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Detection of Irregular Behavior in Room Using Environmental Sensors and Power Consumption of Home Appliances Learning in HMMs

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***Abstract*— We propose a human behavior detect method based on our development system of multifunctional outlet. This is a low-power sensor network system that can recognize human behavior without any wearable devices. In order to detect human regular daily behaviors, we setup various sensors in rooms and use them to record daily lives. In this paper we present a monitoring method of unusual behaviors, and it also can be used for healthcare and so on. We use Hidden Markov Model(HMM), and set two series HMM input to recognize irregular movement from daily lives, One is time sequential sensor data blocks whose sensor values are binarized and splitted by its response. And the other is time sequential labels using Support Vector Machine (SVM). In experiments, our developed sensor network system logged 34days data. HMM learns data of the first 34days that include only usual daily behaviors as training data, and then evaluates the last 8 days that include unusual behaviors.**

***Index Terms*—multifunctional outlet system; behavior detection; hidden markov model; sensor network; support vector machine.**

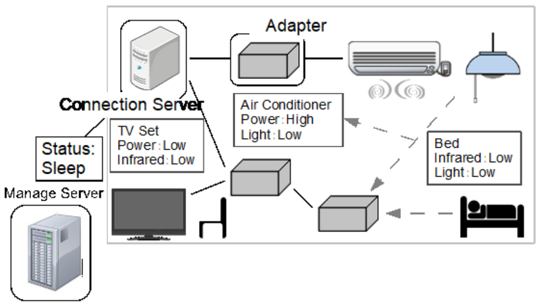
I. Introduction

For saving power consumption we built multifunctional outlet system using adapters that include relay switch circuit between home appliances and outlets [1], and that also include power control functions using sensors. This system can control appliance's power by switching on/off automatically and monitor its power consumption. Our multifunctional outlet system is constructed from three parts: Adapter unit, Communication Control unit and Management Server unit. (1) Adapter unit connect with appliances to control power supply and monitor surrounding environment.(2) Communication Control unit sends data from Adapter to Management Server. (3) Management Server unit analyzes sensor data and create parameters for auto-control.

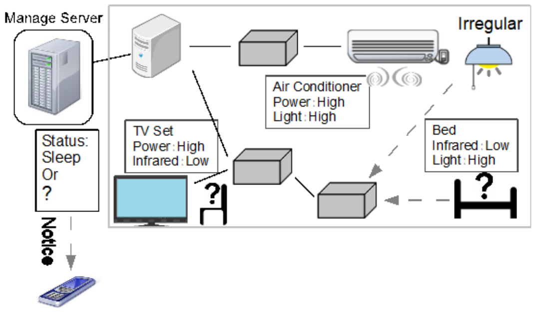
Low-power sensor network system is not a new theme, and there already exist various systems. Such as house setting care system [2], unusual behavior detection system monitored elderly live alone [3] [4] [5] and so on. Most of them need to have users put wearable devices on their body. In our research we propose a method to use environment sensors instead of wearable devices, because the sensors on our multifunctional outlet system can monitor appliances status and human in-room status. Using these status, we try to alert accidents for health care at home without wearable sensors. There are 3 steps: (1) Log time sequential human's in-room daily living patterns, (2) Recognize regular behaviors time sequential, and (3) Detect irregular behavior from regular behavior patterns using the HMM(Hidden Markov Model) that is the stochastic time sequence recognition framework.

II. Multifunctional Outlet System

A. Behavior Detection



(a) Regular detection



(b) Irregular detection

Fig. 1. An example of irregular behavior detection

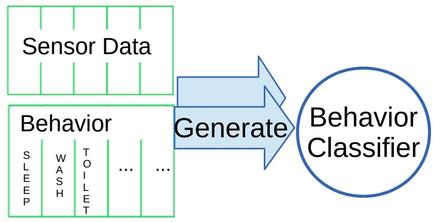
Fig. 1 shows the system structure and behavior detection example. The system estimates "sleep status" from sensors around bed and TV. On the other hand, when sensor variables change to unexpected patterns, the system cannot estimate behavior clearly. Then it sends notice to the user's smart phone, such as "irregular" that means unknown status. This behavior detection method constructs a feasible system of irregular notation.

In this paper, we propose two methods of using time sequential statuses instead of single status recognizing method mentioned above. These time sequential statuses are HMM input data. Statuses generate from sensor data, finally detect irregular behavior from HMM output, the comparison result between "training data" and "test data".

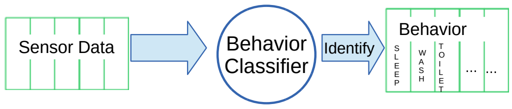
The goal of this paper is to detect the human regular and irregular behaviors using sensors of multifunctional outlet system. The sensor data of this system used to log a user's status of in-room lives and home appliances. Sensor data logs of a few days were used as "training data" that only include regular behavior, and sensor data logs of other a few days were used as "test data" that include irregular behavior. We check the trained HMM unit can detect these irregulars in "test data" or not.

B. HMM

HMM is used in many fields such as voice recognition and statistical translation. We used Baum-Welch algorithm implemented in GHMM [6] to log the sensor data. When the user's action changes, it will make large fluctuation of sensor variables, and we divide sensor data into blocks. In this research, there are two ways to input time sequential statues into HMM.



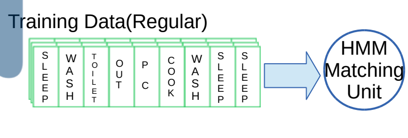
(a) SVM learning from sensor data



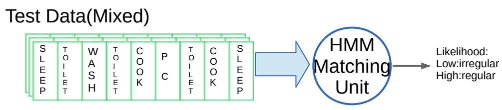
(b) Sequential behaviors generation processing

Fig. 2. Sequential behaviors generation using SVM

As one of the method to recognize the irregular behaviors, we input time sequential labeled behaviors. First, sensor data were clustered by Ward's method [7], and result clusters were classified using SVM in this stage. Fig. 2 shows the process of sequential behaviors generation using SVM. Sensor data with sequential behavior (such as cooking, meal, toilet and so on) are logged by HMM. Then, if we input the sensor data without sequential behavior, identification classifier will output the sequential behavior automatically, and let HMM log them. If the user's daily behaviors are exist in "training data", that is a regular, and if not, we consider it as a irregular behavior.



(a) Learning using training data



(b) Input test data and output likelihood

Fig. 3. Input and output of HMM Matching unit

Fig. 3 shows input and output of HMM unit. In the first stage, we input sequential labels of "training data" and let HMM unit learn these patterns, then we input sequentially labels of "test data", HMM unit will feedback the likelihood value, the comparison result of " training data " and " test data ". Since we used minus likelihood this time, if it outputs a large likelihood value, that means regular and the other

No	Behavior	Assumed Behavior	Actual Behavior
①	Repetition of Behavior	Number of Toilet Increase	Toilet at 20 minute intervals
②	Days order of action change	Day and Night Reverse	Living in the reversal
③	Movement Times Increase	Looking for Things	Room Move for 2 Hours
④	Fall	Consciousness Lost	Not Sleep in Usual Place
⑤	Continuous of Same Behavior	Rest in Sickness	Stay in Bed All Day

means irregular. But if these irregular behaviors are pretty much as similar as regulars that cannot be detected by this method.

As for other method to recognize the irregular behaviors, we input time sequential binarized sensor data blocks to HMM Matching unit. Sensor data were splitted by changes of sensors variable.

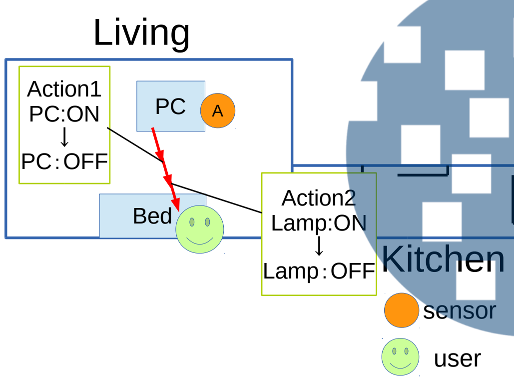


Fig. 4. Sensor data blocks generation using sensor value change

As shown in Fig. 4, sequential behaviors of a single apartment are splitted by the large changes of sensor value. In Action 1, electric current sensor value changed to zero, which means a user turned off the PC's power. In Action 2, light sensor detected lamp's be turned power off, which means a user went to sleep. In this case, we input 3 sequential data blocks into HMM that were divided by these actions.

III. EXPERIMENTS

In this experiment, we use two methods to get input data, and compare these results. One is data using Ward's method and SVM labeling, and the other is binarized sensor data splitted by light and electric current sensor value.

The system above was operated for about a month to monitoring a person living in an apartment. First 26 days data are used as "training data", and the last 8 days are used as "test data" that include reproduced irregular behaviors. Mounted sensors layout is shown in Fig. 5. Sensor A and B setup are the wall, Sensor D is on the bed. Sensor A, C, E are on air conditioner, TV and PC's outlet.

Since irregular daily behavior data is not enough, we reproduce irregular behaviors in last 8 days as shown in Table 1.

Table 1 : Reproduced unusual behaviors

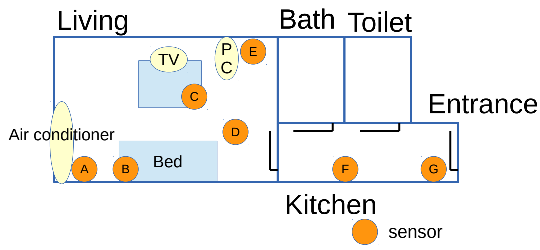


Fig. 5. Sensor layout

A. *Test Using Ward's Method and SVM Labeling*

In this section we use time sequential labels of one day as HMM input using Ward's method and also use SVM from sensor data. The results are shown in Fig. 6. Likelihoods were low totally. The lowest ① and lower behavior ④ were recognized correctly, but 15th was not.

Because labels are all depend on user's behaviors and the sensor's arrangement, these input sequence have some incorrect labels. To evaluate the effect of this problem, the results using completely correct labels that were recorded by the user in Fig. 7. ①, ③, ④, ⑤ were able to be detected as irregular,② was treated regular, and 15th was a irregular.

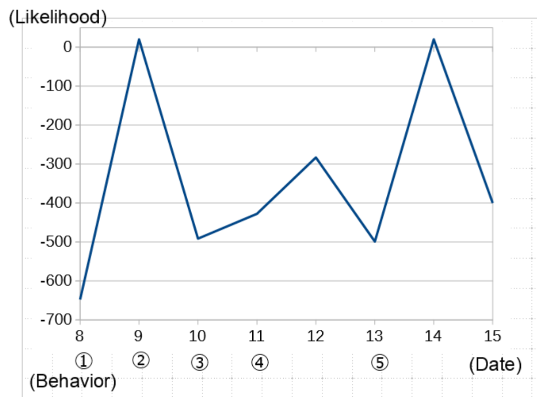


Fig. 6. Likelihood using SVM

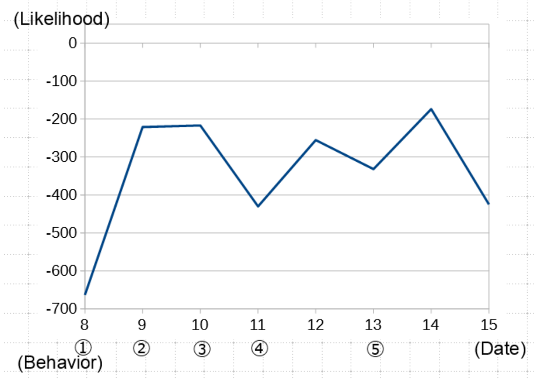


Fig. 7. Likelihood using user recorded labels

According to the user's recorded labels, 15th was a usual day, but that sensor patterns not include in "training data". Likelihood of 15th was so low that it was detected as a irregular behavior.

B. *Test Using Binarized Sensor Data*

In this section, sequential sensor data blocks were used as HMM input. In these blocks, each sensor variables binarized to 1/0 (it means high/low). For example, power on/off, light on/off, temperature hot/cold and so on. If we divide the sensor data into all kinds of sensor value and let HMM learn, that will become a large scale data that HMM cannot afford. So, in this research, we only detect by the appliance power on/off caught by electronic current sensor, infrared sensor, and light sensor's action. The first test is for electronic current sensor and light sensor divided value detection test. And second test is for a infrared sensor divided value detection test.

Fig. 8 shows the result of division by light and current sensors. since the number of divisions of action differs every day, the daily divided in the Fig. 8 is not constant. The likelihood was the lowest on 8th, 11th and 13th. when they were recognized as ①, ④, ⑤. Based on the above, it was detected as irregular behavior in 6 behavior out of 6 behavior.

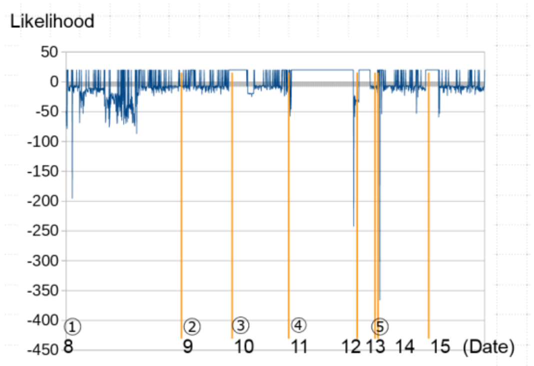


Fig. 8. Likelihood using data blocks (division by light and current sensor)

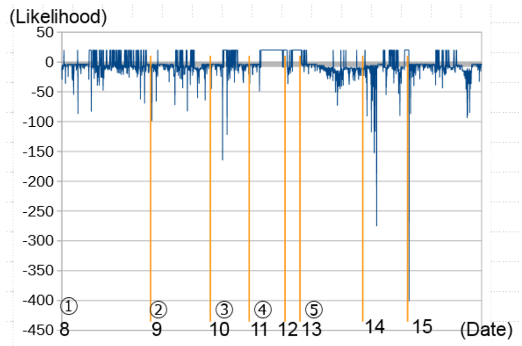


Fig. 9. Likelihood using data blocks (division by infrared sensor)

Fig. 9 shows the result of division by infrared sensor value. In the majority of action ④ and part of 12th, the unlearned statutes continued. The day which the likelihood were the lower 3, the normal day 12th, 14th and the day when action ⑤ occurred. From these results, 3 behaviors of 6 behaviors were able to detect irregular behavior.

IV. Conclusion

In this paper we propose the irregular behavior detection method. Most of irregular behaviors were recognized when sensor data were sliptted by light and electronic current sensor variables. The other way was not so abnormal recognition. However, if the sequentially behaviors are confirmed, they can be detected that it was possible to detect irregular behavior. Through the two methods reproduce in the experiment, the percentage of correctness were 83% using sequential behaviors generation label and 63% using spirited sensor data. In future works, we aim to reduce erroneous detection of irregular behavior and clarify validity of regular and irregular behavior.

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