DEVELOPMENT OF HUMAN DAILY BEHAVIOR MODEL AND IT'S APPLICATION

Yasuyuki Shimada * **Tsutomu Matsumoto** *
Shigeyasu Kawaji **

* *Kumamoto National College of Technology*
** *Graduate School of Science and Technology, Kumamoto University*

Abstract: In this paper, we will discuss the problem how human behavior at home could be detected and how its model could be constructed. Understanding human behavior or action is important to establish a new technology that focuses on individual behaviors. Especially, it is necessary to know human habitual behavior in order to improve life environment. In actual environment, many electric appliances, e.g. TV set, washing machine, microwave stove, used at home. In this study, in order to find human habitual behavior, a sensor for electric appliance is used provided that there exist some relations between turning on/off those electric appliances and our action. Using primitive information of turning on/off, we describe human behavior at home by a binary matrix and uses neural network to express human state at home. The simulation results show that the proposed method has good performance to detect human irregular behavior at home.

Keywords: habitual behavior, human behavior-based system, human behavior model, neural network

1. INTRODUCTION

Many kinds of industrial/electronic technologies have contributed to attain our comfortable and fulfilling lifestyles. Especially, recent mechanization/automation in our daily lives have brought about efficient society to us. Although the technologies have been effective to improve quality of life (QOL), stress and mental/physical disorders with stress has been caused by the technologies. When we have to adjust our behavior or action to our environment or mechanical system, we feel stress and suffering under some situations such as driving a car. A Car does not change own characteristics to adjust to drivers ability. Also, it is difficult for elder people to adjust themselves to their environment or characteristics of machines. Thus, to get rid of our stress, suffering and mental/physical disorders, it is very important to establish a new technology that focuses on individual behaviors. Particularly, it is serious problem in the latest Japan, where a population of elderly people who is sixty five or more years old is rapidly growing. Therefore it is very important to establish a new human behavior-based system technology and to realize a new life support system.

Understanding human behavior or action is important to establish a new technology that focuses on individual behaviors. Especially, it is necessary to know human habitual behavior in order to improve life environment. While, the importance of the research and development is pointed out for supporting the health life of elderly people and improving QOL (Conrad DA *et al.*, 1998)(H. Inada, 1998).

To find the human habitual behavior, many systems to capture human behavior have been reported(Ohta, 2000)(S. Aoki *et al.*, 2004)(J. Yamamoto *et al.*, 1992)(A. F. Bobick and J. W. Davis, 2001). But, only finding irregularity of human behavior was focused on in these studies and no way to model of human behavior was discussed. Furthermore, it is difficult to realize these system because these used to use special devices such as infrared sensors and video cameras.

On the other hand, we proposed the ways to find human behavior at home using electric appliances (T. Matsumoto *et al.*, 2000)(Y. Shimada *et al.*, 2001)(T. Matsumoto *et al.*, 2001)(Y. Shimada *et al.*, 2003)(T. Matsumoto *et al.*, 2003). The basic idea of the method is mentioned as follows. In our daily life, we use many kinds of electric appliances. This implies that a person's action corresponds to an use of the household electric appliances. From this point of view, human behavior at home can be represented using turning on/off electric appliances. Also, we have pointed out that the behavior was combination of several actions and human domestic behavior could be expressed by the limited automaton. From this idea, we have proposed the method of modeling human behavior based on probability of behaviors. The human behavior model based on probability method is very effective under specific situation that the series of behavior is not change even if time lag is happened. But, the performance of the method is directly affected by the change of series of behaviors, and the behavior we seldom do will be regarded as irregular behavior.

In this paper, we propose a method how to model of human domestic behavior. The method is robust against the change of series of human behavior, and it can model the human behavior which is seldom done. The proposed method uses neural network, which is trained human habitual behavior using measured behavior for several days. The performance of the proposed method is examined whether the method can detect human irregular behavior or not. The simulation results show that the proposed method has good performance to detect human irregular behavior at home. Therefore good performance implies that the proposed method can model human behavior at home.

2. REPRESENTATION OF HUMAN BEHAVIOR AND ACTION

In this section, we will give the definition and representation of human behavior and action at home.

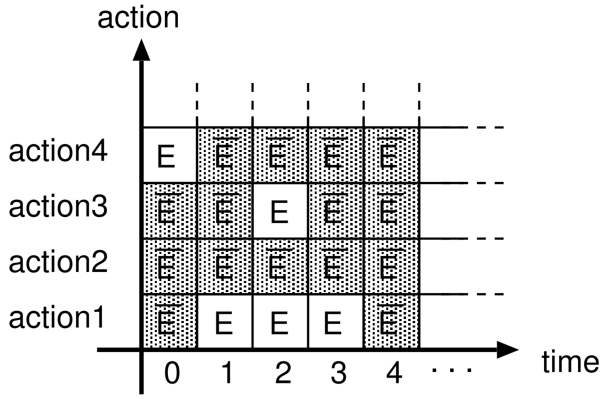

Fig. 1. 2-dimensional expression of behavior

2.1 Analysis of life behavior at home

Generally, people is said to have individual life habit. For example, after we get up in the morning, we wash face, take a shower and have breakfast. We seldom change this series of actions even if a time lag may happen. Of course we sometimes do plural actions at same time like multi-process in computer system. Thus, it is considered that we have our own life pattern fundamentally although there may be daily fluctuation. When the sequence of actions is divided into fine action, the life behavior pattern can be expressed with 2-dimensional image shown in Fig.1.

In Fig.1, the horizontal axis indicates the time and the vertical one indicates the kind of actions. Each cell shows the state of action, where "E" or "$\bar{E}$" means that an action is or not in execution. For instance, let's action 1 be "watching TV" and action 3 be"Toilet". Then, Fig.1 says that the person watched TV at the time 1, went to the toilet at the time 2, returned to the room at the time 3, and finished watching TV at the time 4. Thus, human behavior is represented by combination of some actions. It is seen that the states of action at the time 1 and them at the time 3 are same. So, we can categorize the combination of actions at the time 1 and 3 into same behavior.

2.2 Measuring human behavior at home

As described in previous section, human behavior at home is expressed by combination of actions. In actual environment, it is difficult to measure human behavior because human has many kinds of actions. Therefore a sensor and system to measure all human behavior is complex and expensive. However, sensor and system can be simple if only specific actions are measured which characterize a certain behavior. This fact means that person's action corresponds to a use of the household electric appliances. The present state of appliances can be defined by a vector, and time series of the

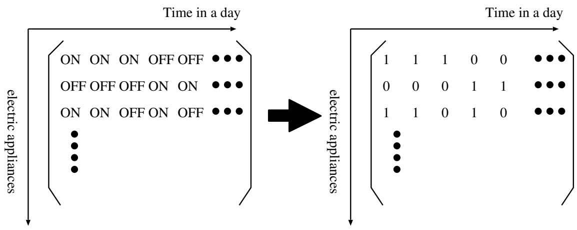

Fig. 2. Image of daily behavior

state can be described by a matrix. A row of the matrix is the number of appliances; a column of the matrix is a length of time. The matrix representation of behavior is shown in Fig.2. Because the matrix also show the subject's state at home, we call the matrix as "behavior model".

3. MODELING OF HUMAN BEHAVIOR AT HOME

Most of human behavior at home is not always same. For example, human behavior may be changed according to environment such as weather, temperature, humidity and so on. Also, an unusual behavior should not be recognized as an irregular behavior even if it is seldom observed. Thus, the human behavior modeling system should be flexible against the change of series of human behavior. To solve this problem, the way to detect person's habit using neural network is proposed in this section. Since the significant feature of neural network is information processing and learning like a human being, the human behavior modeling system based on neural network is robust against the change of series of behavior. We will call the detected habitual behavior as "behavior knowledge".

3.1 Modeling of human behavior

3.1.1. Constructing behavior model As described in previous section, we can obtain a matrix from observed states of electric appliances.

Step1. We will define the use of i-th electric appliances at the time t on d-th day as $E_i(d,t)$, where t is index of a lapse of time. Also, n and m denote the measuring time and the number of electric appliances, respectively. We set $E_i(d,t)$ to 1 if the electric appliance is turned on.

$$E_i(d,t) = \begin{cases} 1 & \text{(the appliance is on)} \\ 0 & \text{(the appliance is off)} \end{cases} \quad (1)$$
$$where \quad (t = 0, 1, \cdots, n), \quad (i = 1, \cdots, m).$$

Step2. We will compute the state of appliances for N days, $E_i(t)$, and calculate the threshold E_{i_thres} for N days.

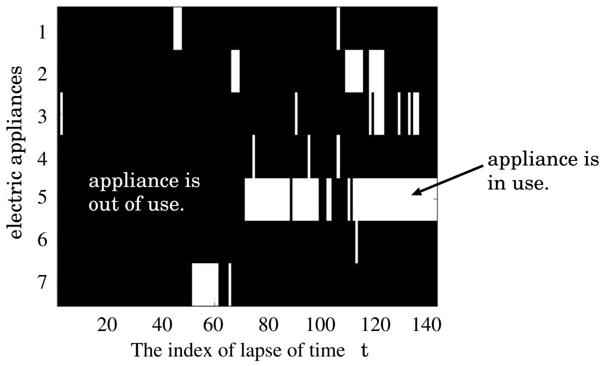

Fig. 3. An example of behavior model

$$E_i(t) = \sum_{d=1}^{N} E_i(d,t), \qquad (2)$$

$$E_{i\_thres} = max(E_i(t)) \times \alpha. \qquad (3)$$
$$where \quad (0 \leq \alpha \leq 1),$$

Step3. Finally, we will obtain the binary data as behavior model, $\tilde{E}_i(t)$, by using the threshold E_{i_thres}.

$$\tilde{E}_i(t) = \begin{cases} 1 & (E_i(t) \geq E_{i\_thres}) \\ 0 & (E_i(t) < E_{i\_thres}) \end{cases}. \qquad (4)$$

Figure 3 shows an example of behavior model which was constructed through above steps.

3.1.2. Constructing behavior knowledge We can construct human behavior model by the method described in section 3.1.1. Now, we have to construct human behavior knowledge to judge whether habitual behavior appears or not. Although it is said that we have individual life habit, we do not always have same behavior at same time. The behavior may change by the day of the week, month and season. Also time lag may happen by our body condition. Therefore the system must construct several human knowledge as follows.

Step1. The proposed system makes neural network train to recognize a behavior model described in section 3.1.1. The neuron responds "1" when an input vector is close to behavior model.

Step2. The system classifies the measured data into high level response group and low level response group based on the output of neural network when measured data is given as input vector.

Step3. The system store the weighted vector of neural network as a behavior knowledge.

Step4. The system calculates a behavior model based on data classified into low level response group.

Step5. The system make neural network train to recognize behavior model described in Step4.

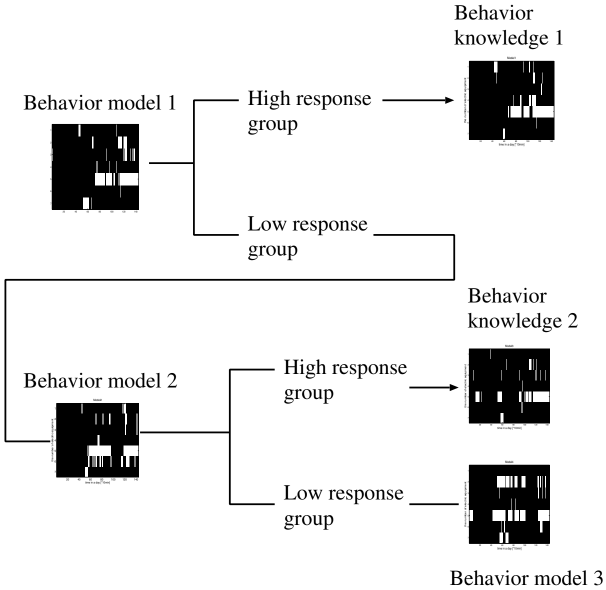

Fig. 4. A hierarchy to construct behavior knowledge

Step6. The system calculates as described in Step3 until all data is classified into high level response group.

Fig. 4 shows a hierarchy to construct behavior knowledge. And learning condition is described in next section.

3.2 Finding non-habitual behavior

The proposed system stores the behavior knowledges to judge whether habitual behavior appears or not. The system calculates the response of neuron in neural network which is trained to learn the behavioral knowledge when the daily behavior is given as input vector. It is recognized that the person's behavior is habitual if the output of neuron is high level. As the result, the system will judge the person's behavior has regularity. On the other hand, it is recognized that the person's behavior is non-habitual if the output of neuron is low level. As the result, the system will judge the person's behavior has irreguralty. Thus we can roughly guess the matching level between the daily behavior and the knowledge.

4. EXPERIMENTAL SETUP

In this section, the effectiveness of the proposed method is verified by experiment. A test subject is sixty age female who lives alone at her home. The turning on/off is captured as subject's behavior at home in actual environment. A sampling interval is 1 minute. The matrix is too large to train neural network. Therefore we will construct behavior model by decimation in time series. We set $E_i(d,t)$ to "1" if the electric appliance is turned on in 10-minutes interval.

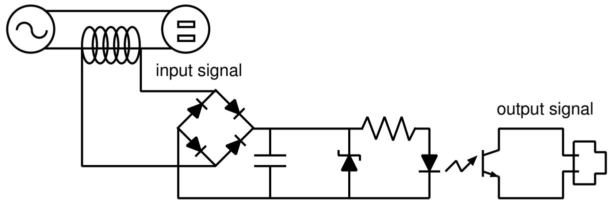

Fig. 5. Sensor for monitoring electric appliances

4.1 Detecting the use of electric appliances

Sensors which monitor the electric appliances are used for constructing the human behavior model. The sensor watches the currents flowing through the inductance and detects if the electric appliance is in use (Fig.5). Thus we can obtain the human behavior with binary image.

The sensors are installed in the wall outlets and the outputs from the sensors are collected by computer. The collected sensor data are transmitted to another host computer by cellular phone once a day.

4.2 Collecting human behavior

In the experiment, seven sensors are installed in a wall under actual environment. Table 1 shows seven sets of electric appliances with the monitoring sensor.

The experiment to measure human behavior has carried out over about one year.

Table 1. List of actions

Action	Electric appliances
A_1	TV set
A_2	Bed room light
A_3	Phone
A_4	Living room light
A_5	Toilet light
A_6	Desk light
A_7	Washing machine

4.3 Learning Condition

The parameters of neural network in the simulation are given in Table 2. The neural network has been trained to recognize the behavioral model of 1×1008 matrix. The neuron responds "1" when an input is close to the model. On the other hand the neuron responds "0" when an input vector is zero matrix. The training stops when the error of mean square drops below 1.0×10^{-5} or the number of times of training reaches 1000. In this paper, the threshold to classify the data into high level response group or another group is set to 0.8.

Table 2. Learning condition of neural network

The number of input	1×1008 vector
The number of output	1
Neurons	10 (single hidden layer)
Training signal	behavioral model
Rule	gradient descent with momentum and adaptive learning rate backpropergation
Threshold of output of neural network	0.8

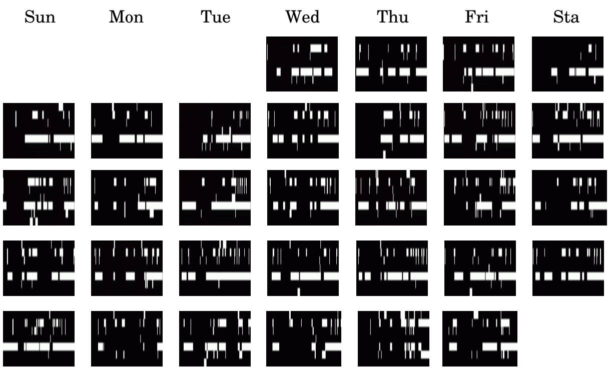

Fig. 6. Daily behavior on Aug. 2001

Table 3. A result of classification of daily behavior to construct behavior knowledge

Knowledge	the date on Aug. 2001 whose data is an element of behavior knowledge
Knowledge1	3,4,6,7,8,10,12,13,14,16,18,20,22,23,25, 29,31
Knowledge2	5,17,21,28
Knowledge3	1,2,9,15,19,26,29
Knowledge4	11
Knowledge5	27,30

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this experiment, the behavior knowledge and behavior model is constructed based on the data measured in Aug. 2001.

Figure 6 shows the daily behavior on Aug. 2001. Using these daily behavior, the system constructs some behavior knowledge. In this experiment, five behavior knowledge were constructed. Table 3 shows the result of classification of the daily behavior.

5.1 Evaluation of constructed knowledge

We carried out computer simulation to evaluate the accuracy of the constructed behavior knowledge. At first, the data measured on 1st Aug. 2001 is applied as an input vector to the neural network. Then the system calculates the response of neuron whose neural network is trained to learn the behavioral knowledge. Also, the data measured on 3rd Aug. 2001 is applied as an input vector and the calculation of the output of neuron is done under the same condition. Table 4 shows the output of neuron, in which the output of neuron is largest when an appropriate behavior knowledge is selected. And the output of neuron calculated based on other knowledge is smaller. Therefore we can see that the system can construct the behavior knowledge appropriately. Next, as an example, the data measured on 1st Sep. 2001 is applied as an input vector to the neural network. The output of the neuron is shown in same table. As shown in the table, the output of neuron is largest when the knowledge 1 is adopted as a behavior knowledge. So, the system will judge that on 1st Sep., the subject has similar behavior to knowledge 1.

Table 4. The output of neuron

Knowledge	1st Aug.	3rd Aug.	1st Sep.
1	0.55	0.92	0.90
2	0.58	0.11	0.45
3	0.97	0.76	0.43
4	0.35	0.12	0.51
5	0.63	0.49	0.74

5.2 Evaluation of accuracy to find non-habitual behavior

According to the previous results, it is considered that the utility of the behavioral model exists in judging an unexpected emergency situation rather than a normal life. The output around 0 from the neural network implies that the subject spent an unusual day. Let's consider how far the change of the daily behavior influences on the output of the neural network. Here, we suppose the situation where some problems occurred at 10:00 (The index of lapse time is 60). And the person could not take any actions for 14 hours because of the happening. As the person cannot operate the electric appliances in above situation, the right side of behavioral image becomes simple horizontal stripes (Fig.7). Table 5 shows the output of neuron. From the simulation result it follows that the neural network trained to learn the behavioral model is useful to express the level of a daily life. If the output of the neuron is around "0", we should consider that the subject spends an unusual life. Of course, it is debatable where the threshold should be set up. Similarly, the shorter the time span with no actions is, the greater the output of the neural network becomes. So, we should select appropriate value for the threshold and span to construct the neural network.

6. CONCLUSION

This paper has proposed a new model to express human behavior at home using neural network, under the basic idea that our various actions at

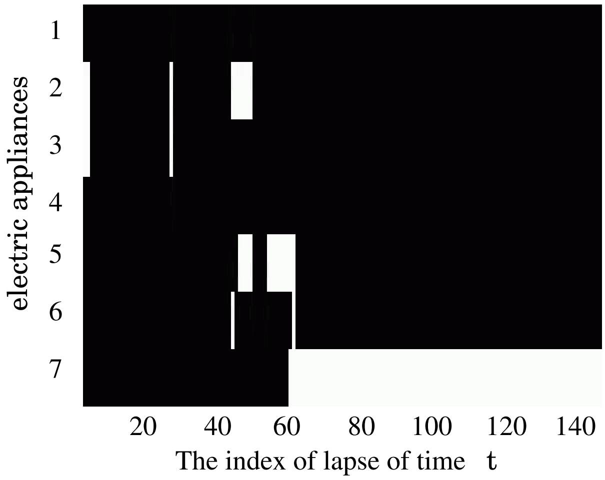

Fig. 7. Behavior in a hypothetical emergency

Table 5. The output of neuron against behavior in a hypothetical emergency

Knowledge	The output of neuron
1	7.473×10^{-2}
2	3.97×10^{-3}
3	7.40×10^{-2}
4	2.35×10^{-2}
5	$6,67\times10^{-4}$

home has relationship with the use of electric appliances. And observation of the state of electric appliances for a few months makes us find a pattern of behavior visually. The experimental results explain that the senior subject living alone has special habit and that the neural network could show a difference in a daily life. Also, the experimental results show that our daily behavior is classified into several groups using neural network.

Next, we have simulated a case where a person does not take any actions of using electric appliances for 14 hours. According to the simulation result, the neural network indicates the obvious difference between the normal life and the exceptions to the normal life. Of course, the accuracy to find non-habitual behavior by the proposed system depends on the threshold to construct behavior model and behavior knowledge, time span for neural network to be learned, period to update behavior knowledge and so on. For increasing the accuracy of the behavioral model, the movement of person among rooms and the state of taps about the water and the gas should be used. From the point of view of software, these extensions can be easily applied to the behavioral model by adding the new actions. This improving accuracy will be in a future work.

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REFERENCES

A. F. Bobick and J. W. Davis (2001). The recognition of human movement using temporal templates. *IEEE Trans. Pattern Anal. & Mach. Intell.* pp. 257–267.

Conrad DA, Maynard C, Cheadle A and Jhonston P (1998). Primary care physician compensation method in medical groups : Does it influence the use and cost of health services forenrolles in managed care organization?. *Journal American Medical Association* pp. 853–856.

H. Inada (1998). Present state and future of home care technology. *The Japan Society of Mechanical Engineers* **101**(950), 4–9.

J. Yamamoto, J. Ohya and K. Ishii (1992). Recognition human action in time-sequential images using hidden markov model. *Proc. IEEE Conf. Comupter Vision and Pattern Recognition* pp. 379–385.

Ohta, S. (2000). Health monitoring system for the aged. *Journal of Information Processing Society of Japan* pp. 639–643.

S. Aoki, Y. Iwai, M. Onishi, A. Kojima and K. Fukunaga (2004). Learning and recognizing behavioral patterns using position and posture of human body and its application to detection of irregular state. *The Journal of The Instisute of Electronics, Information and Communication Engineers, D–II* **J87–D–II**, 1083–1093.

T. Matsumoto, Y. Shimada, K. Shibasato, H. Ohtsuka and S. Kawaji (2000). Creating behavior model of a senior solitary life and detecting an urgency. *Proceedings of the International ICSC Congress on Intelligent System and Applications* pp. 234–238.

T. Matsumoto, Y. Shimada, Y. Hiramatsu and S. Kawaji (2003). Detecting non-habitual life behaviour using probabilistic finite automata behaviour model. *Proceeding of the The Fourth International Conference on Control and Automation* p. P559.

T. Matsumoto, Yasuyuki Shimada, Shigeyasu Kawaji and Yoshio Hiramatsu (2001). Detecting irregular life behaviour at home using probabilistic finite automation life behavior modeling. *Journal of Medical Informatics 2002 (In Japanese)* **22**, 35–42.

Y. Shimada, T. Matsumoto and S. Kawaji (2003). A study for finding human non-habitual behavior in daily life. *Proceedings of ICCAS2003* pp. 491–496.

Y. Shimada, T. Matsumoto, K. Shibasato, H. Ohtsuka and S. Kawaji (2001). Developing of human behavior model at home and its application. *Proceedings of the 10th World Congress on Medical Informatics 2001* **1**, 878.