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Integration of IoT Energy Management System with Appliance and Activity Recognition

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***Abstract*—The Internet of Things (IoT) extends and expands the range of the internet by interconnecting Internet and end device networks. As the raising of awareness about IoT, more and more application may applied for various areas. Especially, how to develop intelligent systems for energy saving becomes a new challenge in all circles.**

This research integrated appliance and activity recognition mechanism for IoT energy management system. It presented a management service layer for the recognition of current household appliances, which not only establishes communication services among various appliances, and deduced human activity conducted for context data using Naive Bayes from the electric appliances in use and the variation of its states. Finally, the proposed system can automatically achieve energy management by controlling electric appliances.

***Keywords*-Internet of Things; Energy Management; Appliance Recognition; Activity Recognition;**

I. Introduction

By definition. the Internet of Things (IoT) is to enable information exchange and create services between items, items and humans, or human to human interconnection. This technology utilizes Radio Frequency Identification (RFID), Global Positioning Satellite (GPS), scanners, infrared rays, and different data transference devices for information acquisition and exchange. The preferential development projects in ICT industry was determined by the EU 7th Framework Programme (FP7) during 2011 and 2012 in work programs of 2011. In August 2009, i-Japan national blueprint was proposed to set a nationwide full time CIO post that manages the promotion of all affairs and social information services that are provided within the Japanese e-Government. This study introduces an electric appliance-oriented IoT energy management system based on electric home appliance recognition technologies. An intermediate layer allows devices to be recognizable in the system and provides an integration gateway to serve devices with different communication protocols. Hence allowing devices with different communicative protocols to be able to inter-operate and exchange data. Descriptions of the contributions of this study are as shown below:

1. Heterogeneous device integration service: When implementation of the current IoT system poses a challenge when trying to integrate devices with different communication protocols for implementing Thing to Thing communication services. This study designs a procedure in adding household devices into the Internet of things and provide a communication mechanism between different protocols.
2. Middleware Hierarchy of SOA: The service-oriented design prevents users from numerous settings, hence achieving Zero Configuration. This solves the problems of complex preparations, ease of integrating service properties, strengthening the management interface of the service, and provides an easier solution for authorization and standardization problems.
3. Appliance aware energy management: This study also determine the current state of the user to the operating state and its many variations of current electric appliances. It can switch the unused appliances to implement an energy-saving service or switch on appliances to provide ease of control.

The remainder of this paper is organized as follows: Section II introduces studies related to current energy management and activity recognition; Section III elaborates on the overall system architecture, various functional modules, and activity recognition methods; Section IV presents the overall prototype, and discusses the experiment and analysis; finally, the conclusions are given in Section V.

II. Related work

This section will introduce Related research of home energy management system and activity recognition.

A. Home Energy Management System

Many current studies have been conducted on HEMS [1-3], including energy management system platform designs, communication protocol designs, and software solutions. The main discussions can be approximately divided into

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power consumption control for household appliances, design of energy saving modules, etc. Young-Sung Sonp [4] proposed using Power Line Communication to construct home energy management systems and to monitor power consumption measured by a smart meter. The users can use the network for remote control, adjust the power utilization decision-making mechanism, and implement the automatic control mechanism according to electric charge requirements. The major problem in this type of system is that the types of electric appliances connected to the socket must first be clearly defined, thus, usability and expandability are lessened. The mechanism designed by Ana Rossello-Busquet [5] is OSGI-based household appliance management; however, the communication protocols of household appliances differ, thus, the rule engine mechanism of knowledge mining is used for analysis to decide the optimal decision mechanism.

B. Appliance and Activity Recognition

Activity Recognition is an active topic evolved from many areas such as image process, pattern recognition, sensor network, appliance detection, data mining, and so on. In the past, los of researchers have presented effective systems with different types of data extracting hardware, grain of activity, recognition model, activity annotation, etc. Most systems of activity recognition perform the process as the four steps, data collection, data annotation, feature extraction, and activity recognition, in the proposed architecture [6] by Chao et al. In aspect of data collection, some systems obtain nearby data with sensors [6-11] and some deal with images taken by video devices [12-14]. However, in Placelab [15], the hardware devices both include sensor and camera for extracting data around themselves. RFID is also utilized to recognize activities. Patterson et al. [16] build the environment in which the objects are installed with a RFID tag, and residents wear a glove with a RFID reader to detect the object instances they touched. According to touch events and object data, they analyze recognizing result with four kinds of probabilistic model, and dynamic Bayes network with aggregates overcomes three others.

Appliance recognition [17-19] provides alternative way to discover human behavior indirectly. Because of the relevance between activity and appliance usage Lee et al. present an energy conservation framework [20] consisting of appliances recognition, activity-appliances model, unattended appliances detection, and energy conservation service. Based on electrical consumption of appliances, recognition component, dynamic Bayesian network model, distinguishes appliance class with features formed from varied statistic as RMS, Mean, Peak, Standard deviation, etc., and then the system calculates the similarity between activity and appliance against activity-appliances model prebuilt by the result of question list. Using appliance state to assist in detecting or recognizing activities is a novel approach; nevertheless, the systems simply recognize the activities involved appliances operated with occupants.

III. The Proposed IoT Energy Management System

A. System Architecture

The overall architecture of this study is as shown in Fig.1. It can be connected to the internet via IP, and the end devices of various protocols can be connected to the bottom. In this study, the devices of ZigBee, Bluetooth, and TCP/IP communication protocols are major devices, and will be classified into three major axes:

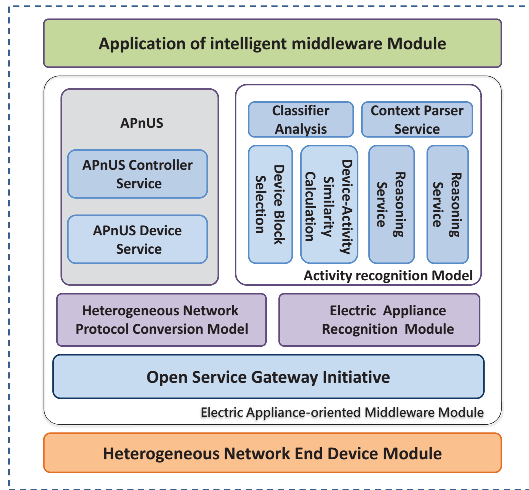

Figure 1. Overall System Architecture

- Heterogeneous network end device module: there are many heterogeneous network devices among the present devices, and this heterogeneous platform device module can effectively convert transmission packets and formats for convenient upload to the mediation module for registration and protocol communication.
- Appliance-oriented middleware platform: middleware design and architecture, Plug and Play system, heterogeneous network protocol conversion system.
- Application of intelligent middleware: to develop system architecture and design, with an Android terminal management interface system and context aware system.

B. Appliance and Activity Recognition Model

The use of electric appliance can reflect human activity activities, especially in HEMS. The electric appliances used in home environments are closely related to human activities at home, and such household appliances are not frequently changed, thus, building the activity recognition model is feasible. The relevance between electric appliance use and human activities is built in this model, which is used to identify the present activities at home, to know which electric appliances may be out of use, and the information of such active nonparticipating electric appliances can be fed back to the client for subsequent processing.

The electric appliances being used under the IoT router gateway can be known from the electric appliance recognition model. The activity recognition model collects context-aware information from the context database in the gateway; the information is analyzed by the context provider bundle and integrated with that from other inductor bundles. The electric appliance and context-aware information are mixed; the activity learning system defines and determines the relevance between activity and electric appliance, which it stores in the activity database. In the activity recognition system, as shown in Fig. 2, the service data of devices are grouped into activities, and the relevance data are formed from these activities and devices.

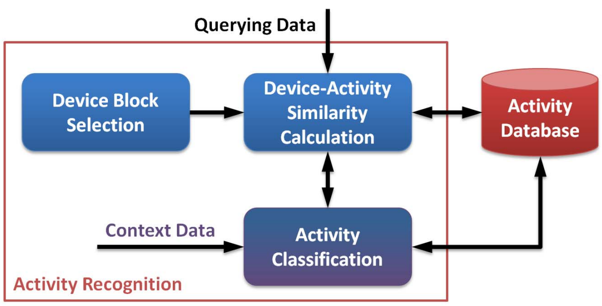

Figure 2. The Detail in Activity Recognition Bundle

1) Device Block Selection Unit: Fig. 3 shows the data block, where four blocks and two segments are indicated by rectangular outlines, the lateral axis represents time (t), the block time is represented by T, and the block name is subscript. For example, TB1 represents the time span of block 1. As TB1 is 10, block 1 (B1) consists of 10 segments; each segment of B1 has the same content of D1, D2 and D3. Afterwards, if the stability threshold is 3 time units, B1, B3 and B4 are stable blocks; B2 is impermanent block, because the block time of B2 is 2, two segments. There are two independent segments S1 and S2 in front of B1, where blocks cannot be formed.

The impermanent block or independent segment is resulted from activities transferred or stopped. The activity transfer can be known from drastic changes in the block state, i.e. block content. B1 to B4 represents an activity transfer, however, as D1 exists in both blocks. It can be inferred that D1 is a long-term operating device, such as a daylight lamp or air conditioner. The activity stop can be regarded as a block content disappearance to the behavior of long-term device status, such as the process of B1 to B3, D3 and D2 disappear in the block, thus, the activity represented by B1 is stopped. In order to allow blocks and activities have better reflection, the independent segment and impermanent blocks are merged to the stable block, upon determination of the stable block.

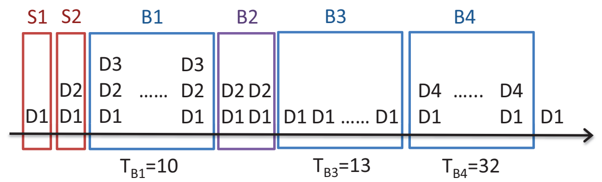

Figure 3. Device Block Diagram

2) Device-Activity Similarity Calculation Unit: In the network, each activity and device is a node, in the same way, one query data is a node. The connection between nodes represents the relation between the nodes; the activity node pointing to the device node means the activity involves the pointed device. The query node is pointed by the device node, meaning the query data consists of the pointed node devices. Multiple query nodes pointing to another query node means the query can be composed of other sub-queries. For example, node I is the union of node q and node q_1

All symbols of the description model are as defined in Table 1. Let t be the number of devices in the activity recognition system, and k_i is a device. Let a_j be a binary random variable associated with activity a_j, and let q be a binary random variable associated with the user query. A t-dimensional vector k is defined by all devices, i.e. $(k_1, k_2, \ldots, k_t)$ where k_1, k_2, ..., k_t are binary random variables.

Table I
NOTATIONS USED FOR INFERENCE NETWORK MODEL

Notation	Definition
t	the number of devices in activity recognition system
k_i	a device, a binary random variable
$\vec{k}$	t-dimensional vector defined by k_1, k_2, . . ., and k_t
q	a user query, a binary random variable
a_j	an activity, a binary random variable
g_i	a function returns the weight associated with the device k_i

The activity ranking about a query q is an observational measurement, and this observation means an activity has numerous obvious supports for query q. In an inference network, the activity ranking is calculated by $P(q \bigwedge a_j)$, q and a_j are short expression of q = 1 and a_j=1. Therefore, the ranking equation is as shown below:

$$P(q \wedge a_j) = \sum_{\forall \vec{k}} P(q \wedge a_j \mid \vec{k}) \times P(\vec{k}) = \sum_{\forall \vec{k}} P(q \mid a_j \times \vec{k}) \times P(a_j \times \vec{k}) = \sum_{\forall \vec{k}} P(q \mid \vec{k}) \times P(\vec{k} \mid a_j) \times P(a_j) \tag{1}$$

because node k_i separates query node q from activity node a_j. The tf-idf mechanism is used to complete the calculation of ranking probability. According to observed activity a_j, the relevance of a device k_i is determined by normalized term-frequency factor, as the following equation

$$p(k_i \mid a_j) = f_{i,j} = \frac{freq_{i,j}}{\max freq_{i,j}} \tag{2}$$

Where, $freq_{i,j}$is the frequency of device k_i in the activity a_j, and the maximum is obtained by all devices in activity a_j. The influence of device node on query node is determined by influence of idf factors; a device active vector is defined as follows :

$$\vec{k_i} = \vec{k} \mid \left(g_i(\vec{k}) = 1 \wedge \forall_{j \neq i} g_i(\vec{k}) = 0 \right) \tag{3}$$

The active vector $\vec{k_i}$ is the state reference for vector $\vec{k}$, meaning node k_i is active to $\vec{k}$ whereas other nodes are inactive. According to active vector, the influence of the device node in the query node q is as shown below.

$$P(q \mid \vec{k}) = \begin{cases} idf_i, \text{ if } \vec{k} = \vec{k_i} \wedge g_i(\vec{q}) = 1 \\ 0, \text{ if } \vec{k} \neq \vec{k_i} \vee g_i(\vec{q}) = 0 \end{cases} \tag{4}$$

Where, idf_1 is a normalized idf factor defined as follows:

$$idf_1 = \log \frac{N}{n_i} \tag{5}$$

N is the total number of activities in the system and n_i is the number of activities where device ki appears. The complete ranking equation can be obtained from the aforesaid equation

$$\begin{aligned} &P(q \wedge a_j) \\ &= \left(\prod_{\forall i} P(\vec{k} \mid a_j) \right) \times P(a_j) \times \sum_{\forall \vec{k_i}} P(k_i \mid a_j) \\ &\times P(q \mid \vec{k_i}) \times \frac{1}{P(\vec{k_i} \mid a_j)} \\ &= c_j \times \frac{1}{|\vec{a_j}|} \times \sum_{\forall i \mid g_i(\vec{d_j}) = 1 \wedge g_i(\vec{q}) = 1} f_{i,j} \times idf_i \\ &\times \frac{1}{1 - f_{i,j}} \end{aligned} \tag{6}$$

IV. System Implementation and Experimental Analysis

This section presents the prototype system of the overall architecture, and experimentally analyses appliance-aware activity recognition. This study tests and analyzes the appliance awareness activities of Recognition, including relevance ranking, time interval, and activity classification, and uses recall (Rec) and precision (Pre) evaluation indices to evaluate test results.

A. Similarity Ranking Analysis

This experiment targets in testing the data similarity ranking, when the system detected all appliances used, the electronic data would be used in the Device-Activity Similarity Model to find the similarity ranking. This experiment first targets the four main activities mentioned above to pick one appliance as the comparison target to perform behavior similarity ranking in getting the top twenty ranked precision an recall. The results are as shown Fig. 4.

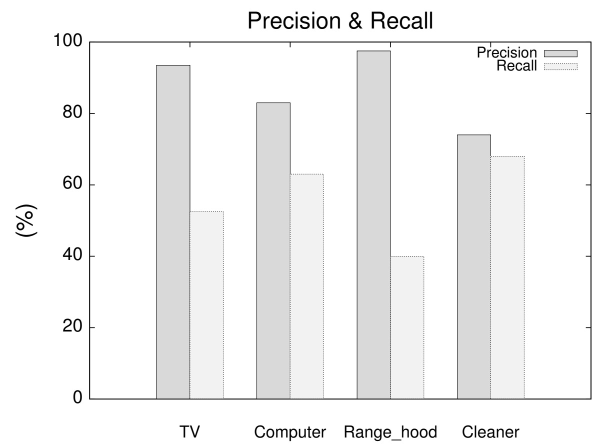

Figure 4. Precision and Recall for Four Appliances

From these results it can be found that because the user often leave the computer on while performing different activities, therefore, the precision is lower compared to others as well as the recall percentage being higher. As for cooking, since the appliance changes very little, the precision of recognition is much higher and recall is less compared to the other values. As a continued experiment, the user was asked to perform a test of the above four activities within an hour, results shown as Fig. 5. Since the user will have appliance state changes even while the user is watching television and cleaning. Therefore the precision and recall percentages are much higher. Using the computer and cooking are activities that require more attention, hence the appliance changes are less creating higher precision.

B. Classifier Analysis

This experiment uses different classifiers, which targets appliance classification analysis research shown as Table 2.

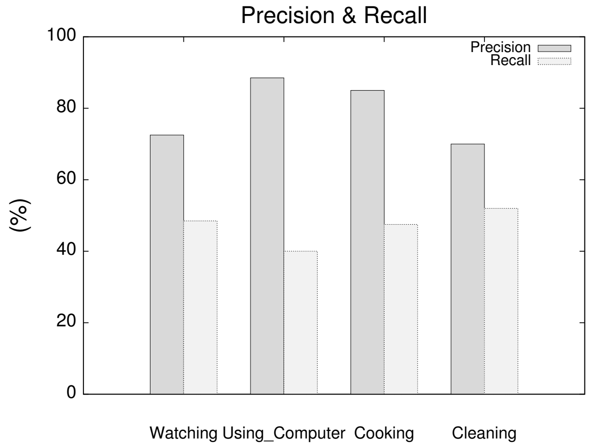

Figure 5. Precision and Recall for four Activities

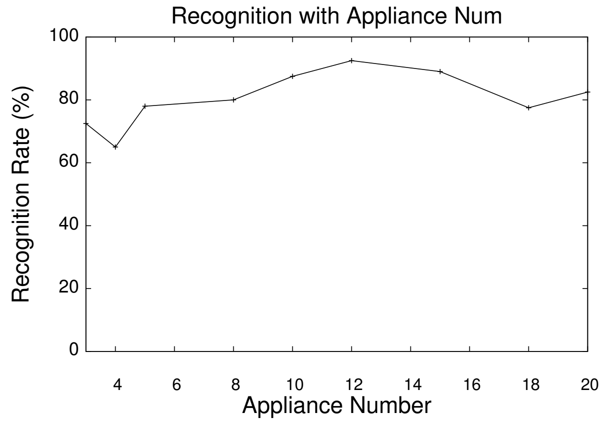

Figure 6. Recognition Precision for Different Number of Appliances

Table II
RECOGNITION ON DIFFERENT CLASSIFIER MODEL

	KNN	Naive Bayes	C 4.5
Precision	87.3	92.5	90.4
Recall	70.8	72.5	67.3

These are KNN, Naive Bayes Method and Decision Tree C4.5. From here we find the Naive Bayes Method has better classification performance.

C. The Effect of Different Appliance Toward Recognition Rate

Considering the effect of number of appliance within the overall environment to the recognition of one activity, if considering one of the activities mentioned above, when watching television the surrounding appliances might have changes. Therefore watching television is used to perform recognition, the results are shown Fig. 6. When number of appliance is less than three, or when the user temporarily performs other activities, the core appliance television, since it is constantly turned on, causes the result to be recognized as watching television. When appliance number exceeds 15 , multiple appliances have state changes causing the similarity ranking to decrease and the overall recognition rate have also decreased.

V. CONCLUSIONS

With the current development of IoT and the popularization of energy-saving, this study introduces an IoT energy management system that is device oriented. Household appliances can be added into the IoT system with device recognition technology without any additional identification devices. The current activity of the user can be determined using device block selection mechanism, and the relation between these activities and devices can be constructed using the inference network model. The activity are classified using context data using Nave Bayes. This system automatically switches devices off or on, or reminds the users instead of controlling the devices directly to achieve energy management. Behaviour still need device identification for simple device oriented recognition. In the future this system can utilize image or location data for hybrid recognition to increase the activity recognition service and attempts to infer the activity to attain higher level of intelligent control.

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REFERENCES

[1] Chu-sing, Y., Ming-yi, L. and Chao-xing, C. (2009) Design and implementation of HEMS based on RFID and OSGi. Anti-counterfeiting, Security, and Identification in Communication, 2009. ASID 2009. 3rd International Conference on.

[2] Dae-Man, H. and Jae-Hyun, L. (2010) Design and implementation of smart home energy management systems based on zigbee. Consumer Electronics, IEEE Transactions on. 56(3) 1417-1425.

[3] Lai, Y.-X., Rodrigues, J. J., Huang, Y.-M., Wang, H.-G. and Lai, C.-F. (2012) An Intercommunication Home Energy Management System with Appliance Recognition in Home Network. Mob. Netw. Appl. 17(1) 132-142.

[4] Young-Sung, S. and Kyeong-Deok, M. (2010) Home energy management system based on power line communication. Consumer Electronics (ICCE), 2010 Digest of Technical Papers International Conference on.

[5] Rossello-Busquet, A., Soler, J. and Dittmann, L. (2011) A Novel Home Energy Management System Architecture. Computer Modelling and Simulation (UKSim), 2011 UkSim 13th International Conference on.

[6] Chao, C., Das, B. and Cook, D. J. (2010) A Data Mining Framework for Activity Recognition in Smart Environments. Intelligent Environments (IE), 2010 Sixth International Conference on.

[7] Tapia, E., Intille, S. and Larson, K. (2004) Activity Recognition in the Home Using Simple and Ubiquitous Sensors Pervasive Computing. In Ferscha, A. and Mattern, F. (eds). Springer Berlin / Heidelberg.

[8] Kasteren, T. v., Noulas, A., Englebienne, G., Kr B., #246 and se. (2008) Accurate activity recognition in a home setting. Proceedings of the 10th international conference on Ubiquitous computing, 1409637 ACM pp. 1-9.

[9] Harris, C. and Cahill, V. (2005) Exploiting user behaviour for context-aware power management. Wireless And Mobile Computing, Networking And Communications, 2005. (WiMob'2005), IEEE International Conference on.

[10] Liao, L., Fox, D. and Kautz, H. (2005) Location-based activity recognition using relational Markov networks. Proceedings of the 19th international joint conference on Artificial intelligence, 1642417 Morgan Kaufmann Publishers Inc. pp. 773-778.

[11] Singla, G., Cook, D. and Schmitter-Edgecombe, M. (2010) Recognizing independent and joint activities among multiple residents in smart environments. Journal of Ambient Intelligence and Humanized Computing. 1(1) 57-63.

[12] Duong, T. V., Bui, H. H., Phung, D. Q. and Venkatesh, S. (2005) Activity recognition and abnormality detection with the switching hidden semi-Markov model. Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on.

[13] Ben-Arie, J., Zhiqian, W., Pandit, P. and Rajaram, S. (2002) Human activity recognition using multidimensional indexing. Pattern Analysis and Machine Intelligence, IEEE Transactions on. 24(8) 1091-1104.

[14] Luhr, S., Bui, H. H., Venkatesh, S. and West, G. A. W. (2003) Recognition of human activity through hierarchical stochastic learning. Pervasive Computing and Communications, 2003. (PerCom 2003). Proceedings of the First IEEE International Conference on.

[15] Intille, S. S., Larson, K., Tapia, E. M., Beaudin, J. S., Kaushik, P., Nawyn, J. and Rockinson, R. (2006) Using a live-in laboratory for ubiquitous computing research. Proceedings of the 4th international conference on Pervasive Computing, 2094967 Springer-Verlag pp. 349-365.

[16] Patterson, D. J., Fox, D., Kautz, H. and Philipose, M. (2005) Fine-grained activity recognition by aggregating abstract object usage. Wearable Computers, 2005. Proceedings. Ninth IEEE International Symposium on.

[17] Ito, M., Uda, R., Ichimura, S., Tago, K., Hoshi, T. and Matsushita, Y. (2004) A method of appliance detection based on features of power waveform. Applications and the Internet, 2004. Proceedings. 2004 International Symposium on.

[18] Gu-yuan, L., Shih-chiang, L., Hsu, J. Y. J. and Wan-rong, J. (2010) Applying power meters for appliance recognition on the electric panel. Industrial Electronics and Applications (ICIEA), 2010 the 5th IEEE Conference on.

[19] Ruzzelli, A. G., Nicolas, C., Schoofs, A. and O'Hare, G. M. P. (2010) Real-Time Recognition and Profiling of Appliances through a Single Electricity Sensor. Sensor Mesh and Ad Hoc Communications and Networks (SECON), 2010 7th Annual IEEE Communications Society Conference on.

[20] Lee, S.-C., Lin, G.-Y., Jih, W.-R. and Hsu, J. Y.-J. (2010) Appliance Recognition and Unattended Appliance Detection for Energy Conservation. AAAI Publications, Workshops at the Twenty-Fourth AAAI Conference on Artificial Intelligence, Westin Peachtree Plaza in Atlanta, Georgia, USA.