people and how technology can be utilized to simplify user interaction with the environment.

Noguchi *et al.* used a summarization algorithm to track the resident by segmenting sensory data [12]. Segments are classified by room states and summarized for activity detection. Isoda *et al.* applied C4.5 algorithm to build spatiotemporal context of the user [13]. 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.

Ma *et al.* utilized Case Based Reasoning (CBR) to make a context aware system [14]. CBR uses previous activities and interactions to provide the solution of current problem. De Silva *et al.* utilized multimedia technology to implement an audiovisual retrieval and summarization system [15]. 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.* used self-adaptive neural network (SANN) to classify activities of daily living [10]. For the purpose, they proposed a Growing Self-Organizing Map (GSOM) based on Kohonen self-organizing map with adaptive architecture. Virone *et al.* applied statistical predictive algorithms to model circadian activity rhythms (CARs) and their deviation [7]. Zhang *et al.* proposed snow-flake data model to classify ADL from the observed pattern and temporal information [16]. The model utilized probabilistic distribution and applicable for multiple inhabitants.

Park *et al.* combined computer vision and RFID sensors to recognize ADL at multiple levels of detail [6]. The system builds a dynamic Bayesian network and can identify coarse-level and fine-level ADL. In 2008, Rashidi *et al.* developed CASAS at Washington State University [17]. It uses Frequent and Periodic activity miner algorithm to discover frequent and periodic activity patterns. Lu *et al.* built CoreLab, a location aware activity recognition system [18]. Instead of using simple sensors, CoreLab employs ambient-intelligence compliant objects (AICO) to detect contact, pressure, power usage and motion. It can cluster ADL by utilizing an enhanced version of naive Bayes classification method.

The major problem related to data classification algorithm is deciding the exact starting and ending point. Researchers try to solve the problem using time frame. But there is a chance to count noisy information because the time frame doesn't consider actual data flow. Others try to implement LZ78 data compression rule but it also has the same short fall. The proposed algorithm solely considers appliance states which is based on sequences characteristics and can accurately identify ADL of the resident.

Previous researches on smart home proposed several multiagent architectures considering various aspects of implementation. Lesser *et al.* and Sterling *et al.* described a higher level software based multiagent model for smart homes [19, 20]. Reaz *et al.* and Assim *et al.* proposed a multiagent system for hardware implementation utilizing VLSI design [21, 22]. Son *et al.* developed an RFID based multiagent middleware to control ubiquitous environment [23].

Task based modelling is another approach to implement multiagent system. Hannon *et al.* described a task oriented agent infrastructure which specifies each of the agents according to functionalities like entertainment, appliance control, inhabitant tracking and so on [24]. MavHome (Managing an Adaptive Versatile Home) consists of cooperating agents which are distributed according to location and appliances [25]. They followed a layered approach to model each of the agents for data acquisition, communication, information processing and decision making. The system developed by Reaz *et al.* and Assim *et al.* is a location based multiagent solution for smart home [21, 22].

Abras *et al.* proposed a service based orientation of agent structure named MAHAS (Multi-Agent Home Automation System) [26]. MAHAS organizes the agents according to services like cooking, heating, washing, vacuuming etc. Besides the load based agents, the system also has energy source controlling agents. The simulated system provides a solution for energy management in smart home.

This research proposes a task based orientation of multiagent system for smart home. Event sequence, temporal information and user location are monitored by individual agents to predict the resident behaviour and actions in smart homes.

2 METHODOLOGY

Human activity is a collection of well define tasks. The tasks can be as simple as coffee making activity, cooking sequence, watching TV or reading books. Some consists of complex long patterns like using the kitchen, toilet and so on. Classification of the task and event according to temporal and location information is an important prerequisite to develop a reliable and sustainable smart home.

Task isolation process requires accurate clustering of unique episode. For the purpose, the actual stating point and ending point of the activities should be properly defined. In the proposed algorithm, a novel clustering method has been developed based on opposite state modeling.

Suppose, we need to identify the living room activities. The activity may be started with the turning ON of the living room light. Then the resident switched ON the TV. After watching the TV program for a while, he turned it OFF. The activity is ended by switching OFF the living room light. Therefore, there is a specific starting point and ending point of the living room activity which are turning the living room light ON and OFF respectively. If we consider cooking activities, there also have a starting point which is turning ON the cooker. And the ending point is the OFF states of the cooker. Similarly, we can classify each and every activities of the resident by considering the ON-OFF states of home appliances.

Fig. 1 shows the pseudo code of the algorithm. It maintains a window to track the events according to the sequence of occurrence. The window is a fixed length array which is defined by the programmer according to desired episode length. The first event of the window is compared with the current event to determine the pattern. If they represent the opposite state of the same entity, then the whole window is added to the episode_database. In case of existing episode, the algorithm updates the frequency count. Finally, the episode_database provides the classified episodes and number of their occurrence.

```
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

2.1 The Multiagent System

The system is composed of four interconnected agents: event prediction agent, temporal prediction agent, location aware agent and supervisor agent. Event prediction agent is responsible for smart home event sequence classification and prediction. Temporal characteristics of the events are extracted by the temporal prediction agent. Location aware agent classifies the sequence based on the user location. These agents exchange information with the supervisor agent to decide the next event utilizing event sequence, time and user location. The skeleton of the multiagent system is illustrated in Fig. 2.

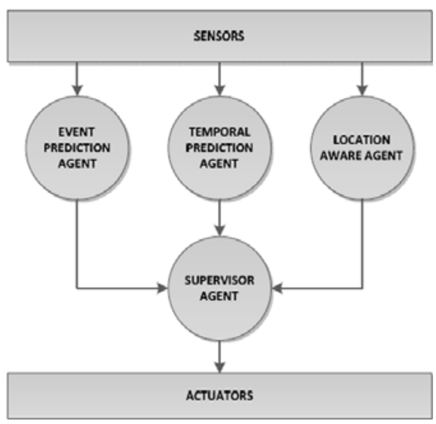

Figure 2. Architecture of the Multiagent System

2.1.1 Agent architecture: a hierarchical approach

The agent architecture follows a layered approach. Fig. 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).

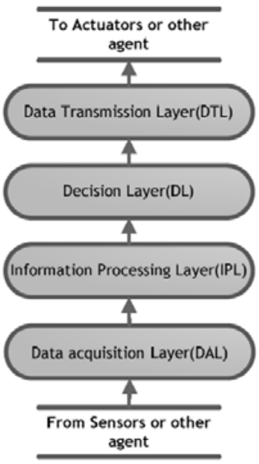

Figure 3. Common Agent Architecture

2.1.2 Agent modeling: task oriented architecture

Event Prediction Agent:
Smart home user activity is a collection of events that consecutively occur inside the home. The event prediction agent observes the sequence of event via DAL. The information is processed by IPL and stored in a data structure. DL manipulates the IPL information to predict the next event. The decision is transmitted to the supervisor agent through DTL.

Temporal Prediction Agent:
Temporal prediction agent predicts the time of the next event occurrence. Its DAL monitors absolute time and relative time of the events. Absolute time is the sum of seconds starts from 12AM. Relative time is the difference of two consecutive events. The information is processed and stored in IPL. The DL predicts the time of the next event. The prediction is shared with the supervisor agent via DTL.

Location Aware Agent:
Location aware agent tracks the resident through DAL. It makes a virtual map of the user route in its IPL. DL shares the user current location information and predicted next location via DTL with the supervisor agent.

Supervisor Agent:
The supervisor agent is the main policy maker and coordinating agent between other active agents. Unlike other agents, its DAL receives processed information from agents. It learns the user location, next event and time to store in IPL. Its DL decides the final prediction of the smart home event. The decision is applied to the home appliance utilizing the DTL.

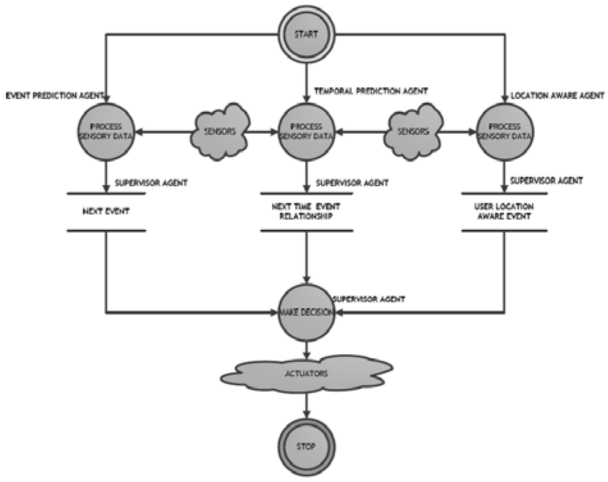

Figure 4. Activity diagram of the proposed multiagent system

2.1.3 Dataflow and Agent Activities

The event prediction, temporal prediction and location aware agents concurrently process sensory information in their DAL. Individual agent processes the information according to agent characteristics in IPL. Every DL takes partial decision which is sent to the DAL of supervisor agent via DTL of these three agents. It integrates the knowledge of the cooperating agents and operates the actuators based on its inferential engines. Fig. 4 illustrates data flow and agent activity diagram of the system.

3 RESULTS AND DISCUSSION

The event prediction agent is developed to predict the next event in smart home. For the purpose, an activity classification algorithm is defined utilizing entity state isolation. The classified episodes are used to train the agent for predicting the future.

To evaluate the algorithm, we used practical smart home date from MavHome project [27]. The project used X10 based devices for home appliance control. There are more than 60 X10 appliances which are divided into 16 zones and identified by a unique id number [4]. Fig. 5 shows MavLab interior map and sensor locations.

The information from the X10 device has been fed into the algorithm as input and it has successfully identified activities of various lengths. The lower pattern length indicates simple task and higher length represents complex activities. Fig. 6 illustrates identified patterns for various lengths. The algorithm has identified total 135 tasks. Small length activities are frequent and more than long tasks. For 2, 3,4,5,6 length episode, the algorithm can classify 25,21,19,12 and 14 distinct activities respectively. The numbers of total tasks reduced to less than 10 if the episode length exceeds 6 events. For example, if the episode consists of 10 events than the total activities reduce to 4. Results show that, the proposed algorithm can identify different length of activity pattern utilizing opposite state episode boundary.

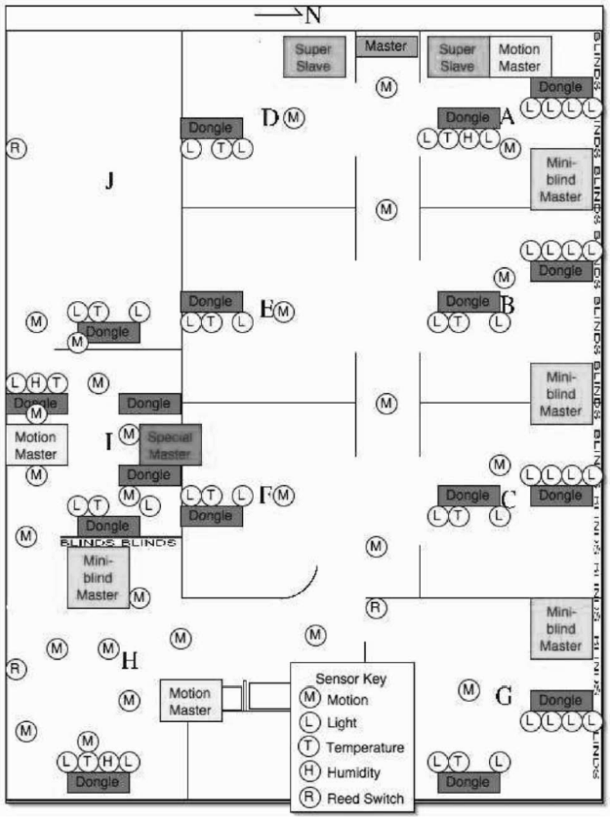

Figure 5. MavLab interior map and sensor locations.

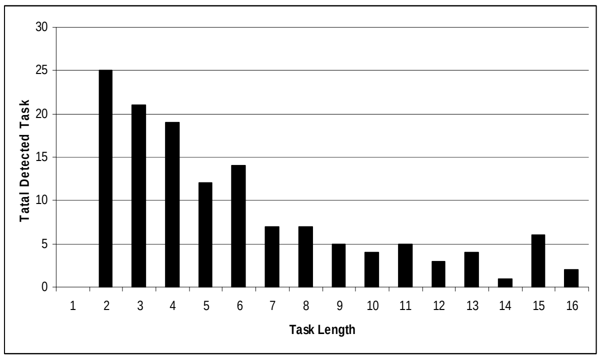

Figure 6. Total number of activities according to episode length.

4 CONCLUSIONS

Recognition of user activities is an essential prerequisite to develop a ubiquities environment. The paper presents an innovative method to detect activities of daily living. Unlike other methods, it is based on dual state entity extraction which considers the common data flow of smart home event sequence. Result proves that, it can successfully classify 135 activities of various lengths. The algorithm presents an alternation way for smart home pattern recognition. The task oriented approach of multiagent system provides an adaptive environment to accommodate new appliances. Hierarchical organization of agent components simplifies agent modelling which reduces design complexity. The supervisor agent provides a cumulative efficiency which is influenced by the effectiveness of the individual agents. Recognition of user activities is an essential prerequisite to develop a ubiquities environment. The paper presents an innovative method to detect activities of daily living. Unlike other methods, it is based on dual state entity extraction which considers the common data flow of smart home event sequence. Result proves that, it can successfully classify 135 activities of various lengths. The algorithm presents an alternation way for smart home pattern recognition.

5 REFERENCES

1. M.C. Mozer, “The neural network house: an environment that’s adapts to its inhabitants”, in Proc. AAAI Spring Symp. on Intelligent Environments, 1998, pp. 110–114.
2. A.-M. Vainio, M. Valtonen, and J. Vanhala, “Proactive Fuzzy Control and Adaptation Methods for Smart Homes,” *IEEE Intell.* Syst., vol. 23, Mar.-Apr. 2008, pp. 42 – 49, doi: 10.1109/MIS.2008.33.
3. T. Adlam, R. Faulker, R. Orpwood, K. Jones, J. Macijauskiene, A. Budraitiene, “The installation and support of internationally distributed equipment for people with dementia,” IEEE Trans. Inform. Technol. Biomed. , vol. 8, pp. 253–257. Sept. 2004.
4. S.K. Das, D.J. Cook, A. Battacharya, E.O. Heierman III, Tze-Yun Lin, “The role of prediction algorithms in the MavHome smart home architecture,” IEEE Wireless Commun., vol. 9, pp.77 – 84, Dec. 2002
5. Y. Rahal, P. Mabilleau, and H. Pigot, “Bayesian Filtering and Anonymous Sensors for Localization in a Smart Home,*” Proc. of 21st Int. Conf. on Advanced Inform. Netw. and Applicat. Workshops*, vol. 2, 2007, pp. 793 – 797, doi: 10.1109/AINAW.2007.108.
6. S. Park, and H. Kautz, “Hierarchical recognition of activities of daily living using multi-scale, multi-perspective vision and RFID”, *Proc. IET 4th Int. Conf. on Intelligent Environments*, 2008, pp. 1 – 4.
7. G. Virone, M. Alwan, S. Dalal, S.W. Kell, B. Turner, J.A. Stankovic, R. Felder, “Behavioural Patterns of Older Adults in Assisted Living”, IEEE Trans. Inf. Technol. Biomed., vol. 12, pp.387 – 398, May. 2008
8. J. Krumm, S. Harris, B. Meyers, B. Brumitt, M. Hale, and S. Shafer, “Multi-camera multi-person tracking for EasyLiving,” *Proc. 3rd IEEE Int.l Workshop on Visual Surveillance*, 2000, pp. 3–10.
9. B. Brumitt, B. Meyers, J. Krumm, A. Kern, and S. Shafer, “EasyLiving: technologies for intelligent environments”, *Proc. 2nd Int. Symposium on Handheld and Ubiquitous Computing*, 2000, pp. 97-119.
10. H. Zheng, H. Wang, N. Black, “Human Activity Detection in Smart Home Environment with Self-Adaptive Neural Networks,” *Proc. IEEE Int. Conf. on Networking, Sensing and Control (ICNSC)*, 2008, pp. 1505 – 1510.
11. S. S. Intille, K. Larson, J. S. Beaudin, J. Nawyn, E. Munguia Tapia, and P. Kaushik, "A living laboratory for the design and evaluation of ubiquitous computing interfaces,” in Extended Abstracts of the 2005 Conference on Human Factors in Computing Systems,2005, pp. 1941 - 1944.
12. H. Noguchi, T. Mori, T. Sato, “Construction of network system and the first step of summarization for human daily action in the sensing room,” in Proc. IEEE Workshop on Knowledge Media Networking (KMN’02), 2002, pp.17- 22.
13. Y. Isoda, S. Kurakake, H. Nakano, “Ubiquitous sensors based human behavior modeling and recognition using a spatio-temporal representation of user states,” in Proc. of the 18th Int. Conf. on Advanced Information Networking and Application (AINA’04), 2004, vol. 1, pp.512-517.
14. T. Ma, Y.D. Kim, Q. Ma, M. Tang, W. Zhou, “Context-aware implementation based on CBR for smart home,” in Proc. Int. Conf. Wireless and Mobile Computing Networking and Communications (WMOB’2005), 2005, vol. 4, pp. 112–115.
15. G.C. De Silva, T. Yamasaki, K. Aizawa, “An Interactive Multimedia Diary for the Home,” Computer, vol. 40, pp. 52 – 59, May. 2007.
16. S. Zhang, S. McClean, B. Scotney, X. Hong, C. Nugent, M. Mulvenna, “Decision Support for Alzheimer's Patients in Smart Homes,” in Proc. 21st IEEE Int. Symp. on Computer-Based Medical Systems (CBMS), 2008, pp. 236 – 241.
17. P. Rashidi, D.J. Cook, “Keeping the intelligent environment resident in the loop,” in Proc. 4th Int. Conf. on Intelligent Environments, 2008, pp. 1 – 9.
18. C.-H. Lu, L.-C. Fu, “Robust Location-Aware Activity Recognition Using Wireless Sensor Network in an Attentive Home,” IEEE Trans. Automation Sci. Eng., to be published.
19. V. Lesser, M. Atighetchi, B. Benyo, B. Horling, A. Raja, R. Vincent, T. Wagner, P. Xuan, and S.X.Q. Zhang, “The intelligent home testbed,” *Proc. Autonomy Control Software Workshop*,1999, pp. 291-298.

20. L. Sterling, and T. Juan, "The software engineering of agent-based intelligent adaptive systems," *Proc. 27th Int. Conf. on Software Engineering*, 2005, pp. 704-705.
21. M. B. I. Reaz, A. Assim, F. Choong, M. S. Hussain, and F. Mohd-Yasin, "Prototyping of Smart Home: A Multiagent Approach," WSEAS Transactions on Signal Processing, vol. 2, 2006, pp. 805-810.
22. A. Assim, M. B. I. Reaz, M. I. Ibrahimy, A. F. Ismail, F. Choong, and F. Mohd-Yasin, "An AI based self-moderated smart-home," *Informacije Midem-Journal of Microelectronics Electronic Components and Materials*, vol. 36, 2006, pp. 91-94.
23. M. Son, J. Kim, D. Shin, and D. Shin, "Research on Smart Multi-Agent Middleware for RFID-based ubiquitous computing environment," *Proc. 9th Pacific Rim International Workshop on Multi-Agents*, 2006, pp. 787-792.
24. C. Hannon, and L. Burnell, "A distributed multi-agent framework for intelligent environments," *Journal on Systemics, Cybernetics and Informatics*, vol. 3, 2005, pp. 1-6.
25. D. J. Cook, M. Youngblood, and S. K. Das, "A multi-agent approach to controlling a smart environment," *Designing Smart Homes*, Springer Verlag, 2006, pp. 165-182.
26. S. Abras, S. Pesty, S. Ploix, and M. Jacomino, "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*, 2008, pp. 1-6.
27. Smart Home Datasets, http://ailab.eecs.wsu.edu/casas/datasets.html.