Behavior Pattern Extraction based on Growing Neural Networks for Informationally Structured Space

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***Abstract*— In this paper, we focus on human pattern extraction using sensor networks and portable sensing system. Behavior analysis is one of the most important tasks, which provides suitable information service to users. This paper proposes a pattern extraction method based on growing neural networks. The learning system is composed of two modules for feature extraction and contextual relation modeling using Growing Neural Gas (GNG) and Spiking Neural Network (SNN). GNG is applied to the feature extraction of human behavior, and SNN is used to associate the features with event information labels. We show several experimental results, and discuss the effectiveness of our proposed method.**

I. INTRODUCTION

As the number of elderly people living alone increases, the need arises to provide support to the aging society. Elderly people have little chances of communicating with other people and may find themselves socially isolated. Ideally, the family members and caregivers of elderly people should create time regularly for social interaction. However, family members are often caught up in their own daily activities and the number of caregivers is not enough to cater for the growing aging society. Additionally, it is difficult for family members at a distant proximity to make regular physical connection with their elderly relatives. The monitoring system is one of possible solutions that can be employed to provide reassurance pertaining to the safety and provision of social connection to elderly people [1,2]. Sensor network or portable sensing devices can be applied to such monitoring systems.

The emerging synthesis of information technology (IT), network technology (NT), and robot technology (RT) is one of the most promising approaches to realising a safe, secure, and comfortable society for the older generation [3]. NT can provide robots with computational capabilities based on various types of information gathered from the robot's external environment. Actually the robot directly receives the environmental information through a local area network without the measurement by the robot itself. Wireless sensor network enables gathering huge data from the environment. However, it is very difficult to store all of the data in real time. Furthermore, the feature extraction of raw sensor data is required to obtain meaningful information. Hence, there is the need to fit wireless sensor networks with intelligent technology.

In previous works, we have developed an information support system by integrating robot technology, network technology, information technology, and intelligent technology based on the concept of cognitive environments. In order to share the information in the cognitive environments between human, sensor devices and robot partner, a structured platform for gathering, storing, transforming, and providing information is imperative. We have called such a platform Informationally Structured Space (ISS) [4]. ISS can integrate people and systems by transforming the data into useful information. In ISS, the concept of sequential "adaptation" and "learning" is important, especially, if the system models human behavior patterns. The model enables the system to provide appropriate services to people. We therefore focus on human behavior pattern modelling based on human daily activities.

Artificial Neural Networks (ANNs) are one of the most efficient approaches for pattern learning. In previous works, several kinds of ANNs have been proposed and applied to behavior recognition:. These include Time Delay Neural Networks, Recurrent Neural Networks, Fuzzy Neural Networks, and so on. However, most of the methods were based on offline approaches. For the methodologies, it is difficult to maintain the accuracy of behavior recognition under real environment. One of the solutions proposed to solve the stability-plasticity dilemma is Adaptive Resonance Theory (ART) [5]. The ART is an unsupervised learning method based on match-based learning using fast learning. The match-based learning allows memories to adapt quickly only when input from the external world is close enough to internal expectations, or when completely new things occur. However, in the ART, contextual relationship between each created cluster is not considered.

This paper proposes a pattern extraction method based on growing neural networks. The learning system is composed of two modules for feature extraction and contextual relation modeling, using Growing Neural Gas (GNG) and Spiking Neural Network (SNN). GNG is applied to the feature extraction of human behavior, and SNN is used to associate the features with event information labels.

The rest of this paper is organized as follows. Section II discusses the application of robotic computing to elder care.

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Section III introduces the developed information support system based on

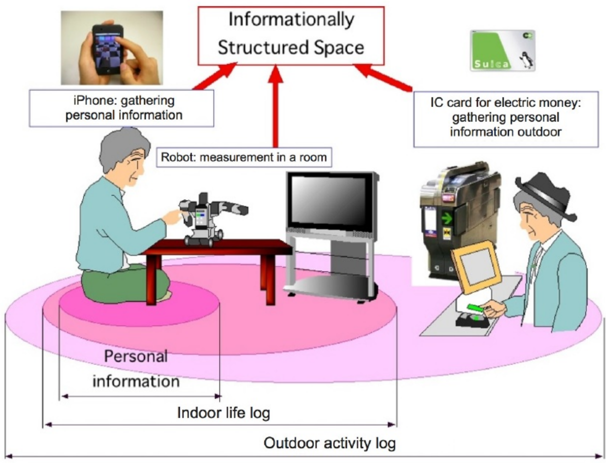


Fig. 1. Informationally Structured Space for Elderly Care.

ISS. Secton IV explains the proposed method. Section V shows an example of experimental result. Section VI identifies ethical privacy issues. Finally, Section VII provides a summary and the presentation of future works.

II. DELIVERING ELDER CARE USING ROBOTIC COMPUTING TECHNOLOGY

Positive results have been reported on the use of robotic computing to support elder care in various applications such as health care, psychological wellbeing and social interaction. In [21], the authors investigated the effect of social robots on the elderly in terms of decreased health, positive mood, decreased loneliness and increased social communication. They reported that assistive social robots were used as an interface to ease communication between the elderly and computing technology. These robots further provide companionship to the elderly and have positive effects on the health and psychological wellbeing of the elderly.

Robots have also been used to care for elders in the areas of monitoring, assistance and companionship [22]. The elderly need to be cared for due to various anomalies which usually occur as a result of the ageing process. Mobility problems can hinder the elderly's ability to perform daily tasks and even to go out on necessary events such as hospital appointments and shopping. Robots can assist by aiding the elderly to make necessary arrangement which can facilitate mobility. Loss of memory which is prevalent in the elderly may prompt for measures of reminders of daily activities such as medication adherence, doctor's appointments, tooth brushing and various other activities. The elderly are susceptible to falls at in their homes. Falls can and often do endanger the elderly. Fall detection mechanism can aid in early detection of falls and assistance can be quickly provided before more danger is incurred.

III. INFORMATION SUPPORT SYSTEM FOR ELDERLY CARE

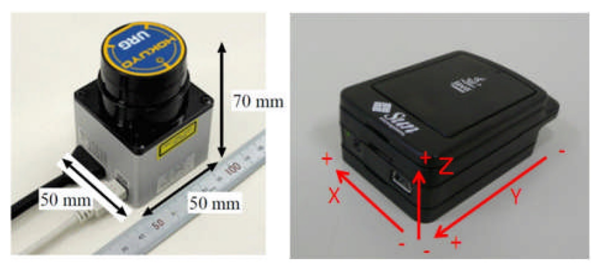
We have developed a system with robot partner in a living room. The developed system is divided into four components; (1) server system, (2) robot system, (3) sensor network system, and (4) human interface system. The sensor network system is based on ubiquitous computing composed of wireless sensors attached to walls, furniture, home appliances, and so on. The measured data is transmitted to the server system. The robot receives environmental information from the server system and provides the human-friendly communication to the people. Furthermore, people can share information with the robot by using the human interface system.

Figure 1 presents the concept of ISS in terms of the levels of measuring lifelog information. Personal information is obtained by the human interface system and robot system. Indoor lifelog is produced by sensor networks, and outdoor information is gathered from the portable sensors implemented into a smartphone. Moreover, a general rechargeable IC card basically stores the history of public transportation and purchase. Hence, setting a stage where shopping and traveling activities of a person can be traced. By modeling the behavior pattern of daily lifelog, users can be supported by detecting the difference between usual and unusual patterns.

IV. BHAVIOR MEASUREMENT AND PATTERN EXTRACTION

A. Indoor Measurement

In related works, various types of sensors have been applied to human behavior measurement systems: accelerometer, gyro sensor, illuminance sensor, pyroelectric infrared sensor, laser sensor, image sensor, and so on. In general, the sensors are selected based on the objective behavioral pattern. It is, however, difficult to predefine desired behavior patterns, because the patterns may vary significantly from situation to situation. Therefore, in such systems, heterogeneous sensors



(a) URG-04LX (b) Sun SPOT

Fig. 2. Sensors for Indoor Measurement.

should perform a complementary measurement to cover the measurement area comprehensively. In this study, we use a measurement system consisting of global measurement sensors and local measurement sensors. Here, the laser range finder (LRF) is used for global measurement, and a wireless sensor device (Sun SPOT) is used as the local measurement sensor.

Figure 2 (a) shows the LRF (URG-04LX) developed by HOKUYO CORPORATION. LRF is a contactless sensing system for measuring 2-dimensional distance based on time of flight principal by using laser. The LRF can measure distances of up to approximately 4,095 [mm] in 682 different directions where the covering measurement range is 240 [deg]. Minimal sampling interval for measurement is 100[ms]. In our system, we apply the LRFs to human detection and tracking in the measurement field.

Sun SPOT is small, wireless, battery-powered device developed at Sun Labs (Fig.2 (b)). The Sun SPOT device has three sensors, accelerometer, illuminance sensor, and temperature sensor. This device can be used in a wide range of applications such as robotics, environmental monitoring, asset tracking and proactive health care. Sun SPOT is powered by a specially designed small-footprint Java virtual machine, called Squawk, that can host multiple applications concurrently, and requires no underlying operating system.

B. Outdoor Measurement

With the rapid development of smartphone devices, the implementation of multiple sensors, high-spec CPU, software libraries is supported as a basic framework. Smartphones therefore have been applied as portable sensor modules in many research fields. To extract outdoor personal movement patterns, we use localization information gathered from the GPS sensor in a smartphone. During data recording, latitude/longitude, velocity, and timestamp are sequentially stored in the database of smartphone.

C. Growing Neural Gas

Unsupervised learning is performed by using only data without any teaching -organized map (SOM), neural gas (NG), growing cell structures (GCS), and growing neural gas (GNG) are well-known unsupervised learning methods. Basically, these methods use the competitive learning. The number of nodes and the topological structure of the network in SOM are designed beforehand [6, 7]. In NG, the number of nodes is fixed apriori, but the topological structure is updated according to the distribution of sample data [8]. On the other hand, GCS and GNG can dynamically change their topological structure based on the adjacent relation (edge) referring to the ignition frequency of the adjacent node according to the error index. However, GCS does not delete nodes and edges, while GNG can delete nodes and edges based on the concept of node ageing [9, 10]. Furthermore, GCS must consist of k-dimensional simplex where k is a positive integer chosen in advance. The initial configuration of each network is a k-dimensional simplex, e.g., a line is used for k=1, a triangle for k=2, and a tetrahedron for k=3 [11, 12]. GCS has been applied to the construction of 3D surface models by triangulation based on 2-dimensional simplex. However, because the GCS does not delete nodes and edges, the nodes and edges keep increasing. Furthermore, GCS cannot divide the sample data into several segments. Therefore, we apply GNG to the behavior pattern extraction by using the data of human position estimated by the human localization method with input from the laser range finder.

We explain the learning algorithm of GNG. The notation used in GNG is shown as follows:

r_i: the n dimensional vector of a node ($r_i \in \mathbf{R^n}$)

A: the set of nodes

N_i: the set of nodes connected to the i-th node

c: the set of edges

$a_{i,j}$: the age of the edge between the i-th and the j-th node

Step 0. Generate two units at random position, r_{c1}, r_{c2} in $\mathbf{R^n}$. Initialize the connection set.

Step 1. Generate at random an input data, v, according to $p(v)$ which is the probability density function of data v.

Step 2. Select the nearest unit (winner) s_1 and the second-nearest unit s_2 by

$$s_1 = \arg\min_{i \in A} \|v - r_i\| \quad (1),$$

$$s_2 = \arg\min_{i \in A \setminus \{s_1\}} \|v - r_i\| \quad (2)$$

Step 3. If a connection between s_1 and s_2 does not exist already, create the connection. Set the age of the connection between s_1 and s_2 to zero:

$$a_{s_1,s_2} = 0 \quad (3)$$

Step 4. Add the squared distance between the input data and the winner to a local error variable:

$$E_{s_1} \leftarrow E_{s_1} + \|v - r_{s_1}\|^2 \quad (4)$$

Step 5. Update the reference vectors of the winner and its direct topological neighbors by the learning rate η_1 and η_2, respectively, of the total distance to the input data:

$$r_{s_1} \leftarrow r_{s_1} + \eta_1 \left(v - r_{s_1}\right) \quad (5),$$

$$r_j \leftarrow r_j + \eta_2 \left(v - r_{s_1}\right) \quad \text{if } c_{s_1,j} = 1 \quad (6)$$

Step 6. Increment the age of all edges emanating from s_1:

$$a_{s_1,j} \leftarrow a_{s_1,j} + 1 \quad \text{if } c_{s_1,j} = 1 \quad (7)$$

Step 7. Remove edges with an age larger than $a_{\max}$. If this results in units having no more emanating edges, remove those units as well.

Step 8. If the error E_q is higher than the predefined threshold, insert a new unit as follows.

i. Select the unit f with the maximum accumulated error among the neighbors of q.

ii. Add a new unit n to the network and interpolate its reference vector from q and f.

$$r_n = 0.5\left(r_q + r_f\right) \tag{8}$$

iii. Insert edges connecting the new unit n with units q and f, and remove the original edge between q and f.

iv. Decrease the error variables of q and f by a fraction α^{gng}:

$$E_q \leftarrow E_q - \alpha^{gng} E_q \tag{9},$$

$$E_f \leftarrow E_f - \alpha^{gng} E_f \tag{10}$$

v. Interpolate the error variable of r from q and f:

$$E_n = 0.5\left(E_q + E_f\right) \tag{11}$$

Step 9. Decrease the error variables of all units:

$$E_i \leftarrow E_i - \beta^{gng} E_i \quad (\forall i \in A) \tag{12}$$

Step 10. Continue with step 1 if a stopping criterion (e.g., net size or some performance measure) has not yet been fulfilled.

D. Spiking Neural Network

Various types of ANNs have been proposed to realize clustering, classification, nonlinear mapping, and control [13, 14]. ANNs are composed of artificial neurons connected and arranged in layers. Artificial neuron models are simplified versions of neuron dynamics with the ignition phenomenon and the propagation mechanism of the pulse between neurons. The McCulloch–Pitts (MCP) neuron model is one of the most famous models. However, to realize more efficient processing for the time-series data, the neuron models should describe the spatiotemporal dynamics of real neuron in more detail. The Hodgkin-Huxley model is one of the classic neuronal spiking models with four differential equations. An integrate-and-fire model with a first-order linear differential equation is known as a neuron model of a higher abstraction level. A spike response model is slightly more general than the integrate-and-fire model, because the spike response model can choose kernels arbitrarily [15, 16].

We use a simplified spike neuron model based on a spike response model. First of all, the internal state $h_i(t)$ is normally calculated as follows;

$$h_i(t) = h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t) \tag{13}$$

where $h_i^{ext}(t)$ is the input to the i-th neuron from the external environment, $h_i^{ref}(t)$ is the refractoriness factor of the neuron, and $h_i^{syn}(t)$ is the synthesis factor. When the internal state of the i-th neuron exceeds a threshold, the spike output is represented as follows;

$$p_i(t) = \begin{cases} 1 & \text{if} \quad h_i(t) \geq q_i \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

where q_i is the threshold. Furthermore, in physiology, there is a period during which the neuron is incapable of firing. This term is called refractory period. The refractoriness factor $h_i^{ref}(t)$ is calculated as follows;

$$h_i^{ref}(t) = \begin{cases} \gamma^{ref} \cdot h_i^{ref}(t-1) - R & \text{if} \quad p_i(t) = 1 \\ \gamma^{ref} \cdot h_i^{ref}(t-1) & \text{otherwise} \end{cases} \tag{15}$$

where γ^{ref} is the discount rate ($0<\gamma^{ref}<1.0$) and $R>0$. R is subtracted from the refractoriness factor when the neuron is fired.

The presynaptic spike output is transmitted to the connected neuron according to PSP with the weight connection. The PSP is calculated as follows;

$$h_i^{PSP}(t) = \begin{cases} 1 & \text{if } p_i(t) = 1 \\ \gamma^{PSP} \cdot h_i^{PSP}(t-1) & \text{otherwise} \end{cases} \tag{16}$$

where γ^{PSP} is the discount rate ($0<\gamma^{PSP}<1.0$). Therefore, the postsynaptic action potential is excitatory if the weight parameter is positive. If the condition is satisfied, the weight

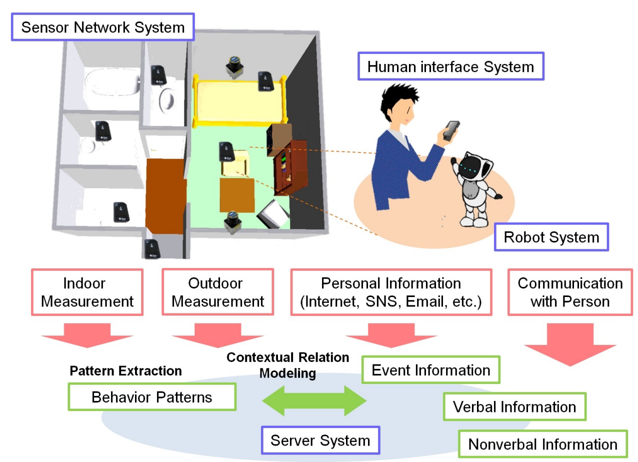


Fig. 3. Overview of the proposed information support system.

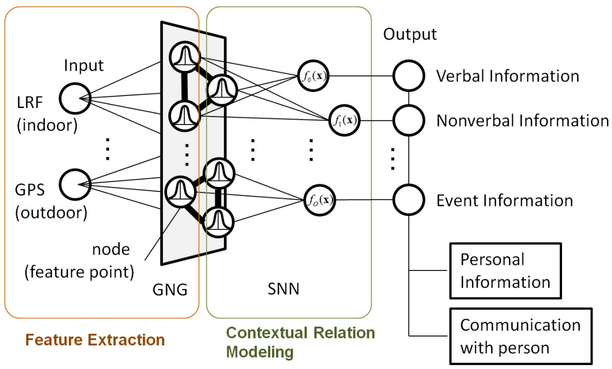


Fig. 4. Structure of pattern learning system.

parameter is trained based on the temporal Hebbian learning rule as follows:

$$w_{j,i} \leftarrow \left(1.0-\xi\right)w_{j,i}+\xi\, h_j^{PSP}(t-1) \quad \text{if } p_i(t)=1 \tag{17}$$

where ξ is a learning rate.

E. Feature Extraction and Contextual Relation Modeling

From the indoor and outdoor measurements, we can gather the sensor data corresponding to human behaviors. Moreover, the system can produce labeled personal information through interaction with the person's histories of Internet, SNS, email, etc. Figure 3 depicts the concept of the proposed framework. In this study, we apply GNG to the human behavior pattern extraction and use SNN for the contextual relation modeling between behavior pattern and personal information.

Figure 4 presents the structure of pattern learning system. In the feature extraction, to build the feature map of human behavior, human movement data gathered by LRF and smartphone is used as the input to GNG. The input is composed of 3 values: latitude, longitude, and velocity. In fact, GNG has a specific ability to adaptively construct a flexible and complex topological map corresponding to data distribution. Here, from the movement trajectory, some clusters can be created base on the characteristic of movement.

The obtained feature points are used as neurons of SNN in the contextual relation modeling. SNN consists of 2 layers: input layer and output layer. After the clustering, the input to SNN is calculated based on the difference between the current position and the reference vectors memorized in GNG as follows;

$$h_{0,i}^{ext}(t)=\exp\left(-\gamma_0^{ext}\left\|\mathbf{v}-\mathbf{r}_i\right\|^2\right) \tag{21}$$

where $h_{0,i}^{ext}(t)$ is represented as an external input to the neuron, $\mathbf{v}$ is the input vector, $\mathbf{r}$ is the reference vector, and γ_0^{ext} is a coefficient value.

In the output layer, the neurons are produced and labelled based on the event information, verbal and nonverbal information. In the contextual relation modeling, connection weights between input layer and output layer are updated by Hebbian learning rule presented in Eq. (17). The input to neurons in the output layer is given by

$$h_{1,j}^{ext}(t)=\exp\left(-\gamma_1^{ext}\sum_{i=1}^{N}\left(h_{0,i}^{PSP}(t)-w_{i,j}\right)^2\right) \tag{22}$$

where $h_{1,j}^{ext}(t)$ is the input, γ_1^{ext} is a coefficient value and N is the number of nodes created by GNG. The neurons have connections with other neurons. Therefore, the synthesis factor is calculated by

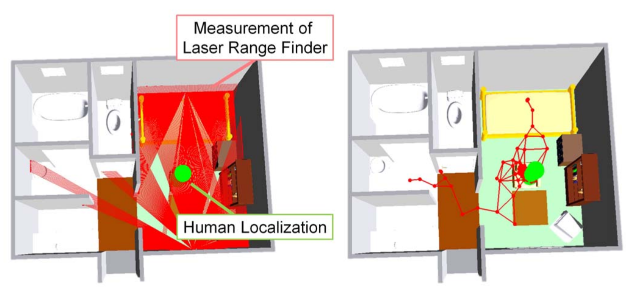
$$h_{1,j}^{syn}(t)=\gamma_1^{syn}h_{1,j}(t-1)+\exp\left(-\gamma_1^{syn}\sum_{k=1}^{M}\left(h_{1,k}^{PSP}(t-1)-w_{j,k}\right)^2\right) \tag{23}$$

where $h_{1,k}^{PSP}(t-1)$ is the presynaptic potential (PSP) transmitted from the k-th neuron at the discrete time $t-1$, M is the number of the verbal labels, and γ_1^{syn} is the temporal discount rate ($0<\gamma_1^{syn}<1.0$). The verbal labels can be selected based on the spike outputs.

V. Experimental Results

This section shows some experimental examples of indoor and outdoor measurements. For the indoor measurement, two laser range finders (LRFs) are used for detecting and tracking the movement of a person. The two LRFs are attached to the wall of a living room. One laser range finder is set up 385 [cm] away from the other, face to face. The maximum measurement range of the LRFs is 4000 [cm]. To recognize the human state of sitting and standing, the attachment height of the first LRF is 50 [cm], while the other one is attached at a height of 100 [cm].

Fig.5 shows the indoor measurement and an experimental result of the feature extraction performed by GNG. The sampling interval of the LRF is approximately 250[ms]. In Fig.5 (a), the measurement area of the LRFs is represented by a



(a) Human Tracking (b) Feature Extraction

Fig. 5. Indoor measurement and feature extraction.

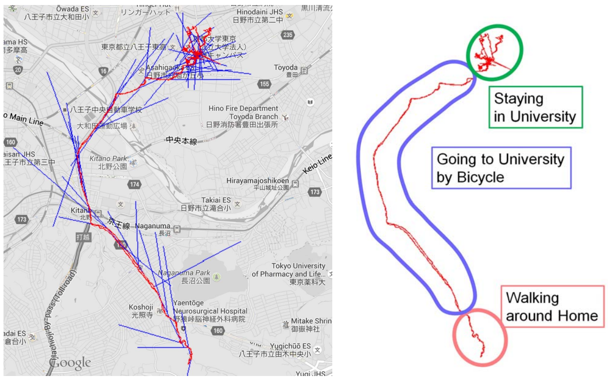
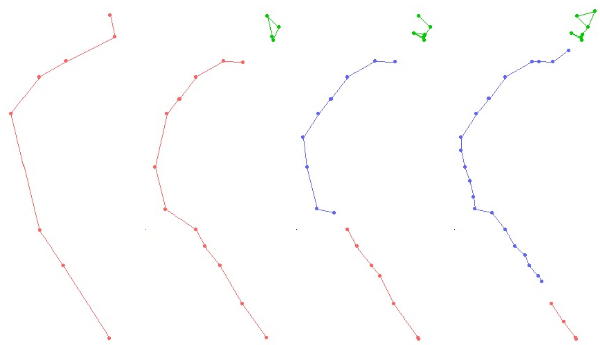


Fig. 6. Measurement GPS data of outdoor movement. In left figure, bule line indicate the vector norm of moving speed, and red line is represented as the trajectory of human movement. The histoy of human state is shown in right figure.



(a) 5000 steps (b) 10000 steps (c) 15000 steps (d) 20000 steps

Fig. 7. Feature extraction of outdoor movement performed by GNG.

red line, and the human position is depicted by a green ball. Figure 5 (b) illustrates the result of the feature extraction. The maximum number of nodes in GNG is 100. As you can see from the figure, the topological map is built based on the probability distribution of human position. Furthermore, Fig.6 presents a measured GPS dataset of outdoor movement. This is the data record of the movement of a university student in one day. In the data, the person went to school by bicycle in morning, after that, the student stayed at the university until evening and finally came back home. Figure 7 shows the feature extraction result of outdoor movement. From the figures, several clusters are produced depending on the procedure of GNG learning. At 5000 iteration steps, the trajectory data is abstracted so much that every data belongs to a same cluster. However, as the number of iteration steps increases, the number of clusters also increases. Finally, at 20000 steps, 3 clusters are created. As a result, the clustering can represent 3 features of the movement corresponding to the actual human state shown in Fig .6.

Furthermore, Fig.8 shows an experimental result of feature extraction and contextual relation modeling. In the right side of the figure, the obtained relationship between features of human movement and verbal information is represented as gray lines. The shading of gray color indicates the strength of connection weight. The verbal information can be gathered by the robot system and human interface system through interactions with a person. After the behavior pattern extraction, the system can apply the pattern information to provide information services for the user, using several human-like verbal expressions.

VI. Elderly privacy concerns and ISSUES

The elderly are always concerned about the intrusion of their privacy with regards to how technology can be applied to monitor their personal lives. Indeed, most technologies that aid ageing-in-place are placed in the homes of the elderly where they carry out their most private activities [17]. For example, though the elderly accept telemonitoring to detect and respond to emergency occurrences, they however are not willing to further expose themselves to other forms of monitoring [18].

Despite the reluctance exhibited towards the acceptance of these systems, technological monitoring systems are designed to provide care and support to the elderly [19]. These monitoring systems have been known to facilitate independent living for the elderly ageing-in-place. There are studies which indicate that older people are ready to accept computing technology for health and care giving information. Elders are willing to accept monitoring systems into their homes if the objective is to provide safety and keep track of their health [17, 20].

The Informationally Structured Space serves as unobtrusive intelligent environment. This environment is designed to provide support for both the elderly and their caregivers. The decision on who has access to the information generated in this

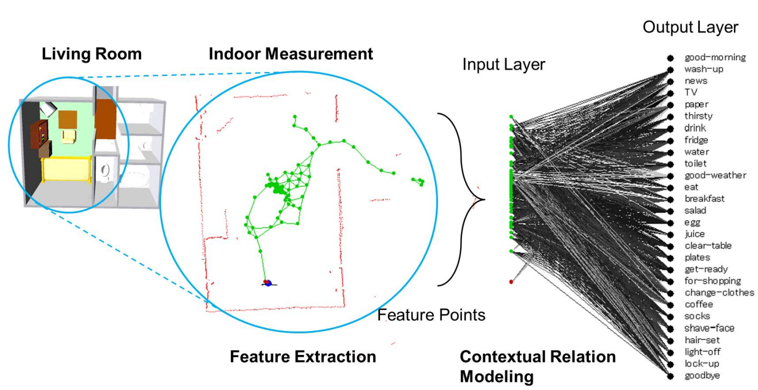


Fig. 8. A result of feature extraction and contextual relation modeling.

space is at the discretion of the elderly. By ensuring that that

VII. Summary

This paper proposes the method of behavior pattern extraction based on GNG and SNN. First, we construct a pattern learning system composed of the behavior pattern extraction and contextual relation modeling. In the pattern extraction, GNG is applied as an incremental learning method to represent the feature of human movement. Each node is created based on the probability distribution of measured data, and the topological structure is produced based on the characteristic of movement: position and moving speed. In the contextual relation modeling, the obtained feature points is associated to the labeled information acquired from the interaction between the system and person. As an experimental result, we showed the pattern learning and estimation of human behaviors. In the future work, we should conduct additional long term experiments by using the proposed method. After which the efficiency of the proposed method will be evaluated and discussed. Another objective of the evaluation is to ascertain privacy concerns of the elderly. Another issue is how to integrate the robot into the living space and how much control the elderly has over the control of the robot.

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