Understanding of living activity in a house for a real-time life support

Katsunori MATSUOKA and Kyoko FUKUSHIMA
Living Informatics Group, Institute for Human Science and Biomedical Engineering
National Institute of Advanced Industrial Science and Technology
1-8-31 Midorigaoka, Ikeda, Osaka 563-8577, JAPAN
E-mail: k.matsuoka@aist.go.jp

***Abstract* - An aware home technology with multiple sensor network installed in a house was developed. It enables to monitor an everyday life activity in a house seamlessly and find unusual situations caused by illness or accidents of residents automatically. To detect unusual situations, an index of "ordinariness of living" was defined, which is calculated with a long-term record of sensor signals. It takes a small value when an unusual situation appears. In this paper, a real-time analysis to evaluate the ordinariness of living is proposed and its performance is discussed with some results obtained with one-year real data.**

I. INTRODUCTION

In Japan, we are now facing to an aging society. Home accidents in Japan are increasing year by year and it becomes serious that death accidents in a home among the elderly persons over 65 years old have been increasing by 1.7 times as many as death traffic accidents [1]. In the present situation, it becomes important and necessary to develop an aware home technology that can be aware of unusual conditions caused by illness or accidents of residents, and support or rescue them.

Living information concerned with everyday life activity has strong relations to individual health, security, and life style. Therefore it is expected to catch an unusual situation to be rescued or supported by understanding individual living information, which is the basis of aware home technology. Some research works on understanding living information have been reported [2,3,4]. In those research works, experimental living spaces were built individually and information processing to estimate resident's condition was studied. However most of them need *a priori* information for their analysis such as a room layout, positions of sensors, types of sensors and so on. For a practical use, it is important to create a generalized method to detect unusual situations, which is not affected by a room layout or a position of sensor, and it is also needed to achieve a process in real time.

In this paper, we propose a method for real-time analysis to understand living activity and detect unusual situations from a long-term record of living information. The superior features of the proposed method are to achieve a real-time analysis without *a priori* information and to be adaptable to an environmental change.

II. MONITORING SYSTEM FOR LIVING ACTIVITY

A. Monitoring system

A simple sensor network system for monitoring life activity was developed. It can be easily installed even in an existing house without any electrical wiring.

The monitoring system consists of three types of sensors: two types of infrared light sensors and an electric power sensor as shown in Fig. 1. Infrared light sensors mounted on a lighting appliance, which is hooked on ceiling of every room, detect human body movements. Switching signal for lighting is also detected in the system. In a small room such as a toilet, another infrared light sensor shown in Fig. 1(b) is set. The electric power sensor shown in Fig. 1(c) is installed on every electric outlet and detects the usage of each electric appliance connected with the sensor. Sampling rate of an infrared light sensor is one second and that of an electric power sensor is one minute. All data from sensors are transmitted by wireless and gathered into a computer.

B. Observation of life activity by the system

We obtained long-term records of living information in 17 houses with the developed monitoring system during periods from one month to one year. All subjects cooperated in writing down their one-day activity and performing a mental test once a week or once a month, which is POMS (Profile of Mood States) test to check

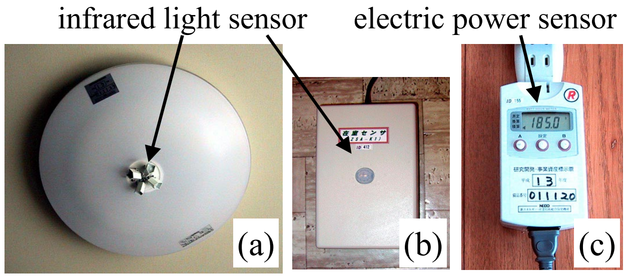

Fig.1 Three types of sensors installed in a house to monitor living activity.

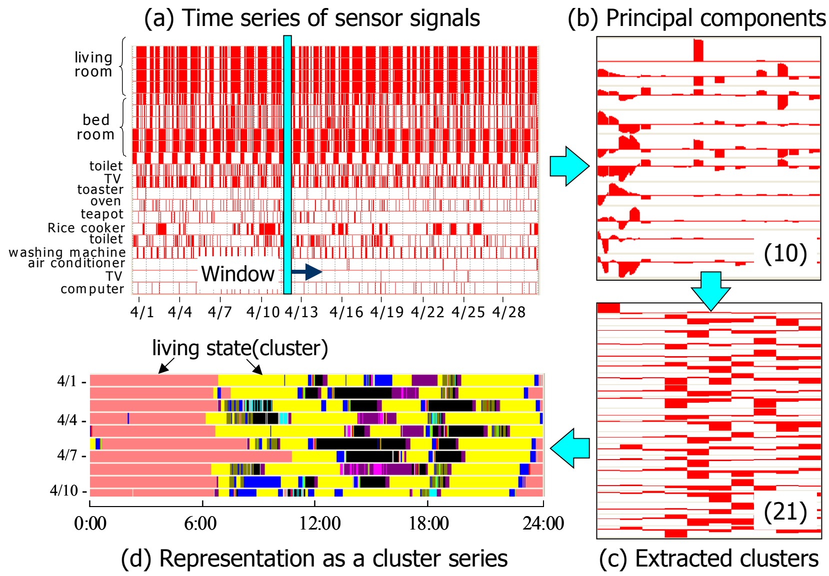

Fig.2 Analysis flow to transpose sensor signals into a time-series of living states

depression condition. In the following sections, all the analysis was carried out on the data for a four-person family obtained during one-year period.

III. UNDERSTANDING LIVING ACTIVITY

To find an unusual situation, it is necessary to understand a usual situation, because an unusual situation is surely depending on an individual life style and cannot be defined uniformly for everyone. So in our approach, a usual living state is extracted from a long-term record of sensor data and an unusual situation is detected as a deviated situation from the usual one [5,8,9].

To compare a current living state with the usual one, we defined an index of "ordinariness of living", which denotes a similarity of a current living state to the usual one [2].

A. Representation of living states

It is very hard to find a significant difference from the direct comparison of time-series of sensor signals, because time-series of sensor signals are not always same even in a same behavior. So we proposed a method to transpose each time-segment of sensor signals into one of a limited number of living states (clusters) and evaluate a similarity of living states by a comparison of transposed series [5].

The proposed method consists of two steps as shown in Fig. 2. The first step extracts principal components from all segments of sensor signals divided with a time window. This process is carried out by the principal component analysis such as the generalized Hebbian algorithm [6]. The second step finds a limited number of clusters to describe living states by classifying the principal component loadings for each segment. This process is carried out with a self-organizing neural network such as the Adaptive Resonance Theory network [7]. These processes can be performed automatically only by deciding two parameters, which are a number of principal components to be used for the cluster analysis and the distance between clusters.

Figure 3 shows an example of cluster series transposed by the proposed analysis. In this case, each segment of

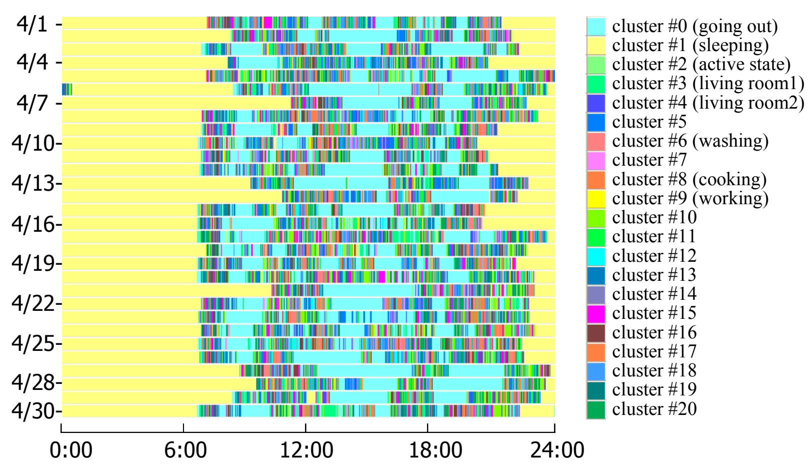

Fig.3 Time series of living states described with extracted clusters.

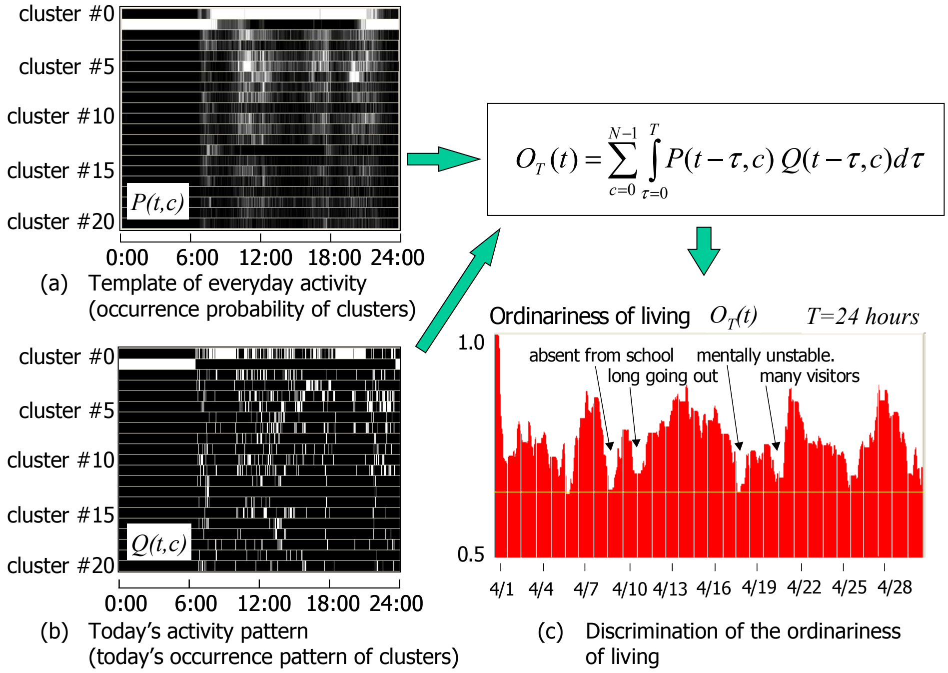

Fig.4 Template of everyday activity and evaluation of "ordinariness of living" for one-month data

sensor signals was extracted at intervals of ten seconds with a two-minute time-window from the everyday data in April. The most significant ten principal components were used for the cluster analysis and the inner product of normalized mean vectors of individual clusters, that indicates the distance between clusters, was decided less than 0.6. The usage of restricted principal components makes the process robust against noise or a small sensor response.

After classifying all segments, it was found that 21 kinds of clusters were significant to describe the family's living activity in this case. Some of the clusters can be given their meanings such as a state of sleeping, a state of going out, or a high activity state.

B. Extraction of a usual living state

An occurrence probability of each cluster at each time can be obtained by a statistical analysis of a long-term cluster-series. A distribution of occurrence probability is a good template describing a usual living state of a family.

Figure 4(a) shows an example of temporal distribution of occurrence probability for each cluster extracted from a cluster series shown in Fig. 3. Each line expresses a temporal distribution for each cluster, and a time zone with white color denotes high occurrence probability.

C. Definition of the "ordinariness of living"

We can define an index of "ordinariness of living" by using a distribution of occurrence probability of clusters as

$$O_T(t) = \sum_{c=0}^{N-1} \int_{\tau=0}^{T} P(t-\tau,c)\, Q(t-\tau,c)\, d\tau, \qquad (1)$$

where $O_T(t)$ denotes an index value of ordinariness of living at time t for a evaluation period of T, $P(t,c)$ denotes the occurrence probability of the cluster c at time t, $Q(t,c)$ denotes the current occurrence of the cluster c which value is one when the cluster c appears at time t and otherwise zero, and N denotes the total number of clusters. The index $O_T(t)$ takes a small value as a pattern of current cluster occurrence deviates from the template large more.

As shown in Fig. 4(c), an index of ordinariness of living for each day was calculated at every 10 seconds by applying T=*24 hours* to Eq. (1). Then it was discriminate automatically unusual days such as a day when a child was absent from school, a day with long going out, a day with many guests, or a mentally unstable day indicated by the POMS test.

D. Statistical property of the ordinariness of living

In the case of Fig. 4(c), the ordinariness of living was evaluated with a delay of one day. For practical use, it is necessary to evaluate it in a short time to achieve a real-time life support. It is expected to get a real-time index by applying a short evaluation period T to Eq. (1). However it was found its statistical property is changing with time. That means the index $O_T(t)$ with a short time evaluation period should not be discriminate with a fixed threshold.

For example, mean values and standard deviations of the index of ordinariness of living for the data of Fig.3 were obtained at intervals of 10 seconds as shown in Fig.5. The evaluation period was one hour. It is shown that a mean value and a standard deviation vary depending on time.

E. Normalized-deviation score

To evaluate the ordinariness of living without being influenced by the change of statistical property, we propose a normalized-deviation score $\hat{O}_T(t)$ that is defined as

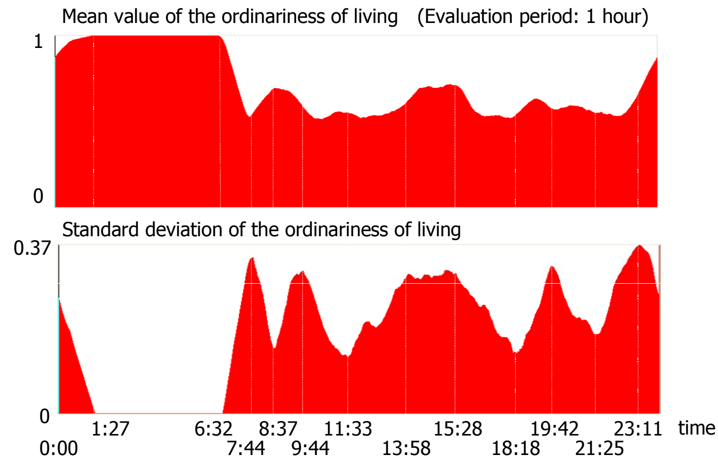

Fig.5 Mean and standard deviation of the ordinariness of living

$$\hat{O}_T(t) = \frac{O_T(t) - \overline{O}_T(t)}{\widetilde{O}_T(t)} + \overline{O}_T(t), \tag{2}$$

where $\overline{O}_T(t)$ denotes the mean of $O_T(t)$ at time t, and $\widetilde{O}_T(t)$ denotes the standard deviation of $O_T(t)$. This normalized-deviation score has a fixed standard deviation which value is one at all times and the same mean values as the index value of ordinariness of living defined by Eq. (1).

Figure 6 illustrates the meaning of the conversion into the normalized-deviation score. The thick line shows the mean value of the ordinariness of living and the dark area shows the standard deviation width from the mean at each time. Even when a same index of the ordinariness of living is obtained at time *t1* and *t2*, each of normalized-deviation score takes a different value according to the standard deviation width. Thus, by using the normalized-deviation score, it becomes possible to evaluate the index according to its usual fluctuation width even with a fixed threshold.

F. Real-time evaluation for the ordinariness of living

An appearance of unusual situation can be detected as two kinds of states of the normalized-deviation score; one is a large decrease under a threshold and another is a long continuous decrease. To combine these two states into one index, we used the following evaluation index *R(t)* described as

$$\begin{cases} R(t) = \int_{t0}^{t} \hat{O}_T(\tau)\, d\tau & \text{if } \hat{O}_T(\tau) < 0 \ \text{ for } t0 \le \tau \le t, \\ R(t) = 0 & \text{otherwise.} \end{cases} \tag{3}$$

It takes an integration value when the normalized-deviation score is negative and otherwise zero. Then unusual situations can be detected by discriminating a large negative of evaluation index *R(t)* with a fixed threshold.

IV. Application to One-Year Data

A. The whole process of the proposed method

To verify the performance of the proposed method to detect unusual situations, we applied it to the one-year data.

Figure 7(a) shows an example of sensor signals to be used in the analysis. They were transposed into a cluster series as shown in Fig. 3 and the usual living state was extracted as a temporal distribution of occurrence probability of each cluster as shown in Fig. 4(a).

The index of ordinariness of living was obtained as shown in Fig. 7 (b). It was calculated at intervals of 10 seconds with a one-hour evaluation period. Then the normalized-deviation score was obtained as shown in Fig. 7 (c), and a time transition of the evaluation index *R(t)* was obtained as shown in Fig. 7 (d). These processes can be performed in real time.

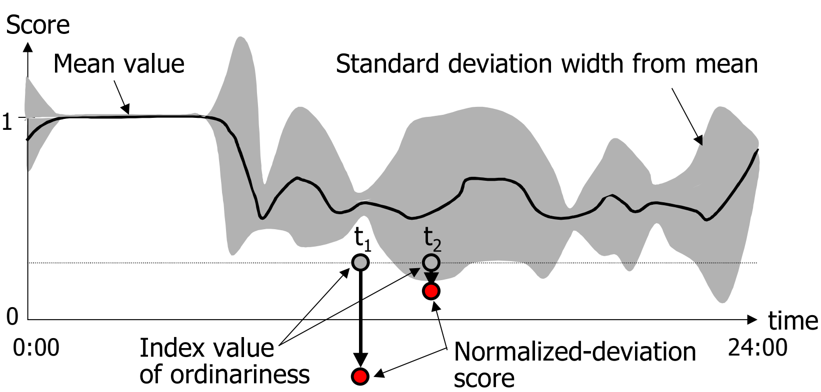

Fig.6 Meaning of the conversion into the normalized-deviation score

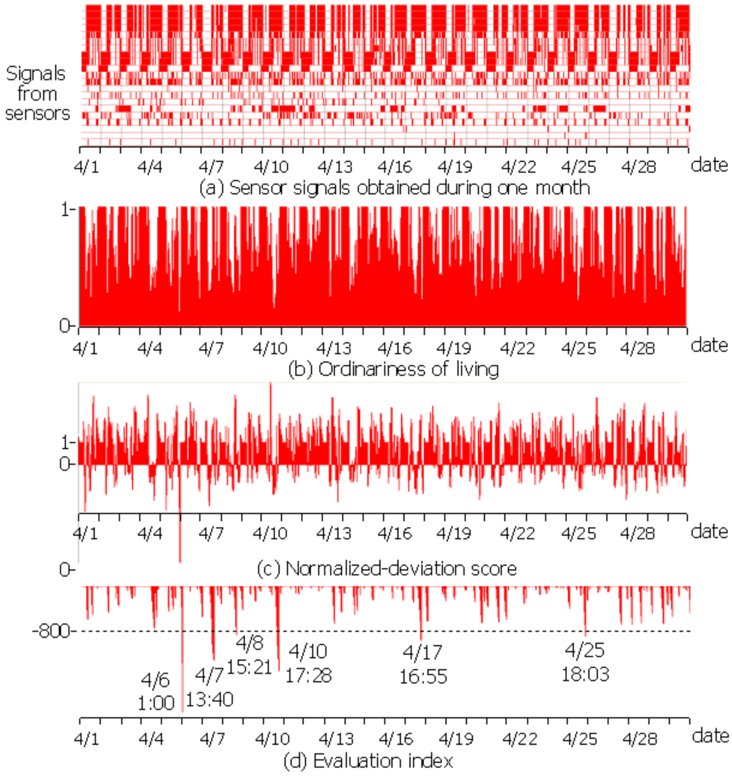

Fig.7 Analysis for detecting unusual situation from the index of ordinariness of living of the family

By discriminating the evaluation index with a fixed threshold as shown in Fig. 7 (d), the time when unusual situations appeared can be detected. In Fig.8, the time zone where unusual situation was detected is displayed as a black zone on the chart of time-series of clusters.

Most of the unusual situations detected by the proposed method agreed with the declarations of daily events by the family; for example, staying late at night on April 6, long going out on April 7 and 10, absent from school on April 8, and mentally unstable day on April 17.

B. Result of detecting unusual situations

By applying the proposed method to the data for 9 months in the one-year data, 75 cases of unusual states was detected as shown in Table 1. The 54 cases of them seemed to be related with the declarations of daily events, but there was no declaration in other cases. On the other hand, 31 declarations were related with illness and 20 cases of them were not detected by the proposed method. In 8 cases of them, someone was absent from school or from work and 4 cases of them were detected by the proposed method.

The detection rate in the weekend was 3.8 times as many as that in the weekday. However the declaration rate in the weekend was also 4.6 times as many as that in the weekday. Therefore, it seems that the result was not affected greatly by applying the same template for the evaluation of ordinariness to the weekend data and the weekday data in this case.

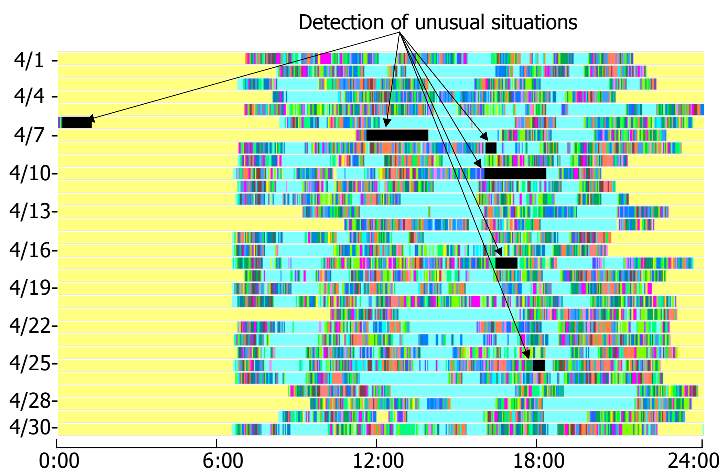

Fig.8 Time zones detected as unusual situations appeared in everyday life by the proposed analysis

Table 1 Count of unusual situations detected by the proposed method for one-year data (a) and count of declared daily events by the family which seems to be related with the unusual situations (b).

(a) unusual situations detected by the proposed method

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	total
February									1		1												1		1							4
March		1							1									1			1						1		1	1		7
April						1	1	1		1							1								1							6
May			1		1					1													2	1		1						7
June	1	2							1				1									3	1			1			1			11
July						1	1						3	1				1	1	1	1				1		1	2				14
August		1	1	1						1					1				1	1												7
September							1	1	1		1					1						1						1				7
October					1	1					1	1	1	1				1	2	1						1	1					12
																																75

(b) declaration of daily events

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	total
February											1												1		1							3
March		1							1									1			1									1		5
April						1	1	1		1							1															5
May			1		1																		1	1		1						5
June	1	1							1				1									1	1			1			1			8
July						1	1						1	1				1			1				1		1	2				10
August		1	1	1											1				1													5
September								1														1						1				3
October					1	1					1	1	1	1					1	1						1	1					10
																																54

:weekend :national holidays

V. CONCLUSION

An aware home technology to detect unusual situations automatically by using a simple multiple-sensor network was developed. The proposed analysis was applied to one-year data obtained with a four-people family and it was verified that the proposed method has the ability to transpose sensor signals into a series of a limited number of living states automatically and it has the potentiality to detect unusual situations in real time by evaluating the ordinariness of living. The most important feature of the proposed method is it does not need *a priori* information about room layout, type of sensor, or position of sensor.

To improve the proposed method, it will be needed to create the method to evaluate the ordinariness with multiple templates; for example, templates for weekend and weekday, template of cluster transition, template of cluster period, and so on. The combination of the evaluations with multiple templates will improve the correct detection of unusual situations.

It is also required to establish the experiment technique that can perform objective evaluation for the detection of unusual situations. The declaration by the subjects tends to describe daily events and it does not explain the unusual situation in many cases.

The aware home technology will provide a new personal-fit service to a person when it is required. The technology to understand human condition in real time will become a key to enhance the quality of individual life in the future.

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