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An Intelligent Human Behavior-Based Reasoning Model for Service Prediction in Smart Home

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ABSTRACT With the rapid development of technologies and improvement of living conditions, people are increasingly concerned about their life safety, convenience, and comfortableness. Household intelligence starts to play an increasingly important role in improving people living environment. This paper focuses on service prediction in smart home automatic control systems, and proposes an intelligent human behavior-based reasoning model on the basis of linear prediction and case-based reasoning. Hardware and software are designed after analysis of the embedded architecture. In addition, an embedded smart home platform is built up and implemented to validate the proposed human behavior-based reasoning algorithm.

INDEX TERMS Internet of Things, service prediction, human behavior-based reasoning, intelligent embedded system.

I. INTRODUCTION

The Internet of Things (IoT) is closely related to people daily life, especially with the appearance of smart city. Smart city systems improve the quality of life, and greatly progress the management efficiency in reality. The concept of smart city including smart building construction, smart grids, waste management and gradually spans to some key areas, for example, the energy saving supervision [1]. The increasing request of energy is a main feature in modern society. According to the BP Corp's data from 2001 to 2004, it shows a global raise about 3.7% [2]. With a conservative evaluation of 2% growth per year, the requirement for principal energy maybe two times as much as present by 2037 [3]. Besides, with the advance of wealth and culture, peoples demands for life quality and living environment are increasing [4]. Along with the overall energy utilization globally, buildings energy exploitation takes about 35%∼40%. Although the majority research concentrated energy savings for the duration of in use time, there are shocking amount of energy wasted for the period of free time in business buildings. At least five detailed energy audits were carried out in the hot and dry climates of Botswana and South Africa. The result indicates that the majority of energy is used throughout the free time (56%) than during working hours (44%). This is mainly caused by occupants' behavior of leaving lights and equipment on all the time and poor controls. There is an urgent need for smart building management in reality [5]. For the sake of instant household consumption feedback shortage, the homeowners electricity consumption has increased by approximately 6∼10% [6]. After a qualitative study of fifteen households and their current management practices around electricity in the home, it has been found that the energy consumption is mostly invisible to householders [7], which result in more energy consumption.

In order to manage increasing domestic appliances as well as reducing energy wastes, smart home systems are emerging. One of the key technologies for smart homes is to accurately predict the future status of home appliances, such as light, air conditioner and so on. Due to the increasing amount of sensors, how to predict future events and provide corresponding services, such as turning on the equipment in advance and turning it off when users leave home to work, to minimize energy wastes becomes an important research direction [8].

II. LITERATURE REVIEW

One of the key challenges in smart home systems is the service prediction algorithm [9]. A number of prediction schemes have been proposed in smart home scenarios [10]. The structural design of smart homes is often characterized as a layered model. For example, a four-layered model is proposed in [11]. The top layer of this model is the ''decision layer'', which makes decisions on service actions by integrating data provided by other layers. The other layers communicate with physical hardware, store the information obtained, and pass it to the decision layer.

The most popular models used by prediction algorithms for smart homes are the Markov model and Bayesian networks. For example, Hidden Markov Model (HMM) [12], [13], which works on unknown or hidden system states, is often used to model human behavior and maintain the Markov property. Compared to Markov model, Bayesian network (BN) is a more common. However, BN is too rigid and has trouble to adopt the "exact probabilistic inference" [14]. Beyond Markov model and Bayesian networks, LZ78 algorithm has been proposed by Ziv and Lempel [15]. As LZ78 cannot be used in practice due to its high complexity in the compression of individual sequences, LeZi update [16] is proposed to partially solve the efficiency of built-in predictive power. With the intention of conquer these restrictions, Gopalratnam and Cook [17] introduce for smart home environments the Active LeZi, which is derived from an information theoretic approach, derived from the acclaimed LZ78 family of data compression algorithms. Fang and Ruan [18] propose an enhancement for Active LeZi as time-varying LeZi (TALZ). The improvement is rooted in the inspection that human behavior happen tendency in a periodical pattern [19].

Current studies can be further improved in the following aspects. Firstly, the prediction model structure could be further simplified according to the functional requirements of Internet of Things (IoT). Secondly, the former estimation algorithms, such as Markov model and Bayesian network, depend only on the direct prior state and ignore all other history states. Self-educated process that utilizes the historical data more sufficiently may further improve the performance [20], [21]. Finally, users sometimes just want to get services immediately when they are back home, while neglecting how long these services have been initiated in advance. Consequently, the corresponding consideration about real daily living scenario should also be taking into account.

Beyond the prediction algorithm, the design of smart control terminal, which is the most important equipment in home environment, is still immature. There are a number of different schemes for smart home have been proposed, such as internet of things (IoT), intelligent control, home automation, and energy management [22], [23]. The first design mainly focuses on appliance management by using keyboard, infrared universal remote controllers, touch panels and LCD displayers. Nevertheless, this approach requires the terminal design of software and hardware, resulting in expensive costs and complicated design process. The second design employs personal computer (PC) as control terminal, which is inconvenient due to the low mobility of PC. The third design leverages smart phone as control terminal, which connects with appliances through wireless networks, such as Wi-Fi, Bluetooth, and GSM [24]. This is convenient and handy. However, it is not implemented widely due to the bad user experiences and complex design challenges.

Therefore, in this work, we mainly contribute from two aspects: service prediction model and smart home platform design and implementation. In particular, an intelligent human behavior-based reasoning (HBR) model is proposed for service prediction in smart homes. In the proposed model, auto regressive algorithm is used as preprocessing to further improve the prediction accuracy. Additionally, the proposed model makes full use of the historical data and is proved to have better performance when compared with other existing schemes. Meanwhile, because of the model prediction accuracy, it will help to save energy in our daily life. Besides, we cut down the former four-layer architecture into a three-layer structure, which aligns with the well-designed necessities of IoT.

Furthermore, to solve the smart home control problems, this paper uses the latest technologies, including embedded systems, ZigBee wireless communications [25], and appliance control protocols. Based on these, we implement a smart home platform to verify the efficiency of proposed human behavior-based reasoning (HBR) scheme.

The rest of this paper is organized as follows. In Section III, the proposed HBR model, including the detection method, human behavior characteristics and system flow, is presented. In Section IV, a real embedded smart home platform has been built up to test the proposed scheme. In Section V, the performance of proposed approach is analyzed, and numerical experiment results are presented. Section VI concludes this paper.

III. SYSTEM MODEL

A. TIME DEVIATION / TIME SIMILARITY

In order to provide service prediction, we need to first find out users daily equipment usage patterns [26]. Therefore, the notion of time division is established. Time division indicates a time interval which is determined through statistical analysis of the households turning on moment over a period of time. For some devices, they may have more than one time divisions during a day.

Specifically, we explain the concept of time division through an example of the turning on time for a home TV. Through the statistics and analysis of users' actions in a certain period of time, time interval can be derived. The steps are as follows:

1) A record of the turning on time of a TV within five days is shown in Table 1.

TABLE 1. TV turning-on time in five days.

Day	Time		
1	7:30	13:00	20:30
2		12:50	20:32
3	7:10,7:20	13:10	21:01
4	7:35		20:40
5	7:25	12:45	19:00

The turning-on timing in Table 1 could be arranged in ascending order as follows.

$$\{7:10,7:20,7:25:7:30,7:35,12:45,12:50, 13:00,13:10,19:00,20:22,20:30,20:40,21:01\}$$

2) We then collect the data within the same hours into the same group, which results in multiple data groups with the interval length ranging from $0 \sim 60$ minutes.

Group 1 : 7:10, 7:20, 7:25, 7:30, 7:35
Group 2 : 12:45, 12:50
Group 3 : 13:00, 13:10
Group 4 : 19:00
Group 5 : 20:22, 20:30, 20:40
Group 6 : 21:01

Among the time data obtained through these preliminary groups, the difference between the second group and the third group is quite small. Similarly, the fifth and sixth groups of data are also very close. By adjusting the grouping data, more meaningful data will be obtained.

3) Compare the grouped data in chronological order, that is, compare the first data of the latter group with the last time data of the previous group. If the time difference between the two is less than or equal to λ (i.e. $\lambda = 30$ min), then the two data groups will be merged into one. The above adjustment can be repeated until no more groups can be merged. The six groups in step two can be merged into four groups as follows. Each group is then called a time division.

Time division 1 : 7:10, 7:20, 7:25, 7:30, 7:35;
Time division 2 : 12:45, 12:50, 13:00, 13:10;
Time division 3 : 19:00;
Time division 4 : 20:22, 20:30, 20:40, 21:01.

To make data more accurate, we will compensate the error through statistical approaches. Specifically, within each time division i, for a given appliance j, we consider its initial launching time and the average launching time as α and β, respectively. Then we define time deviation as

$$\xi_{i,j} = \left|\alpha_{i,j} - \beta_{i,j}\right| \tag{1}$$

which is independent for different appliance.

In addition, we further define time similarity as follows.

$$\tau(\alpha_{i,j}, \beta_{i,j}) = 1 - \frac{\xi_{i,j}}{\varepsilon} \tag{2}$$

where ε represents the time span as twenty-four hours. The time deviation and time similarity will be used as inputs for the following auto regressive enhanced prediction.

B. AUTO REGRESSIVE ENHANCED PREDICTION

Next, the proposed scheme in this paper applies linear prediction in the preprocessing of received historical device turning on data. In the setting of time slack p in $AR(p)$, the procedures are as follows. At the beginning, the historical data will be firstly split into two data sets, that is, training set and test set. Moreover, the training set will be used to make forecast through the linear prediction algorithm while the test set verifying its accuracy. Furthermore, when its precision meets the requirement, the time slap p at the moment will be adopted in the model.

The received signal time series can be expressed as $\left\{W_t, W_{t-1}, W_{t-2}, \cdots, W_{t-p}\right\}$. In $AR(p)$ scheme, samples $\left\{W_t, W_{t-1}, W_{t-2}, \cdots, W_{t-p}\right\}$ are used to predict the condition of house appliance. The forward prediction value at time t denoted by a_t is calculated as

$$W_t - \varphi_1 W_{t-1} - \varphi_2 W_{t-2} - \cdots - \varphi_p W_{t-p} = a_t, \quad t = 0, \pm 1, \pm 2, \cdots \tag{3}$$

where $\varphi_i (i = 1, 2, .., p)$ is the coefficient. The retardation factor B is an operator, which follows $B^k W_t = W_{t-k}, k \geq 1$. The stipulation of appliance a_t is then defined as

$$(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p) \cdot W_t = a_t \tag{4}$$

When $\Phi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$, the above mentioned equation can be illustrated as

$$\Phi(B) \cdot W_t = a_t, \quad t = 0, \ \pm 1, \ \pm 2, \cdots \tag{5}$$

Auto regressive scheme is a generally method in the analysis of linear algebra [27]. Based on this approach, some signal statistics will be defined, which reveal distinctive features only in the presence of house appliance. This discrimination will improve the probability of detection.

In the function $W_t = \Phi^{-1}(B) \cdot a_t$, in which $G(B) = \Phi^{-1}(B) = \sum_{k=0}^{\infty} G_k B^k$, $|B| < 1$, we see that $W_t = \sum_{k=0}^{\infty} G_k a_{t-k}$ where $G_k, k = 0, 1, 2, \cdots$ is the Green function of $AR(p)$ model. Similarly, in $a_t = \Phi(B) \cdot W_t$ where $I(B) = \Phi(B) = G^{-1}(B) = I_0 - \sum_{k=1}^{\infty} I_k B^k$,$|B| < 1$ $(I_0 = 1)$, we can obtain $a_t = W_t - \sum_{k=1}^{\infty} I_k W_{t-k}$. It can be revealed from the function that $I_k, k = 0, 1, 2, \cdots$ is the inverse function for $AR(p)$.

From the stationary sequence $\{W_t\}$, which $W_k, W_{k-1}, W_{k-2}, \cdots$ is known, it can be get $\hat{W}_j = W_j (j \leq k)$, $\hat{a}_{k+l} = 0 (l \geq 1)$. With these processes, some signal statistics estimate equations are derived below.

$$\hat{W}_k(l) = \varphi_1 \hat{W}_k(l-1) + \varphi_2 \hat{W}_k(l-2) + \cdots + \varphi_p \hat{W}_k(l-p), \quad l > q \tag{6}$$

$$\hat{W}_k(l) = \sum_{j=1}^{\infty} I_j^{(l)} \cdot W_{k+1-j}, \quad l \geq 1 \tag{7}$$

where

$$\begin{cases} I_j^{(1)} = I_j & j \geq 1 \\ I_j^{(l)} = I_{j+l-1} + \sum_{m=1}^{l-1} I_m I_j^{(l-m)} & j \geq 1, \ l \geq 2. \end{cases}$$

After the above auto-regressive prediction, we will be able to obtain the estimated time deviation / time similarity as $\xi'_{i,j}$ and $\tau(\xi'_{i,j})$. According to the relationship between the estimated time similarity $\tau(\xi'_{i,j})$ and the actual time similarity extracted from historical data $\tau(\xi_{i,j})$, we define the valid interval as follows.

When the estimated value $\tau(\xi'_{i,j})$ falls in the range of $(\tau(\xi_{i,j}), 1)$, we call $(\tau(\xi_{i,j}), 1)$ as a valid interval, and $(0, \tau(\xi_{i,j}))$ as an invalid interval.

In view of the scenario that one device maybe repeatedly turned on and off during a day, the equipment consequently has multiple time similarities. As a result, the time similarity of house appliance A at $t_1, t_2, \cdots, t_k, \cdots$ can be notated as $\tau_1 \Big|_{t_1}^{A}, \tau_2 \Big|_{t_2}^{A}, \cdots, \tau_k \Big|_{t_k}^{A}, \cdots$ respectively. Analogously, we see that $\tau_1(\alpha_1, \beta_1) \Big|_{t_1}^{A}, \tau_2(\alpha_2, \beta_2) \Big|_{t_2}^{A}, \cdots, \tau_k(\alpha_k, \beta_k) \Big|_{t_k}^{A}, \cdots$. In valid interval, the maximum time similarity can illustrated as $\tau_{\max}(\alpha_k, \beta_k) \Big|_{t_k}^{A}$, while the minimum one could be notated as $\tau_{\min}(\alpha_k, \beta_k) \Big|_{t_k}^{A}$. Hence, they can be denoted as $\tau_{\max} \Big|_{t_k}^{A}$ and $\tau_{\min} \Big|_{t_k}^{A}$ for short.

The time deviation $\xi_{i,j}$ actually reflects appliances' turning on patterns. For example, when $\xi_{i,j}$ is small, the time similarity $\tau(\xi_{i,j})$ will be quite large, while the effective interval will be narrowed accordingly, which reveals strong patterns of users' daily living behaviors. In contrast, when $\xi_{i,j}$ is large, time similarity $\tau(\xi_{i,j})$ will be small, and then the effective interval will be large, indicating that the house appliances' turning on behavior has a weak pattern.

C. HUMAN BEHAVIOR CHARACTERISTICS

In this section, we will discuss the collection of human behavior characteristics. In particular, the raw data such as Table 1 is taken as input. Then, we define a fixed number of days (i.e. m) as the time of human daily living behavior turning into a habit. For a specific appliance, if its usage duration begins at day D, and ends at day $D + m$. In addition, as each day is divided into several time divisions (as discussed in Section III.A), we convert the raw data into Table 2.

As shown in Table 2, each column represents one day and each row represents one time division (TD). The value α_{kl} represents the initial launching time of the appliance at day l time division k. The human behavior employs natural number coding, that is, for the device n turning on behaviors, each of them takes an integer value from 1 to m (i.e. the maximum value). A user appliance turning on behavior structure is then created like this,

R	n	D	m

where R indicates the starting time division (TD) expressed by the row number in Table 2, n shows the number of permissible time divisions, and D represents the starting date expressed by column number.

TABLE 2. The relationship between device and time interval.

	D_1	D_2	…	D_l	…	D_M
TD_1	α_{11}	α_{12}	…	α_{1l}	…	α_{1M}
TD_2	α_{21}	α_{22}	…	α_{2l}	…	α_{2M}
…	…	…	…	…	…	…
TD_k	α_{k1}	α_{k2}	…	α_{kl}	…	α_{kM}
…	…	…	…	…	…	…
TD_N	α_{N1}	α_{N2}	…	α_{Nl}	…	α_{NM}

For each appliance A, based on the user behavior characteristics structure, we are able to calculate the maximum time similarity $\tau_{\max} \Big|_{t_i}^{A}$ as the best possible result.

D. HUMAN BEHAVIOR-BASED REASONING SERVICE

Our original motivation is to make the smart home system analyze user daily living behavior automatically, so that it can gradually have the ability to learn user operating behavior, and then be able to actively provide desired service. Therefore, the proposed human behavior-based reasoning (HBR) model is based on auto regressive prophecy and case based reasoning (CBR) [28], [29].

As we know, CBR implies use previous knowledge to identify with and work out new issues [30]. In CBR, a reasoner can memorizes the former case which has some features in common with the present, then deal with the encountered subject. CBR also indicates that adjusting previous methods with new requirements, using former cases to deal with new circumstances. Besides, CBR is also used in machine learning field to solve problems. It combines aspects from the knowledge-based systems in addition to from the machine learning field.

Specifically, we consider users' daily living behavior as cases, for example, the retrieval item of appliance turning on time. In order to better understand its characteristics, first, we divide the household equipment turning on time into several intervals after the statistical analysis in a period of time. Then, its similarity could be calculated according to equation (2) mentioned above. Additionally, in the light of CBR methodology, we index similarity to match different cases for further prediction. The proposed human behavior-based reasoning (HBR) model, which designed to enhance the service prediction accuracy is shown in Fig. 1.

For the HBR model training with historical data, the procedures are as follows. First, search all the stored human daily living behaviors to find out which appliance has the similar turning on time with the current user. Second, utilize the linear prediction method to improve the accuracy of service prediction. Third, gather and analyze the timing factor of

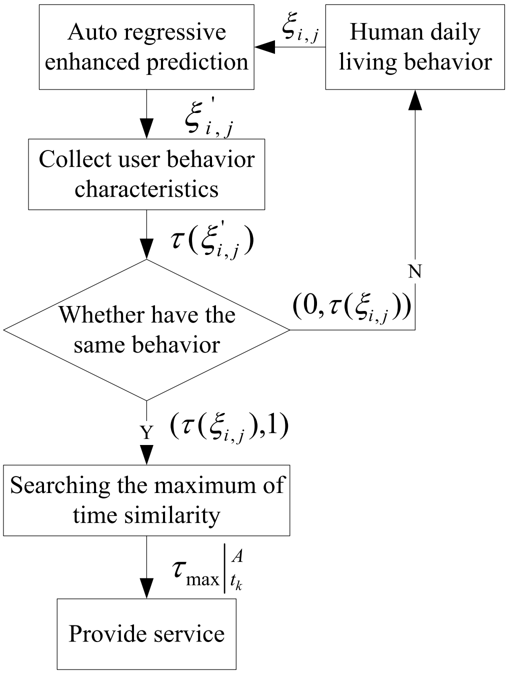

FIGURE 1. Flow chart of the human behavior-based reasoning model.

users' operation behaviors to identify the user with the same daily living habits. Fourth, repeat the previous three steps again to find its nearest neighbor and calculate the time span between them. Fifth, update the searched user in view of their daily living behavior. At the end, double check just to make sure on the necessity of service providing.

E. USER BEHAVIOR SIMILARITY

As users may occasionally have a delay during the daily living activities, it may result in $\tau(\xi'_{i,j})$ falling in the invalid interval. To handle this special scenario, beyond the above HBR modeling process, we also introduce the concept of user behavior similarity. Frequently, the household construction set consists of feature set and relation set, which can be indicated as $U : U = \{Feature, Relation\}$. Moreover, the configuration set U may also include some other users' properties. For example, with the users different behavior, it may contain the weight coefficient w, that is, $U : U = \{Feature, Relation, Weight\}$.

Suppose that $User1$ and $User2$ match all the characteristics, then we have $U_1 = U_2$. If they only have some features in common, they are partially similar. We proposed to use Sim to represent the similarity between two users. The collection of any two separate users can be defined as $V_A = \{a_1, a_2, \cdots, a_n\}$, $V_B = \{b_1, b_2, \cdots, b_n\}$, hence the similarity between them can be illustrated as

$$Sim(A, B) = \frac{1}{n}\sum_{i=1}^{n} \sin(a_i, b_i) \tag{8}$$

Considering the scenario that user operation behavior maybe abnormal, the conception of corresponding weight has been introduced. As a result, the equation of behavioral similarity could be expressed as

$$Sim(A, B) = \frac{\sum_{i=1}^{n} \sin(a_i, b_i) w_i}{\sum_{i=1}^{n} w_i} \tag{9}$$

where $\sin(a_i, b_i) = \begin{cases} 1, a_i = b_i \\ 0, a_i \neq b_i \end{cases}$, and a_i stands for the appliance to be predicted, while b_i express the stored home appliances. At the moment when $a_i = b_i$, the forecast result is true, $\sin(a_i, b_i) = 1$; while otherwise, $\sin(a_i, b_i) = 0$. Concurrently, the weight coefficient w_i can be defined elasticity on account of different condition.

IV. EMBEDDED SMART HOME PLATFORM

A. INTEGRAL STRUCTURE DESIGN

In fact, the traditional smart home scheme also requires user operation from time to time. Besides, the terminal design of software and hardware is complicated, whereas the cost is very high. Moreover, its interaction is usually not user friendly, resulting in difficulties to operate, especially for senior people. Additionally, its related service is typically static and not customized for individual users, which cannot adapt to user living behavior in daily life.

Considering the above disadvantages, our proposed model aims to satisfy users' individual demands by making the services more customized. In addition, the prediction method will help the control of home equipment to make users feel more comfortable. According to the functional requirement of Internet of Things [31], which includes comprehensive perception, reliable delivery and intelligent processing, we propose to divide the smart home system into three layers as follows: perception layer, network layer, and application layer, as illustrated in Fig. 2. Among them, the function of perception layer is to collect data by using various sensors, and then sends these data into network layer. The network layer requires realizing a smart home gateway based on the proposed human behavior-based reasoning (HBR) algorithm. On the one hand, it can connect home network with the Internet. On the other hand, the intelligent gateway can also coordinate the data from perception layer with the command from application layer. The application layer needs to realize a web-page interface and Android client to deal with the data from server, and to carry on human-computer interaction.

The intelligence of home equipment largely depends on the algorithm embedded in smart home gateway. The intelligence degree of proposed HBR model is mainly reflected in the number of times that smart home platform can provide users with the desired services, such as turning on the devices (e.g. light, air conditioner, washing machine and so on) in advance and then turning them off when after the usage if users forgot, which is greener compared with traditional home automation system.

The embedded smart home platform combines the control center with sensor terminal [32], which mainly includes the front data center, remote monitoring terminal, and the server.

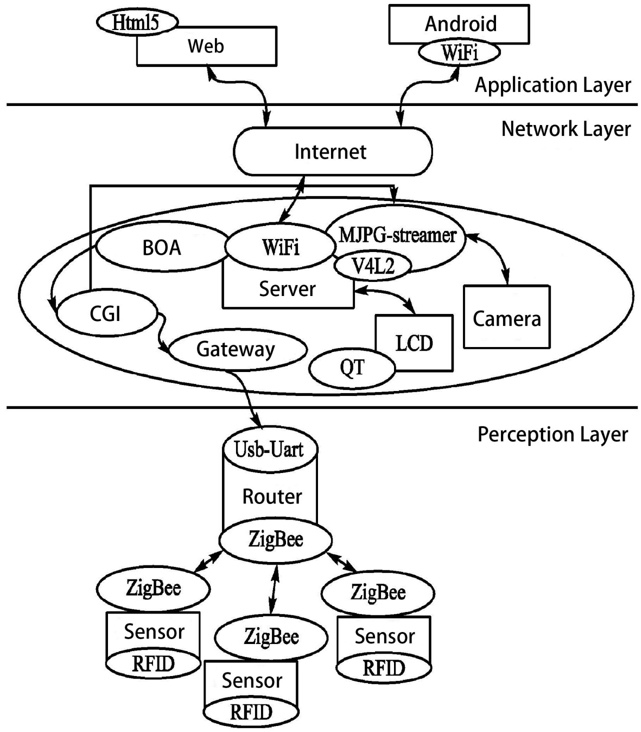

FIGURE 2. Schematic design of the embedded smart home platform.

This enables the proposed model to master and control their appliances' condition. At first, the data receiver module accepts the data from sensor terminal through ZigBee, including the home temperature, humidity and intensity of illumination. Then the data will be sent to the control center. After the data processing module receives the message, it will activate the database thread to save the data. Meanwhile, it will also activate the memory data to update the real time context data. Finally, a decision on whether to raise an alarm or not will be made based on the message mentioned above. In addition, through the smart home gateway which embeds the intelligent HBR algorithm, users could supervise their house automatically and get the desired services. The hardware design diagram of embedded smart home control center and sensor terminal are given in Fig. 3 and Fig. 4.

The sensor terminals are mainly responsible for all kinds of indoor information collection and uploading, giving timely responses to the system instructions at the meantime. The indoor related information generally includes temperature, humidity, light intensity, buzzer, LED and so on. Smart home control center communicates with the sensor terminals through ZigBee module, which has a lower cost and power consumption. Temporarily, for the exploit of bidirectional conversion chip SC16IS752, the on-chip limited UART resources have been greatly saved. Moreover, sensor terminals can send *NEWNODE* data to control center through the ZigBee module, and then the control center could read the data through *MainReadThread*. After that, *MainHandlerThread* will handle the following process as illustrated in Fig. 5.

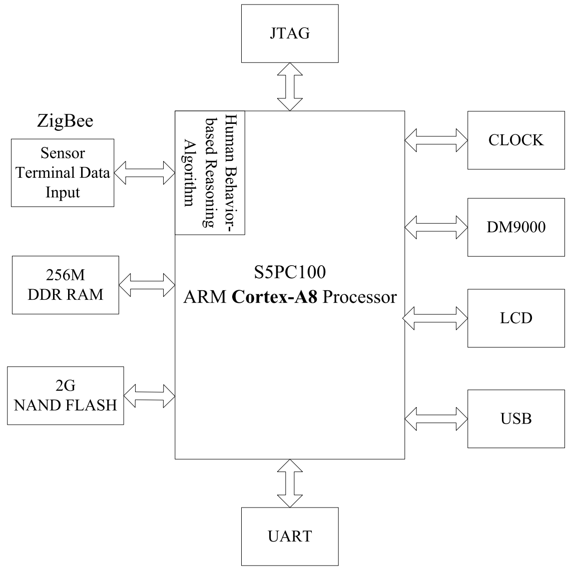

FIGURE 3. Hardware design scheme of embedded smart home control center.

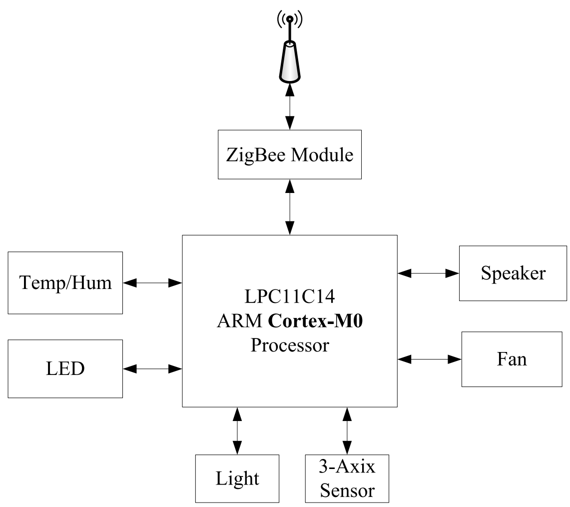

FIGURE 4. Structure diagram of sensor terminal.

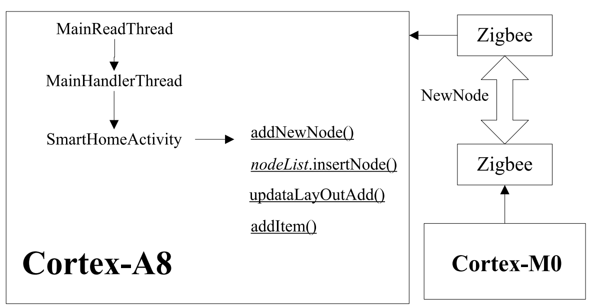

FIGURE 5. Flow chart of data process.

B. SOFTWARE CIRCUMSTANCE

1) U-BOOT TRANSPLANT

The function of U-Boot is to put the kernel into Dynamic Random Access Memory (DRAM). The U-Boot downloaded from the Internet only has the universal code, and could not support and recognize some specific hardware on the platform. Therefore, we need to modify the U-Boot to distinguish the devices.

U-Boot transplant can be divided into two stages: in the first stage, we should finish the devices initialization, prepare Random Access Memory (RAM) space for loading the code, set up Stack Pointer (SP), and jump to the C entrance point of the second stage. During the second stage, the work mainly includes using assembly language to jump to main( ) function, initializing the hardware devices, checking memory map of the system, loading image file, and setting up kernel start parameters. The u-boot.bin programmed successful interface is shown in Fig. 6.

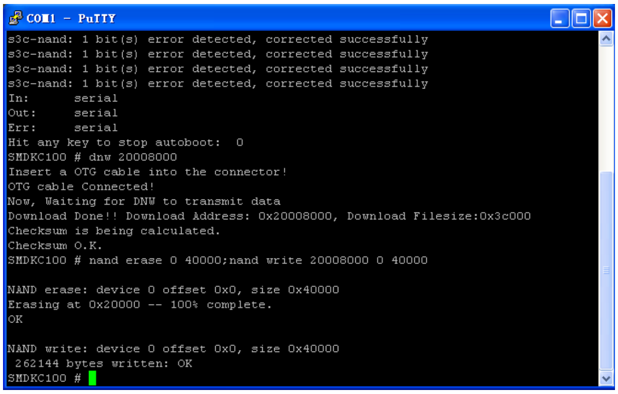

FIGURE 6. The u-boot.bin programmed successful.

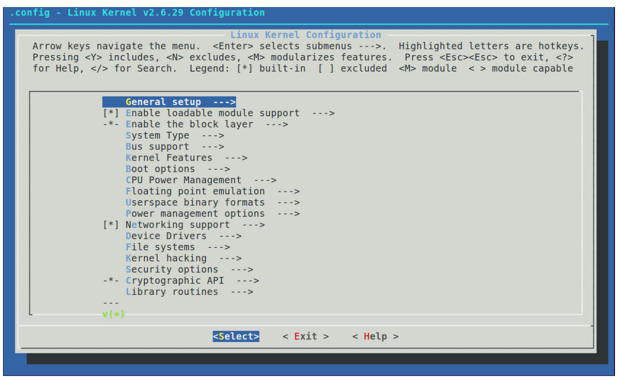

FIGURE 7. Linux kernel configuration.

2) LINUX KERNEL TRANSPLANT

The kernel handles all interactions between the CPU and the external world, and determines which programs will share processor time, and in what order. Linux kernel is an open source operating system, which adopts the modular design framework.

Here, we retain the necessary functional module, and delete the redundant one, then compile the kernel once again, making the hardware resources lessen. In this design, the kernel transplant includes: add the network card driver, NAND FLASH driver, USB device driver, and SD card driver. The Linux kernel configuration interface is shown in Fig. 7.

In order to add temperature sensor on the platform, we need firstly insert its description file in the kernel of S5PC100. The specific procedure a as follows: firstly, open the platform source code file through input the order of *$ vim (kernel_dir)/arch/arm/mach-s5pc100/mach-smdkc100.*

Secondly, put in the following codes

static struct i2c_board_info i2c_devs0[ ] __initdata =
{
{I2C_BOARD_INFO("lm75", $0 \times 90 \gg$ 1), },
};

under *static struct platform_device ∗smdkc100_devices[ ] __initdata ={};*

Finally, install *i2c_register_board_info(0, i2c_devs0, ARRAY_SIZE(i2c_devs0))* after the function of *smdkc100_machine_init.*

3) ROOT FILE SYSTEM

The Linux operating system design is centered on its file system; almost everything is represented as a file under Linux, or can be made available via special files. Files are arranged in directories, which may also contain sub-directories. These form the familiar file system hierarchy. Root file system is the basic of other file systems, which includes the necessary catalogue and critical file. Making root file system includes establishing the content structure, adding the command program, copying C library, and configuring the NFS. The BusyBox configuration is shown in Fig. 8.

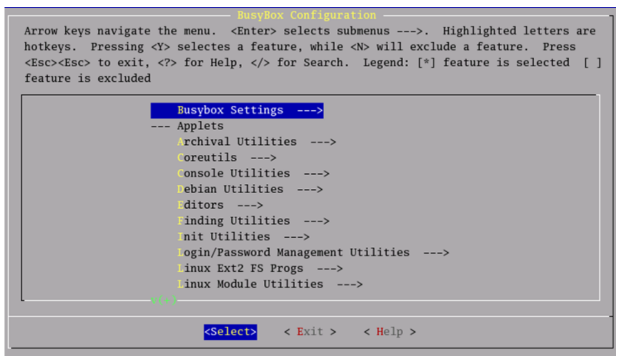

FIGURE 8. BusyBox configuration.

V. EXPERIMENTS AND ANALYSIS

Experiments based on the embedded smart home platform are made to check the performance of proposed human behavior-based reasoning (HBR) model in this section, as shown in Fig. 9.

Since HBR model is on the basis of auto regressive and CBR, each of them is also separately utilized. Moreover, the HBR scheme is used for service prediction, training window can be more time-correlated by setting the past two months data accordingly. Although human behavior on weekends and weekdays maybe different, the overall usage of house appliances is similar. Therefore, the experiments only consider weekdays. Besides, we use different numbers to symbolize diverse appliances. The data of domestic appliances usage with time applied in the embedded smart home system platform is shown in Table 3, where "Device" stands

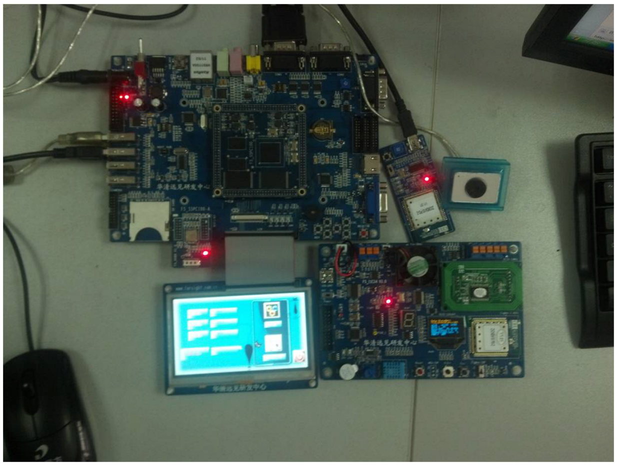

FIGURE 9. Model platform of HBR.

TABLE 3. Domestic appliances usage with time in statistics.

	A	B	…	M
1	t_{1A}	t_{1B}	…	t_{1M}
2	t_{2A}	t_{2B}	…	t_{2M}
…	…	…	…	…
N	t_{NA}	t_{NB}	…	t_{NM}

for different households, "Time" indicates the turn on or turn off time which formulate the human behavior, while "Day" denotes the working days of user.

Afterward, the experimentation is carried out on the embedded smart home platform to analyze the effect of HBR model. Specifically, we take LED prediction, which stands for the restroom lamp in smart home, as an example to illustrate the effect of HBR model. Through testing, we get the statistics data of one user turning off time and the HBR model successfully forecasting number with time. As illustrated in Fig. 10, where the "Whole" represents the total device action number in daily living, while the "Success" means that the correct foresight number for service prediction throughout the HBR method. By compare the result between study group and control group, we can get the outcome as follows.

During the past eight weeks, we can see the successful number is increasing week by week, which reflects the HBR model learning ability as time goes on. Generally speaking, the service prediction success rate heavily depends on human behavior detection algorithm, and the model intelligence degree mainly reflected on how many times it can successfully provide the desired services. That is, the more services provided by HBR model matching with human users' needs,

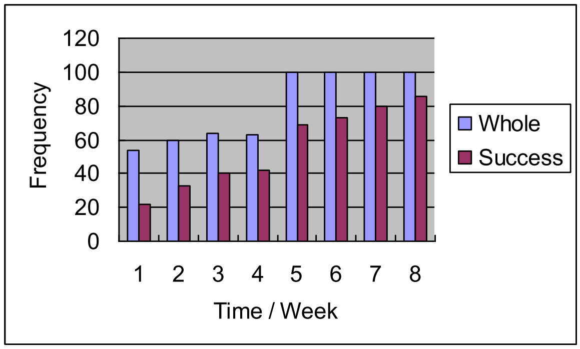

FIGURE 10. Service chart of the HBR model.

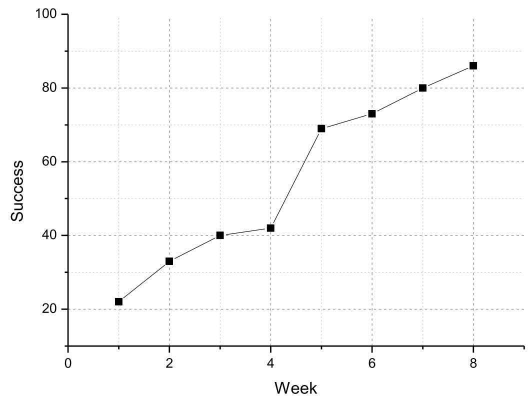

FIGURE 11. Prediction success number of HBR model.

the higher successful forecasting rate it is. Furthermore, its intelligence level is also convinced.

After calculation and analysis, the success number of HBR model during the past eight weeks are improved dramatically compared to that in the beginning, and then stays stable, as shown in Fig. 11. The horizontal axis represents the number of weeks and the vertical axis means the number of successful predictions based on the proposed HBR model. The successful prediction number increase smoothly during the first four weeks, which reflects the learning ability of the proposed HBR model. Then, for the raise of user action, which also means the user turning off time, the successful prediction number increases sharply from weeks 4 to 5. Moreover, in the following four weeks, the HBR model provides stable and high quality service for users, which reflects HBR model learning ability.

Correspondingly, the success rate can be illustrated as Fig. 12. It can be clearly noticed that the trend of the proposed HBR model success rate grows monotonically in the entire duration. Although the device number has been increased from the fourth to the fifth week, the successful prediction rate does not appear dramatic changes at the time, indicating a better performance compared to the case based reasoning scheme and the auto regressive algorithm.

As we known, people sometimes forget to turn off the light when they leave home, which result in the waste of energy. If user realize this situation, they would turn off it instantly. In order to prevent the unnecessary energy consumption,

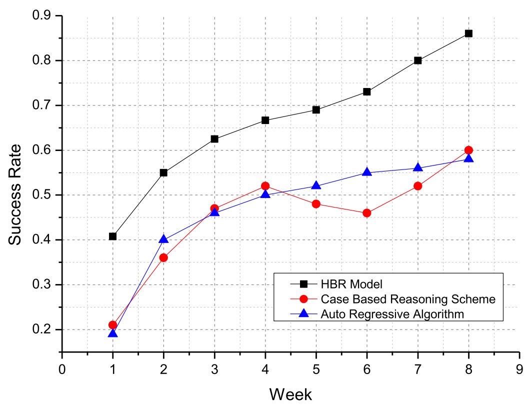

FIGURE 12. **Success rate comparison of different prediction methods.**

some measures should be taken to make up user's negligence. Usually speaking, user have good behavior in the most of time. The numerical experiments illustrated that the forecasting performance is improved by combining the training samples, and the improvement is repeatable for different house appliances data. Therefore, by launching the proposed scheme, it can be make the home greener to some extent.

VI. CONCLUSION

Energy waste has become a big portion of energy consumption in people daily lives. In order to decrease the unnecessary energy consumption, this paper has introduced an intelligent human behavior-based reasoning (HBR) model in smart home to make the home automation system greener. Through the mixture of linear prediction and human behavior of daily living reasoning, the prediction accuracy has been improved stably, which has a significant influence on improving the traditional poor control methods. In addition, we implement a smart home platform by integrating the latest hardware and software technologies, including embedded systems, ZigBee wireless communications, and appliance control protocols.

After experiments of proposed model on designed IoT platform, the results show that the proposed HBR model outperforms the comparison schemes, especially for the scenario that the appliances' number of actions increases, demonstrating the effectiveness of the proposed model in smart automatic control system. Furthermore, this technology is expected to make people daily lives in the future smart homes and smart buildings more convenient and energy efficient.

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