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# Evolution Strategy for Anomaly Detection in Daily Life Monitoring of Elderly People

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**Abstract:** Recently, various types of daily life monitoring methods have been proposed for elderly care. We have proposed the concept of informationally structured space (ISS) and applied ISS using robot partners and sensor network devices to daily life monitoring. One of the most important roles in daily life monitoring is anomaly detection. Anomaly detection is to identify or detect items, events or data not conforming to expected patterns from dataset. In this paper, we apply evolution strategy to the anomaly detection in daily life monitoring. First, we explain how to use ISS for robot partners and wireless sensor networks. Next, we explain two main components of (1) human localization by spiking neurons and (2) daily life pattern extraction by Gaussian membership functions in the daily life monitoring. Next, we propose an anomaly detection method using evolution strategy. Finally, we present numerical experimental results and discuss the effectiveness of the proposed method.

**Keywords:** Informationally Structured Space; Anomaly Detection; Elderly Care; Evolution Strategy.

## 1. INTRODUCTION

The number of people aged over 80 years by 2050 will reach 10% of the population by 2050 across OECD countries [1]. The required cost for elderly care is also increasing rapidly. Therefore, the extension of healthy life expectancy is very important.

The time budget research is used to analyze daily activities of a person or group, week to week or day to day in order to explore issues related to the style of life; to establish social indicators; and to assess wellbeing and the quality of life. Most of traditional time budget studies were related with one temporal variable, i.e., the duration of activities [2]. Afterward, temporal attributes such as timing, duration, frequency, and sequential order of human activities were systematically recorded for quantitative analysis [3]. NHK (Nippon Hoso Kyokai) has conducted Japanese Time Use Survey aimed at youths and adults aged 10 and older every five years since 1960. The major classification is categorized to (1) necessary activity (sleep, meals, personal chores etc.), (2) obligatory activity (work, schoolwork, housework, commutation, etc.), (3) free activity (leisure activities, conversation, mass media use, etc.), and (4) other/ activity unknown. The measurement data are used for the assessment of elderly activities and health promotion [4].

Information and communication technology is one of the promising approaches to extend healthy life expectancy of elderly people. Steve Jobs explained that a Mac, in a short time, could serve as the Digital Hub that unites those disparate points in our digital life (January 9, 2001). Based on the concept of Digital Hub, we proposed the concept of Life Hub that unites a person with physical and virtual information in addition to real world, e.g., people, communities, events, places, goods, environmental data, other robots, Internet information, and personal information (Fig.1) [5, 6]. Based on Life Hub, people are able to interact with life environment by conversational interfaces [7]. Furthermore, the environment system can use Internet of Things (IoT) and Ambient Assisted Living (AAL) technologies to actively support people [8, 9]. A wireless sensor network system can measure the number of people, human motions and behaviors as well as environmental state surrounding people. Furthermore, robot partners can ask elderly people about their daily activities through verbal communication. However, we have to deal with huge size of measurement data gathered from different types of sensors simultaneously. Therefore, the environment surrounding people and robots should have a structured platform for gathering, storing, transforming, and providing information. Such an environment is called Informationally Structured Space (ISS) [10, 11] (Fig.2).

Various types of daily life monitoring methods have been proposed for elderly care and health promotion. We applied ISS using robot partners and sensor network devices to daily life monitoring. One of the most important roles in daily life monitoring is anomaly detection [12, 13]. Anomaly detection is to identify or detect items, events or data not conforming to expected patterns from dataset. In this paper, we apply evolution strategy to the anomaly detection in daily life monitoring. Anomaly is also referred to as outlier, noise, or exception. Furthermore, abnormality is also included in anomaly, but we deal with a wide meaning of anomaly in this paper. Basically, there are three categories of anomaly detection; unsupervised anomaly detection, supervised anomaly detection, and

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semi-supervised anomaly detection. The unsupervised anomaly detection detects anomalies from a test dataset after learning or extracting standard patterns, while the supervised anomaly detection detects anomalies from a test dataset after learning by using normal or abnormal labels given to teaching dataset. Since we focus on the change or difference from daily life patterns, we take the methodology of unsupervised anomaly detection.

We can divide the anomaly of elderly people into cognitive anomaly and physical anomaly. In general, the unsupervised anomaly detection is composed of four stages; (1) feature extraction as preprocessing, (2) learning of patterns, (3) pattern matching, and (4) evaluation of anomaly.

First, we explain how to use ISS for robot partners and wireless sensor networks. Next, we apply spiking neural network (SNN) to extract daily life activities based on human location (stage 1). Then, we conduct fuzzy modeling to generate daily life patterns through the daily life monitoring (stage 2). Next, we propose an anomaly detection method using evolution strategy (stage 3). The similarity between a daily life log and daily life pattern is used for evaluation of anomaly (stage 4).

This paper is organized as follows. Section 2 explains robot partners, sensor network devices, and informationally structured space for daily life monitoring and anomaly detection. Section 3 presents numerical experimental results of anomaly detection where we assume an apartment for elderly person living alone. Section 4 summarizes the paper, and discusses the future direction on this research.

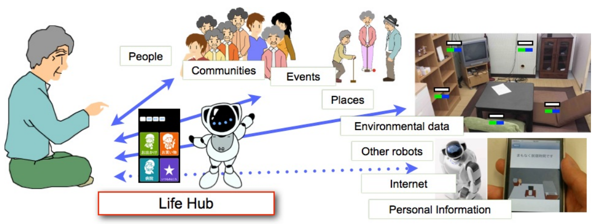



Fig.1 A life hub connecting a person with information

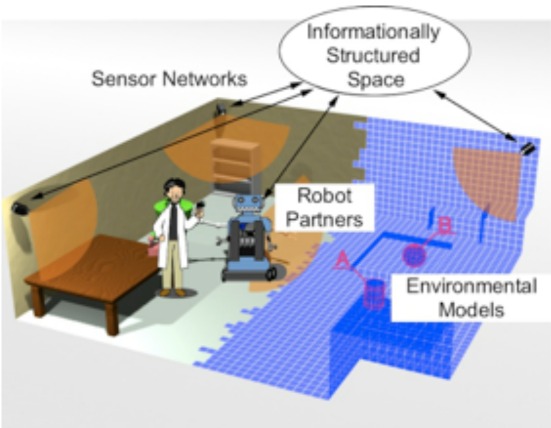
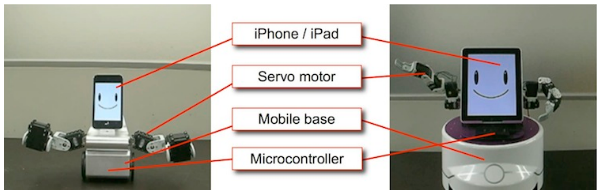



Fig.2 Informationally Structured Space

## 2. INFORMATIONALLY STRUCTURED SPACE FOR DAILY LIFE MONITORING

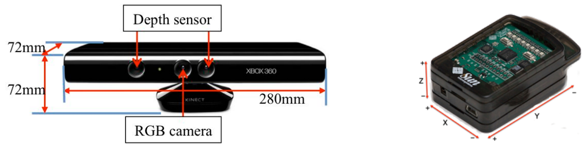
### 2.1. Robot Partners and Sensor Network Devices

Our robot partners called iPhonoid and iPadrone are shown in Fig.3 [14]. The robot is enough to be equipped with only cheap range sensors, because iPhone is equipped with various sensors such as gyro, accelerometer, illumination sensor, touch interface, compass, two cameras, and microphone [15]. The robot partner is equipped with 4 or 6 servomotors (2 or 3 degrees of freedom (DOF) to each arm). Wireless LAN and wireless PAN (Bluetooth) can be used in addition to a wired serial communication to control the actuators of the robot partner from a smart phone or a tablet PC [16]. The robot partners are used for measuring the human position and human activities through the communication with people.




(a) iPhonoid (b) iPadrone

Fig.3 iPhonoid and iPadrone




(a) Kinect sensor (b) Sun SPOT

Fig.4 Sensor devices

Table 1 Specification of Kinect sensor

| | |
|---|---|
| Size | 282×72×72 [mm] |
| Measurement range | 57×43 [deg] |
| Measurement distance | 0.5–7.0 [m] |
| Resolution | 320×240, 640×480 [pixel] |
| Sampling rate | 30 [fps] |

Table 2 Specification of Sun SPOT

| | |
|---|---|
| Size | 41×23×70 [mm] |
| Weight | 54 [g] |
| 3-axis accelerometer range | 2G/6G |
| Light sensor range | 0–750 [raw reading from lx] |
| Battery | 720 [mAh] lithium-ion |
| OS | Squawk VM |
| Wireless Radio | 2.4 GHz, IEEE 802.15.4 |

We use Microsoft Kinect sensor as a 3D range sensor shown in Fig.4 (a) and Table 1 for global observation in a room [17]. The human gesture and behavior recognition is mainly performed by Kinect sensor, and OpenNI is applied for human detection. OpenNI is intended to help in developing the applications that use 3D vision inputs such as full body control.

Sun SPOT (Sun Small Programmable Object Technology) is a wireless sensor network (WSN) developed by Oracle Corporation (Sun Microsystems) [18]. The device, shown in Fig.4 (b) and Table 2, is built upon the IEEE 802.15.4 standard. Sun SPOT is small, wireless, battery-powered device developed at Sun Labs. This device can be used in a wide range of applications including robotics, environmental monitoring, asset tracking, proactive health care and many others. Sun SPOT is powered by a specially designed small-footprint Java virtual machine, called Squawk that can host multiple applications concurrently, which requires no underlying operating system.

We discuss how to use ISS based on robot partners and sensor network devices from the viewpoint of bottom-up access and top-down access. ISS can be considered as a typical client-server system where a robot partner or sensor network device is a client (physical node) shown in Fig.5. A physical node uploads information to the ISS server and downloads information from the ISS server. This kind of local information processing is considered as the bottom-up access. On the other hand, the ISS can control or manage each physical node from the global point of view. For example, the ISS can set the sampling interval of each sensor network device according to human states and behaviors in the perception level. This kind of global information processing is considered as the top-down access.

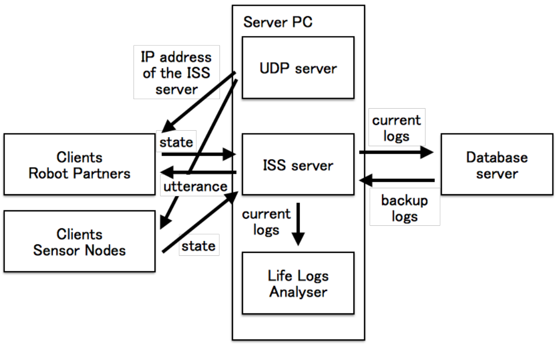



Fig.5 Information flow among robot partners, sensor network devices, and ISS

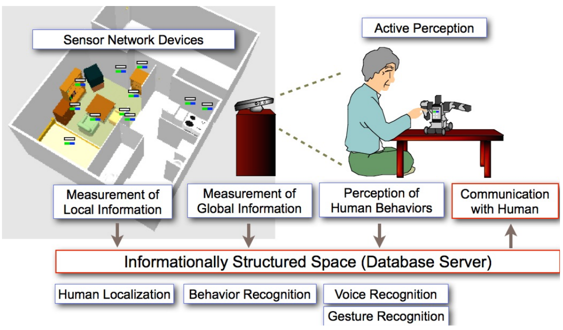
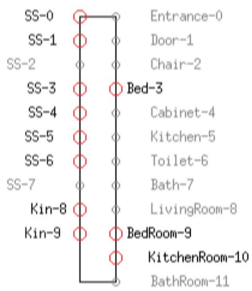


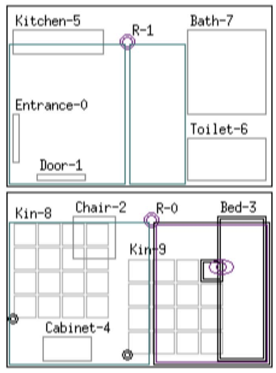

Fig.6 ISS for elderly care in a room

## 2.2. Daily Life Monitoring

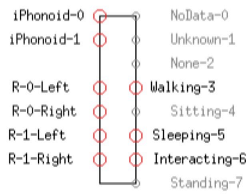
Basically, the daily life monitoring for elderly people is done by a time series of human life logs. Human life logs are extracted by human localization, activity recognition, and voice recognition. Sensor nodes can specify the human position in the house. Here we assume a one-room apartment, and use the sensor nodes at the entrance door, doorway of the living room, chair in the living room, bed, cabinet, kitchen, toilet, and bath room (Fig.6). We show an example of daily life monitoring based on ISS in Fig.7. In this example, we use Sun SPOT and Microsoft Kinect as sensor nodes expressed as SS and Kin, respectively. Furthermore, we use two robot partners named iPhonoid and iPadrone. When a sensor node is activated, sensor node receives the IP address of the ISS server by UDP server, and connects to the ISS server (see Fig.8). At that time, the sensor node is added to the activated sensor list of the ISS, its corresponding state is shown in the activation state (Fig.7 (a)). If each sensor node detects a person, its corresponding human position is highlighted (Fig.7 (b)). The labels of “Bed-3” and “BedRoom-9” are highlighted in this example, because SS-3 and Kin-9 detect a person. Furthermore, we can use the sensors equipped with robot partners. The sensing range of camera of a robot partner is divided into right area (R-Right) and left area (R-Left). If a camera detects a person, its corresponding human position is highlighted (Fig.7 (b)). In this example, the labels of “Walking-3”, “Sleeping-5”, and “Interacting-6” are highlighted (Fig.7 (c)), because the person just moved to the bedroom from the kitchen area.




(a) Activation states




(b) Visualization in ISS




(c) States of robot partners and human activities

Fig.7 An example of daily life monitoring based on ISS

We use a simple spiking neuron to estimate human position [19]. If the spike output is done, the monitoring system detects a person at its corresponding position. Human movement transition probability is calculated by the time series of life log data. The internal state $h_i(t)$ of a spiking neuron is calculated as follows;

$$h_i(t) = \gamma^{sys} h_i(t-1) + h_i^{ref}(t) + h_i^{ext}(t) \quad (1)$$

where $h_i^{ext}(t)$ is the input to the $i$th neuron from the external environment; $h_i^{ref}(t)$ indicates the refractoriness factor of the neuron at the discrete time $t$; $\gamma^{sys}$ is the temporal discount rate. When the internal state of the $i$th neuron is larger than the predefined threshold, a pulse is outputted in the following;

$$p_i(t) = \begin{cases} 1 & if\ h_i(t) \geq P \\ 0 & otherwise \end{cases} \quad (2)$$

where $P$ is a threshold for firing. The presynaptic spike output is transmitted to the connected neuron according to the PSP with the weight connection. The PSP is calculated as follows:

$$h_i^{PSP}(t) = \begin{cases} 1 & if\ p_i(t) = 1 \\ \gamma^{PSP} h_i^{PSP}(t-1) & otherwise \end{cases} \quad (3)$$

where $\gamma^{PSP}$ is the discount rate. Furthermore, $R$ ($R$>0) is subtracted from the refractoriness value in the following,

$$h_i^{ref}(t) = \begin{cases} h_i^{ref}(t-1) - R & if\ p_i(t) = 1 \\ \gamma^{ref} h_i^{ref}(t-1) & otherwise \end{cases} \quad (4)$$

where $\gamma^{ref}$ is a discount rate. The input to the $i$th neuron corresponding to the direction of $d_i$ is calculated in the following;

$$h_i^{ext}(t) = \exp\left( -\frac{\left(x(t) - x(t-1)\right)^2}{\alpha^{ext}} \right) + \sum_{j=1, j \neq i}^{n} w_{j,i} h_i^{PSP}(t-1) \quad (5)$$

where $x(t)$ is a measurement value of the $i$th sensor node and it is normalized from the corresponding sensory data [11]; $w_{j,i}$ is the connection weight from the $j$th neuron to the $i$th neuron. If the connection weight is positive, PSP is transmitted as the excitatory postsynaptic potential (EPSP). If the values of both $p_i^{PSP}(t)$ and $p_j^{PSP}(t-1)$ are larger than the learning threshold, the connection weight is updated by

$$w_{j,i} \leftarrow w_{j,i} + \gamma^{wht} h_j^{PSP}(t-1) h_i^{PSP}(t) \quad (6)$$

where $\gamma^{wht}$ is a learning rate for temporal Hebbian learning. Therefore, the connection weight can learn the activities transition over time. Figure 8 shows an example of the learning by SNN.

We can analyze the human life pattern by tracing state transition of human activities. The monitoring system is redundant, because several sensors often cover the same area with different resolutions. For example, the camera of a robot partner monitors the same area with the Kinect sensor. Figure 7 (c) shows an example of simultaneous firing patterns. If the simultaneous firing occurs in the sensor node, its corresponding connection is highlighted strongly.

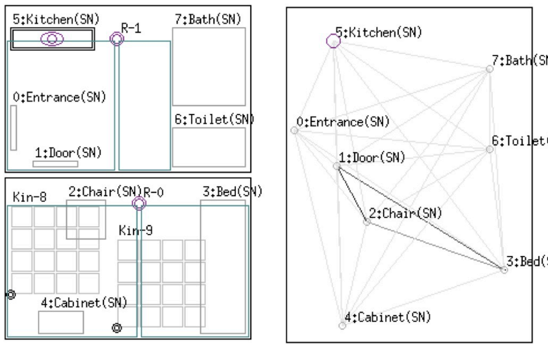
The daily life pattern is extracted from the time series of life log data as the learning stage of patterns. Each activity in the daily life pattern is represented by the set of Gaussian membership functions over time,

$$\mu_{A_{i,j}}(t) = \exp\left( -\frac{(t - a_{i,j})^2}{b_{i,j}^2} \right) \quad (7)$$

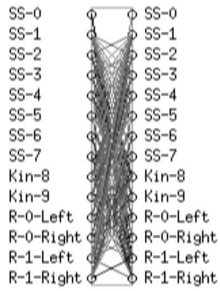
where $t$ is the input time; $a_{i,j}$ and $b_{i,j}$ are the central value and width of the $j$th class of the $i$th activity, respectively. When the $i$th activity is observed, if $\mu_{A_{i,j}}(t) \leq \theta$, then we use the simple update rule;

$$\begin{cases} a_{i,j} \leftarrow (1-\alpha) a_{i,j} + \alpha (s_i^L + 0.5 \cdot d_i^L) \\ b_{i,j} \leftarrow (1-\alpha) b_{i,j} + 0.5 \cdot \alpha \cdot d_i^L \end{cases} \quad (8)$$

where $s_i^L$ is the starting time and $d_i^L$ is the consumption (duration) time of the $i$th activity; $\alpha$ and $\theta$ are the learning rate and the threshold, respectively. If not, a new cluster is added to the daily activity pattern clusters. We can generate (1) overall daily life pattern, (2) seasonal daily life pattern, (3) monthly daily life pattern, and (4) daily life pattern by the day of the week.




(a) Monitoring state (b) Human movement transition




(c) Simultaneous firing of sensor nodes in a house

Fig.8. An example of learning by SNN based on ISS

## 2.3. Evolution Strategy for Anomaly Detection

We apply an evolution strategy (ES) to correspond a daily life log to a daily life pattern for calculating the similarity. In ($\mu$+$\lambda$)-ES, $\mu$ and $\lambda$ indicate the number of parents and the number of children generated in a single generation, respectively. Here we use ($\mu$+1)-ES to enhance the local hill-climbing search. In ($\mu$+1)-ES, only an existing solution is replaced with the candidate solution generated by crossover and mutation. ($\mu$+1)-ES is considered as a steady-state genetic algorithm with the least fitness deletion.

The genotype is composed of {0, 1, 2, and 3} shown in Fig.9 to evaluate the correspondence between $m_i$ and $l_i$. Figure 10 shows an example of correspondence between an input daily life log $L$ and the $M_k$th daily life pattern by using the $j$th candidate solution.

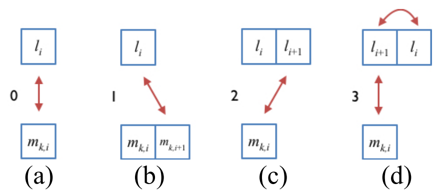



Fig.9. Correspondence by genotype; (a) shows a standard correspondence (no operation), (b) $m_{k,i}$ is skipping, (c) $l_i$ is skipping, and (d) correspondence after $l_i$ is exchanged with $l_{i+1}$

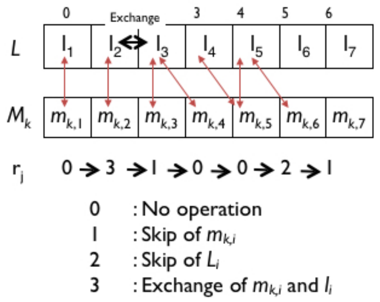



Fig.10. An example of correspondence between an input daily life log $L$ and the $M_k$th daily life pattern by using the $j$th candidate solution

The fitness value of the $j$th candidate solution is calculated by the following equation

$$fit_j = \max_k \sum_{i \in m_k} fit_{j,k,i} \tag{9}$$

$$fit_{j,k,i} = fit^S_{j,k,i} + fit^D_{j,k,i} \tag{10}$$

where $fit_{j,k,i}$ is the similarity measure in $i$th correspondence with the $k$th daily life pattern according to the $j$th candidate solution; $fit^S_{j,k,i}$ and $fit^D_{j,k,i}$ are evaluation values on the starting time and duration calculated by

$$\begin{cases} fit^S_{j,k,i} = \beta^S \cdot \exp\left( -\dfrac{(s^M_{k,i} - s^L_i)^2}{c} \right) \\ fit^D_{j,k,i} = \beta^D \cdot \exp\left( -\dfrac{(d^M_{k,i} - d^L_i)^2}{c} \right) \end{cases} \tag{11}$$

where $s^M_{k,i}$ and $s^L_i$ are the starting time of the $i$th correspondence in the $k$th daily life pattern and input daily life log, respectively; $d^M_{k,i}$ and $d^L_i$ are the duration time of the $i$th correspondence in the $k$th daily life pattern and input daily life log; $\beta^S$ and $\beta^D$ are weight values. If the fitness value is lower than the threshold, an anomaly is included in its corresponding daily life log.

We use an elitist crossover, uniform crossover, simple mutation, exchange mutation, and inversion. The elitist crossover conducts an exchange between the best candidate solution and a randomly selected candidate solution according to the crossover rate.

## 3. NUMERICAL EXPERIMENTS

We show a numerical experiment using artificial life log data obtained by the human life simulator.

The obtained simulation results are used as daily life patterns by the fuzzy modeling on the day of week from Sunday to Saturday. Next, we generate artificial life log data for 30 days by the human life simulator to evaluate the proposed anomaly detection method. Figure 11 shows daily life patterns generated from fuzzy modeling.

The number of candidate solutions is 100, and the number of evaluation times is 100000 where the number of generations in a standard ES is considered as 1000. The elitist crossover rate is 0.5 and the mutation rate is 0.1 per candidate solution.

Figure 12 shows a history of fitness values in the simulation result of the proposed anomaly detection method. If the fitness value is high, the daily life log is similar to the previously obtained daily life patterns. The fitness values of the 8th and 17th days are lower comparing with others. Figure 13 shows the observed daily life log of these two days. Figure 14 (a) and (b) show the evaluation result of similarity. The evaluation results show that the daily life logs of the 8th and 17th days are quite different from the daily life patterns of Thursday and Tuesday. Furthermore, Fig.14 (c) illustrates an evaluation result of the daily life log on the 3rd day and daily life pattern of Monday. The evaluation result of the similarity shows the detection of midnight wander with low similarity. In this way, the proposed anomaly detection method can detect the difference from daily life patterns.

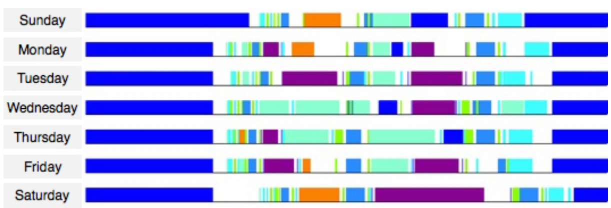



Fig.11 Daily life patterns generated from fuzzy modeling

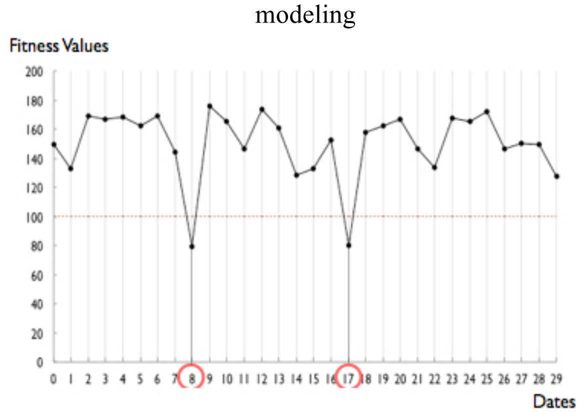



Fig.12. A history of fitness values in the simulation result of the proposed anomaly detection method

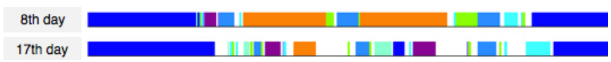
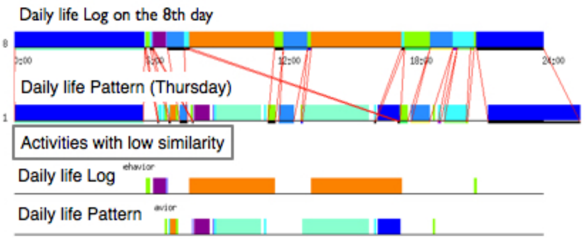
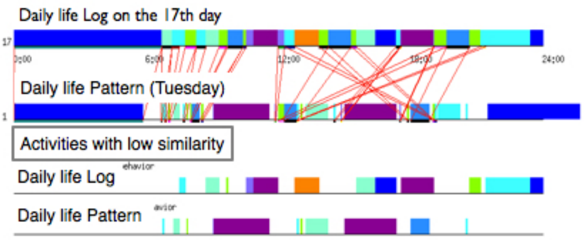


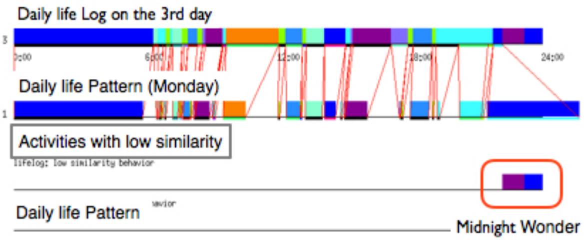

Fig.13. Daily life log on the 8th and 17th days




(a) Similarity on the 8th day




(b) Similarity on the 17th day




(c) Similarity on the 3rd day

Fig.14. Evaluation of similarity between daily life log and daily life pattern

## 4. SUMMARY

This paper proposed an unsupervised anomaly detection method in daily life monitoring for elderly people. The proposed method is composed of 4 components. We applied a spiking neural network to extract daily life activities based on human location. Next, we applied fuzzy modeling to generate daily life patterns through the online daily life monitoring. Then, we applied evolution strategy to pattern matching for the anomaly detection. Finally, we proposed an evaluation method of anomaly based on similarity between a daily life log and daily life pattern. The numerical experimental results support the effectiveness of the proposed method. On the other hand, we can apply a method of dynamic time warping (DP matching), but the DP matching cannot conduct the exchange operation. The genotype encoding of the proposed method can flexibly deal with permutation problems in the pattern matching between daily life logs and daily life patterns.

As a future work, we intend to apply the proposed method to elderly care, and discuss its effectiveness. Furthermore, we will develop the next generation of iPhonoid and iPadrone for elderly care with new appearance.

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