Informationally Structured Space for Life Log Monitoring in Elderly Care

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***Abstract* — Recently, various types of wireless sensor network systems have been developed to realize daily care for elderly people living alone. Furthermore, visualization methods of life logs have been presented. However, it is important to integrate different types of data measured by each sensor node to estimate human states and behaviors. Therefore, we have proposed the concept of informationally structured space (ISS). This paper proposes a methodology to deal with data measured by sensor nodes in wireless sensor networks on ISS. First, we explain how to use ISS for wireless sensor networks. Next, we apply the proposed method to elderly care. We propose four different components such as (1) human localization by spiking neurons, (2) human movement transition probability, (3) redundant monitoring by simultaneous firing of sensor nodes, and (4) temporal life pattern extraction by Gaussian membership functions. Finally, we show several simulation results and discuss the effectiveness of the proposed method.**

Keywords; Informationally Structured Space; Elderly Care; Life Hubs; Multimodal Monitoring;

I. INTRODUCTION

Recently, the rate of elderly people living alone is increasing and this has become a serious problem in Japan [1]. Many elderly people spend the daytime by watching TV, not often going out. Therefore, elderly care and health promotion are very important to extend the healthy life expectancy of elderly people. Information and Communication Technology (ICT) such as a smart phone, personal computer (PC), and tablet PC was introduced to improve the quality of life (QOL). Furthermore, ICT can bind the relationship in the social community to increase the quality of community (QOC). In general, there is a significant difference between watching TV and using ICT devices from the viewpoint of personal experiences. For example, we can listen to daily news and weather information from TV, but this is a passive behavior. On the other hand, we can actively use keyboard or touch interface in case of smart devices. However, we should consider that it is difficult for elderly people to manage personal computers (PC). Various types of robots such as amusement robots, robot pets, and robot partners have been developed so far [2-4]. A smart device and a human-friendly robot partner can be a possible solution for elderly care. A smart device such as a smart phone or tablet PC provide us with the human-friendly interface and wireless communication methods in addition to sensors for voice recognition, motion estimation and other tasks.

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). We extended the concept of Digital Hub to 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].

For health care monitoring and anomaly detection, mainly there are two kind of approches so far. One is monitoring the human behavior and life pattern [7-12], another one is monitoring the human's bio-signal and motion [7,13,14]. The anomaly detection can be divided into two categories: short-term and long-term anomaly detection. There are several data mining techniques to detect anomaly: classification based, clustering based, and statistical based approaches. The human behavior and life pattern monitoring can mainly be divided into two categories from the measurement point of view: noncomputer vision-based methods and computer vision-based methods.

A wireless sensor network system can measure the number of people, human motions and behaviors as well as environmental state surrounding people, but 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) [15,16] (Fig.2). The robot can directly receive and share the environmental information through a wireless network without any measurement process, through ISS if it is available. We have proposed several application examples of communication systems using robot partners based on ISS [6]. In [6] the robot partner applies both verbal as well as non-verbal communication using ISS to understand human. In the non-verbal communication, environmental and human state data along with gesture recognition can be utilized by ISS.

Nevertheless, we have to design how to use and update ISS in a more useful way for sensor network devices and robot partners. In this paper, therefore, we propose a methodology to manage sensor network devices based on ISS according to

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human states and behaviors. Next, we apply the proposed method to life log measurement in elderly care. Finally, we show several experimental results and discuss the effectiveness of the proposed method.

This paper is organized as follows. Section II explains robot partners and sensor network devices. Section III explains the basic concept and application of ISS. Section IV presents how to apply ISS to elderly care and shows simulation examples for life log extraction in elderly care. Section V summarizes the paper, and discusses the future direction on this research.

II. ROBOT PARTNERS FOR INFORMATION SUPPORT

A. *Robot Partners and Sensor Network Devices*

We have been developing on-table small size of robot partners called iPhonoid and iPadrone illustrated in Fig.3 [17]. Since iPhone is equipped with various sensors such as gyro, accelerometer, illumination sensor, touch interface, compass, two cameras, and microphone, the robot itself is enough to be equipped with only cheap range sensors [18]. The robot partner is equipped with 4 or 6 servomotors (2 or 3 degrees of freedom (DOF) to each arm). In order to control actuators of a robot partner from the smart phone or tablet PC, we can use wireless LAN and wireless PAN (Bluetooth) in addition to a wired serial communication [19].

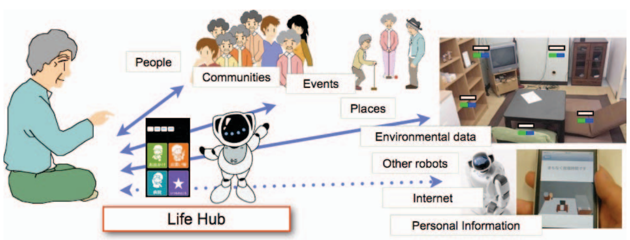


Fig.1. A life hub connecting a person with information

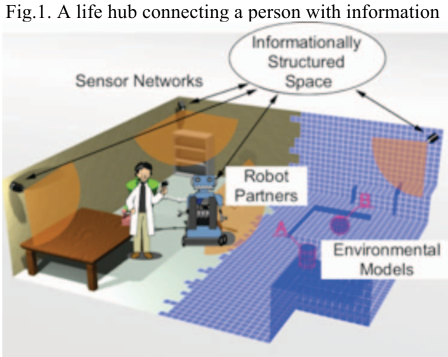
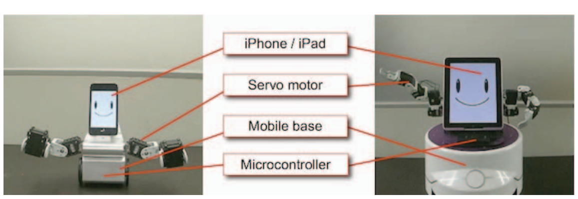
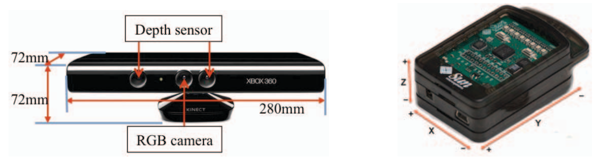


Fig.2. Informationally Structured Space



(a) iPhonoid (b) iPadrone

Fig.3. iPhonoid and iPadrone



(a) Kinect sensor (b) Sun SPOT

Fig.4. Sensor devices

In this research, the robot partner needs not only to measure the human position but also to perform gesture recognition. We apply Microsoft Kinect sensor presented in Fig.4 (a) and Table I. [20]. The gesture 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 by breaking the rigid connection between the application and the sensor and/or vision algorithms. Sun SPOT (Sun Small Programmable Object Technology) is a wireless sensor network (WSN) developed by Oracle Corporation (Sun Microsystems) [21]. The device, depicted in Fig.4 (b) and Table II, 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.

TABLE I. 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 II. 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 battery
OS	Squawk VM
Wireless Radio	2.4 GHz, IEEE 802.15.4

B. *Communication System*

The communication system of robot partners with people is composed of (1) Daily conversation mode, (2) Information support mode, and (3) Scenario conversation mode shown in Fig.5. The daily conversation is done according to daily life style extracted by life logs. If we can prepare the daily life pattern or schedule for an elderly person, the robot can make time-dependent utterances. The information support is done by three different kinds of utterances; (1) Reminder support based on attention information in abnormal situations of people and rooms; (2) Daily information support on weather forecast and news for daily life extracted from web pages, and social networking service such as Facebook and Twitter; (3) Information retrieval support based on hobby and interest of a person. The scenario conversation mode is done by three interrelated modules; topic selection module, conversation control module, and utterance selection module. The topic selection module decides the global flow of conversation based on the selection probabilities of topics. The conversation control module controls the flow of utterances based on transition probabilities of utterances. Furthermore, scenarios are downloaded periodically from the database server through the Internet.

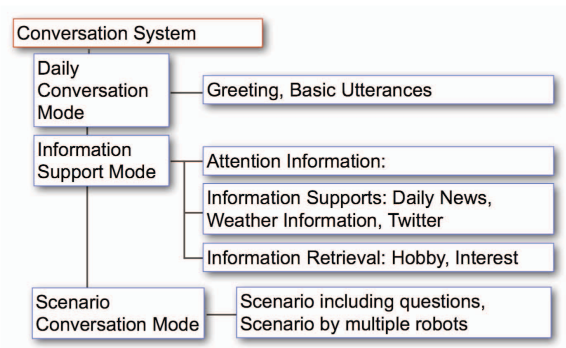


Fig.5. A conversation system for robot partners

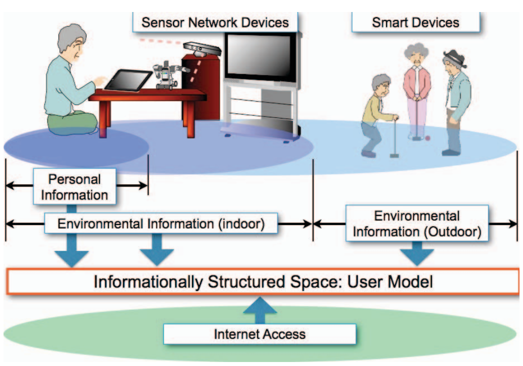


Fig.6. Measurement range of Life Hub

The verbal communication of robot partners is done by (1) random utterance, (2) time-dependent utterance, or (3) event-driven utterance. Event-driven utternace is done according to the states of sensors, e.g., touch interface on the screen of iPhonoid, activation of sensor nodes, and multi-robot conversation based on the request by other robot patners.

The reaction to a person is done by (1) reply, (2) simple repeat, (3) sympathic nodding, and (4) funny reaction. Basically, the reply is done according to a set of words obtained by voice recognition. The sympathic nodding is done with simple utterances such as “Yes”, “I understand”, “I see” and “That’s alright”. The sympathic nodding is used as an attentive listener for elderly people.

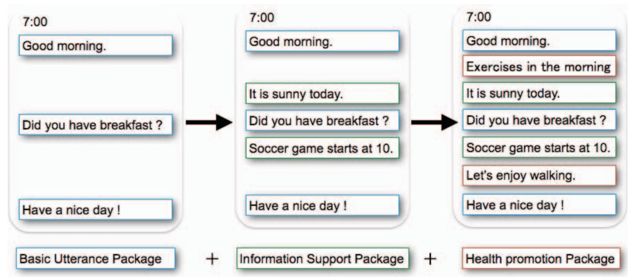


Fig.7. Modularity of packages for services

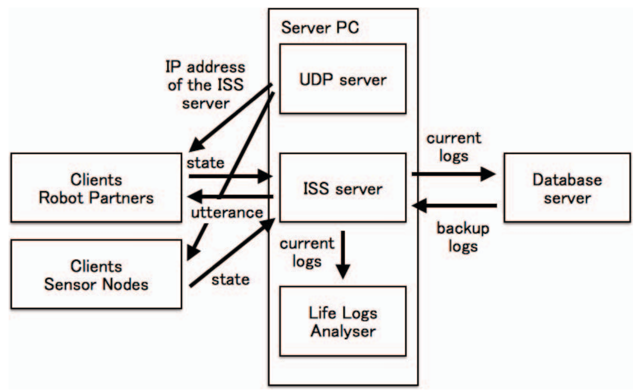


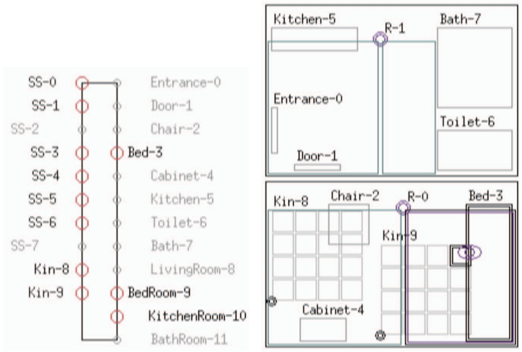
Fig.8. Information flow among robot partners, sensor nodes and ISS

III. INFORMATIONALLY STRUCTURED SPACE

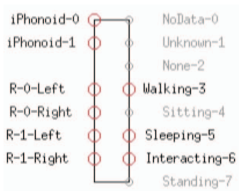
ISS can be discussed from the information type based on the measurement range and measurement methods (Fig.6), e.g., (1) personal information, (2) environmental information (indoor), (3) environmental information (outdoor), and (4) Internet information. These kinds of information types are used to build an individual personal model. ISS is used for services such as elderly care, child nursing, information support, and environmental monitoring in public areas.

We assume each service used as a software component should be designed with learning module and utterance module according to the aim to use ISS. Furthermore, software component can be easily added to the basic control architecture based on basic utterance package from the viewpoint of modularity (Fig.7).

We discuss how to use ISS 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.8. 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.



(a) Activation states (b) Visualization in ISS



(c) States of robot partners

Fig.9. Connectivity of sensor nodes with ISS

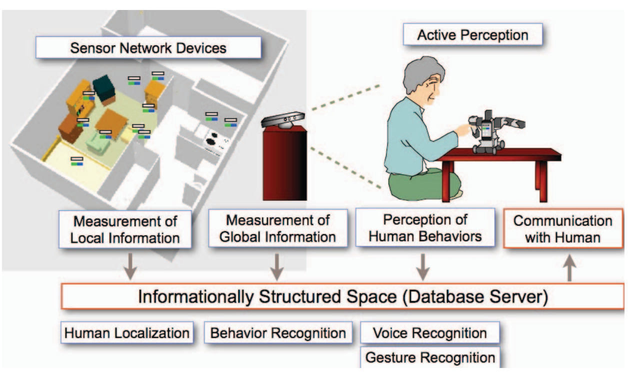


Fig.10. ISS for elderly care in a room

We show an example of ISS in Fig.9. In this example, we use Sun SPOT and Microsoft Kinect as sensor nodes expressed as SS and Kin, respectively (in Fig.9). 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.9 (a)). If each sensor node detects a person, its corresponding human position is highlighted (Fig.9). In this example, the labels of "Bed-3" and "BedRoom-9" are highlighted , because SS-3 and Kin-9 detect a person. Furthermore, we can use the sensors that the robot partners equipped with. The sensing range of the 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.9.(c)). In this example, the labels of "Walking-3", "Sleeping-5", and "Interacting-6" are highlighted, because the person just moved to the bed room from the kitchen area.

IV. Application to Elderly Care

A. Monitoring System

Basically, elderly care is done by a time series of human life logs. We can divide the anomaly of elderly people into cognitive anomaly and physical anomaly. Human life logs are extracted by human localization, behavior recognition, and voice recognition (Fig.10). 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 (Fig11 (a)).

We use a simple spiking neuron to estimate human position [8]. For sensor and information fusion one can refer to our previous work [6,16]. The redundant data are pre-processed before the learning stage. 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 (Fig.11 (b)). We can analyze the human life pattern by tracing state transition of human behaviors, while we can detect measurement errors by tracing the simultaneous firing of sensor nodes in the house. 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. If a breakdown or error happens to a sensor node, we can detect different pattern in the simultaneous firing of sensor nodes. Figure 11 (c) shows an example of simultaneous firing patterns. If the simultaneous firing occurs in the sensor node, its corresponding connection is highlighted strongly.

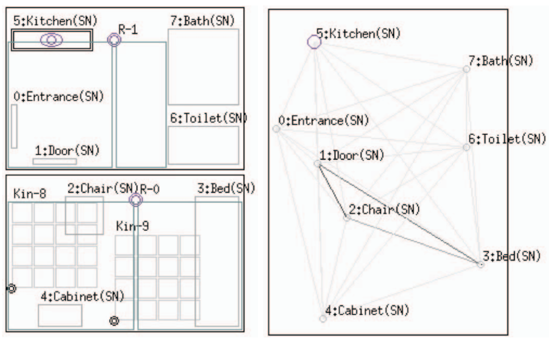
The daily temporal pattern is extracted from the time series of life log data. Each behavior in the daily temporal pattern is represented by the set of Gaussian membership functions over time,

$$\mu_{A_{i,j}}(t) = \exp\left(-\frac{(t-a_{i,j})^2}{b_{i,j}^2} \right) \tag{1}$$

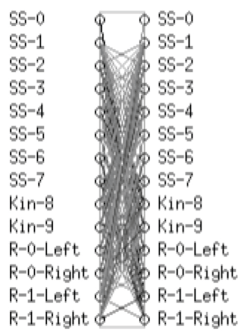
where t is the input time; $a_{i,j}$ and $b_{i,j}$ are the central value and width of the jth class of the ith behavior, respectively. When the ith behavior is observed, if $\mu_{A_{i,j}}(t) \le \theta$, then we use the simple update rule;

$$\begin{cases} a_{i,j} \leftarrow (1-\alpha)a_{i,j} + \alpha \cdot (x_i + 0.5 \cdot w_i) \\ b_{i,j} \leftarrow (1-\alpha)b_{i,j} + 0.5 \cdot \alpha \cdot w_i \end{cases} \tag{2}$$

where x_i is the starting time and w_i is the consumption time of the ith behavior; α and θ is the learning rate and threshold, respectively. If not, a new cluster is added to the temporal behavior pattern clusters. We use (1) overall daily temporal pattern, (2) seasonal daily temporal pattern, (3) monthly daily temporal pattern, and (4) daily temporal pattern by the day of week.



(a) Monitoring state (b) Human movement transition

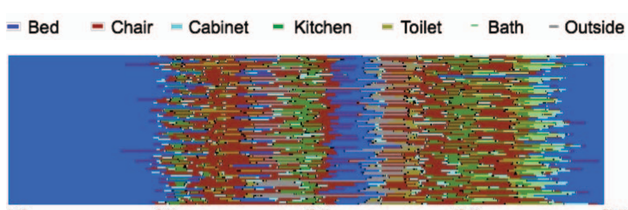


(c) Simultaneous firing of sensor nodes in a house

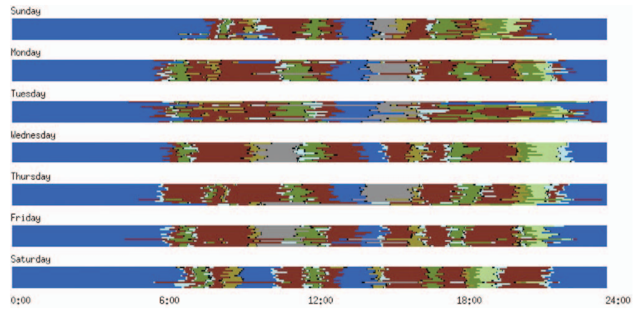
Fig.11. Visualization based on ISS

B. Simulation Results

We show a simulation example using artificial life log data obtained by the human life simulator. The size of human life log data is 90 days. The learning rate (α) is 0.1 and the threshold (θ) is 0.15. Figure 12 shows a simulation result of life logs for 90 days; (a) Life logs for 90 days and (b) Life logs by the day of week for 90 days. The simulation results show that the person almost takes a regular life by the day of week.



(a) Life logs for 90 days



(b) Life logs by day of week for 90 days

Fig.12. Visualization of life logs in ISS

Figure 13 shows temporal visualization of behaviors in ISS; (a) Temporal pattern of each behavior for the first day, (b) Temporal pattern of each behavior for 90 days and (c) Temporal pattern of each behavior on Sunday. These results show that the proposed method can add clusters of each behavior to the temporal life pattern step by step. The value is calculated by the following equation

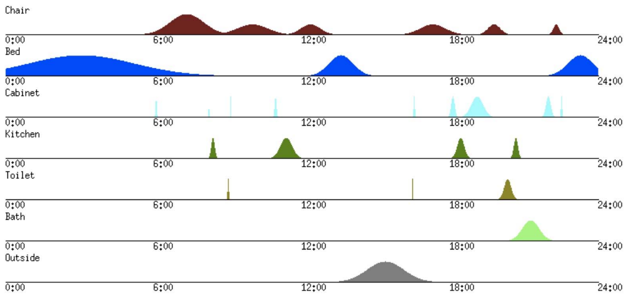
$$\mu_{A_{i,j}}(t) = \frac{T_{i,j}}{MaxT_i} \exp\left(-\frac{(t-a_{i,j})^2}{b_{i,j}^2} \right) \quad (1')$$

where $T_{i,j}$ is the selection times of the jth cluster of the ith behavior; $MaxT_i$ is the maximal selection times. Therefore, the height of Gaussian membership function is the relative selection frequency. The comparison result shows several differences, e.g., the wake-up time on Sunday is a little later than that of all days; the person takes short nap in the afternoon everyday; the person goes out on Sunday afternoon.

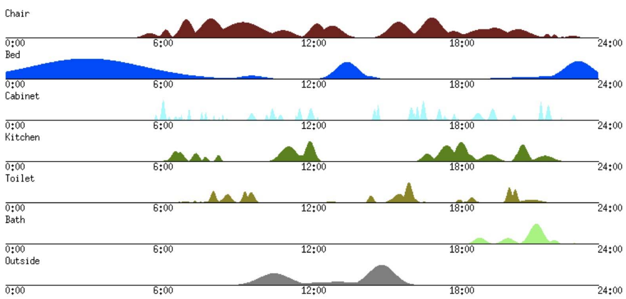
V. SUMMARY

This paper discussed informationally structured space based on wireless sensor networks composed of sensor network devices, Kinect sensors, and sensors that robot partners equipped with. Next, we apply the proposed method to life log measurement for elderly care. We proposed four different components such as (1) human localization by spiking neurons, (2) human movement transition probability, (3) redundant monitoring by simultaneous firing of sensor nodes, and (4) temporal life pattern extraction by Gaussian membership functions. Finally, we show several simulation results using artificial data obtained by the human life simulator. These simulation results show that the proposed method can extract human temporal life patterns.

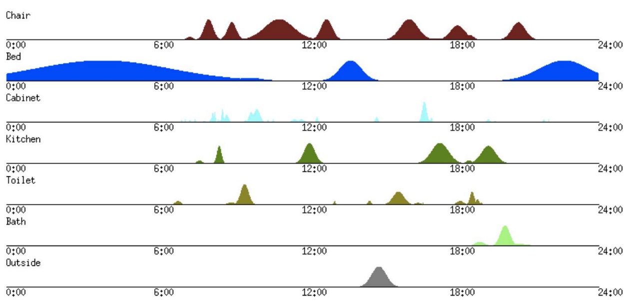
As a future work, we intend to propose the method for anomaly detection from the life log data. Furthermore, we will develop the total architecture of ISS as a middleware. Furthermore, we will develop the next generation of iPhonoid and iPadrone for elderly care with new appearance.



(a) Temporal pattern of each behavior for the first day



(b) Temporal pattern of each behavior for 90 days (overall)



(c) Temporal pattern of each behavior on Sunday

Fig.13. Temporal visualization of behaviors in ISS

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