Self-organizing Symbol Acquisition and Motion Generation based on Dynamics-based Information Processing System

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Abstract

The symbol acquisition and manipulation abilities are one of the inherent characteristics of human beings comparing with other creatures. In this paper, based on recurrent self-organizing map and dynamics-based information processing system, we propose a dynamics based self-organizing map (DBSOM). This method enables designing a topological map using time sequence data, which causes recognition and generation of the robot motion. Using this method, we design the self-organizing symbol acquisition system and robot motion generation system for a humanoid robot.

1 Introduction

The symbol acquisition and manipulation abilities are one of the most inherent characteristics of human beings comparing with other creatures [1]. The conventional artificial intelligence designs the symbol manipulation rules with the given symbols using the learning methods. The solution algorithm is come down to the optimization problems and succeeded to design the symbol manipulation system in the changing and unknown environments using the calculation tools with plasticity. However, for the robot in the real world, the symbol grounding problems [2] that connects the symbols and substances are postponed. Though, so far, this connection is given by the designers based on their knowledge, it is necessary to design the symbol acquisition system for the intelligent robot to move in the real world by itself. On the other hand, Deacon [3] stated the hierarchy for the symbols (icon, index and symbol) based on the abstraction process. The icon means the similarity based classification, the index represents the interrelation of the subjects, and the symbol represents the indication of the rules and customs. The symbols have not only the higher level abstraction but also the lower level one that is self-organized by the similarity based classification. In this paper, we design the self-organized symbol acquisition system for the cyclic whole body motion data. The main purpose of this research is to acquire the discredited symbols form the continuous time sequence data by the self-organizing way. In general, the time sequence data does not have the start and end points, which requires the momentarily processing.

Kohonen proposed the self-organizing map (SOM) for the self learning method that obtains the lower dimensional topological map using the input signals keeping the neighborhood relationship of the data by the unsupervised learning way [4]. Based on the SOM, Heikkonen proposed the recurrent self-organizing map (RSOM) [5] that enables the processing of momentarily time sequence data. The RSOM obtains the weighted mean of the data. It enables the symbol acquisition from the data, however, it is impossible to generate the time sequence data from the symbols. So far, we have proposed the dynamics-based information processing system that processes the time sequence data using the dynamical system (dynamics)[6]. In this system, the humanoid whole body motion is represented by the attractor of the dynamics, and the motion of the dynamics is represented by the static parameter, which means the dynamics-based information processing system has the capability to connect the discrete system with the continuous data.

In this paper, based on the dynamics-based information processing system and the RSOM, we propose a dynamics-based self-organizing map (DBSOM) and design the self-organizing symbol acquisition system for humanoid robots. The purpose of this research is to classify the humanoid robot motions based on the similarity and design the symbol map that enables the generation of the time sequence data of the whole body motion, which corresponds to the emergency of the icon or index.

2 Symbols and dynamics-based information processing

2.1 Self-organization of the symbols

The symbol is the manageable representation of the object with abstraction eliminating the time-space continuity and dynamic characteristics of the object. The conventional artificial intelligence tried to imitate the human intelligence based on the highly abstract characteristic of the symbols. The symbols are given by the designer's knowledge apriori, however, the knowledge based symbols are monochromatic and the symbols in the real world have some classes according to the acquirement process. Clancey divides the symbols to four classes [7]. The lowest symbol is 'Virtual Structure' which is concrete because the real data is encoded. Steels connects the brain map and exciting parts of the body of owl monkey [8]. His results show the self-organizing function of the brain. Freeman shows the dynamically changing map of the brain and smell by using a rabbit's olfactory [9], which means the context dependent mapping of the symbols and the sensor data.

These results have coincidences as follows from the topological map of organism point of view.

(1) The correspondence of the stimulus and topological map is self-organized.

(2) The symbols corresponding to the stimulus are self-organized.

And the topological map

(3) is organized based on the similarity of the stimulus, which means the similar stimulus is arranged neighborhood.

These results shows the symbol acquisition process at a basic level, which coincides to Deacon's hypothesis [3]. For the formation of the highly level symbols, the self-organized icon (or index) based on the similarity is necessary.

2.2 Symbol acquisition based on the dynamics-based information processing

2.2.1 Dynamics-based information processing system

The dynamics-based information processing is illustrated in this section [6]. In the dynamics-based information processing system, a humanoid robot motion is embedded to the dynamics as an attractor. Consider the whole body motion $\mathcal{M}$ of the humanoid robot with N joints. From the time sequence data of the joints angle vector $\boldsymbol{\xi}[k]$, we defines the following matrix Ξ.

$$\begin{aligned} \Xi &= \begin{bmatrix} \boldsymbol{\xi}[1] & \boldsymbol{\xi}[2] & \cdots & \boldsymbol{\xi}[m] \end{bmatrix} \in \boldsymbol{R}^{N\times m} && (1) \\ \boldsymbol{\xi}[k] &= \begin{bmatrix} \xi_1[k] & \xi_2[k] & \cdots & \xi_N[k] \end{bmatrix}^T \in \boldsymbol{R}^{N} && (2) \end{aligned}$$

where m means the number of data. By assuming the motion $\mathcal{M}$ is cyclic, Ξ is the set of the points on a closed curved line C in the N dimensional space. On the other hand, consider the discrete time dynamics shown in the following equation.

$$\boldsymbol{x}[k+1] = \boldsymbol{x}[k] + \boldsymbol{f}(\boldsymbol{x}[k]) \tag{3}$$

When the dynamics in equation (3) has an attractor on C, which means the state vector $\boldsymbol{x}[k]$ starting from an initial value $\boldsymbol{x}_0$ coincides to $\boldsymbol{\xi}[k]$ for the larger k, the dynamics memorizes the time sequence data Ξ of the motion $\mathcal{M}$ and is able to reproduce it. By the ℓth order polynomial representation of $\boldsymbol{x}$, $\boldsymbol{f}(\boldsymbol{x}[k])$ in equation (3) is represented by

$$\boldsymbol{x}[k+1] = \boldsymbol{x}[k] + \Phi\boldsymbol{\theta}(\boldsymbol{x}[k]) \tag{4}$$

where Φ means the coefficient matrix of the polynomial, $\boldsymbol{\theta}(\boldsymbol{x})$ consists of the power of the element of $\boldsymbol{x}$. In the case of $N = 2$ and $\ell = 2$, Φ and $\boldsymbol{\theta}(\boldsymbol{x})$ are represented as follows,

$$\Phi = \begin{bmatrix} a_{20} & a_{11} & a_{02} & a_{10} & a_{01} & a_{00} \\ b_{20} & b_{11} & b_{02} & b_{10} & b_{01} & b_{00} \end{bmatrix} \tag{5}$$

$$\boldsymbol{\theta}(\boldsymbol{x}) = \begin{bmatrix} x_1^2 & x_1x_2 & x_2^2 & x_1 & x_2 & 1 \end{bmatrix}^T \tag{6}$$

which means the dynamics design problems substitutes for the design of Φ that is obtain by the least square method. The design algorithm of Φ is shown in Appendix A.

2.2.2 Symbols in the dynamics

The embedment of the whole body motion to the dynamics as an attractor means to encode the real data to the parameter of the dynamics that is the basic level of symbols. Based on the parameter of the dynamics, we can design the topological map. The followings are necessary for the topological map so that it works as the symbols.

(1) Allocation based on the similarity Because one parameter matrix Φ of the dynamics corresponds to one motion, Φ has to be allocated so that the neighbor Φs represent the similar motions.

(2) Self-organized allocation The self-organizing algorithm of designing a topological map of Φ is necessary.

(3) Motion generation and recognition The designed map generates and recognizes the memorized motion so that the map works as symbols, which means the similar motions are evaluated as 'similar'.

From these considerations, the self-organization of the symbols means the self-organized grouping of the set of dynamics parameters. In the next section, we propose the dynamics-based self-organizing map for the symbol acquisition.

3 Dynamics-based self-organizing map (DBSOM)

3.1 Self-organization

First, we will show the characteristics of the SOM. The SOM has a $L \times L$ matrix and each elements has parameters that are to be learned. The characteristics of the SOM are as follows.

Self-organizable The learning method of the SOM is unsupervised. Some units compete and only the winner (BMU : best matching unit) and around that unit learn the input signal. Because of this algorithm, the topological map is self-organized.

Phase conservation Because the learning is made to the BMU and around it, the SOM has a phase conservation characteristic, and the topological map is designed based on the similarity of the inputs.

3.2 Recurrent self-organizing map (RSOM) [5]

The RSOM is proposed by Heikkonen based on the SOM. The purpose of the RSOM is to handle the time sequence data. The design algorithm of the ROSM is illustrated in Appendix B. Each unit of the RSOM learns the weighted average of the time sequence data, which means the RSOM emerges symbols from the time sequence data, however, is unable to reproduce the time sequence data from the symbols.

3.3 Dynamics-based self-organizing map and its learning rule

In this section, we propose the dynamics-based self-organizing map (DBSOM) and its learning rule. The DBSOM has a $L \times L$ matrix structure same as the SOM and RSOM. Each unit U_{ij} has the data of coordinate value $\boldsymbol{r}_{ij} = (i,\ j)$ and parameter Φ_{ij} of the dynamics in equation (4). By the same way as RSOM, the BMU and around it learn Φ_{ij} based on $\boldsymbol{x}[k]$ at time k and $\boldsymbol{x}[k+1]$ at time $k+1$. The DBSOM is self-organizable, has phase conservation characteristic and enables to reproduce the time sequence data using Φ_{ij}. The design algorithm of the DBSOM is as follow.

Step1 Set $L \times L$ array matrix. Each unit U_{ij} has Φ_{ij} (the initial value is set by random function).

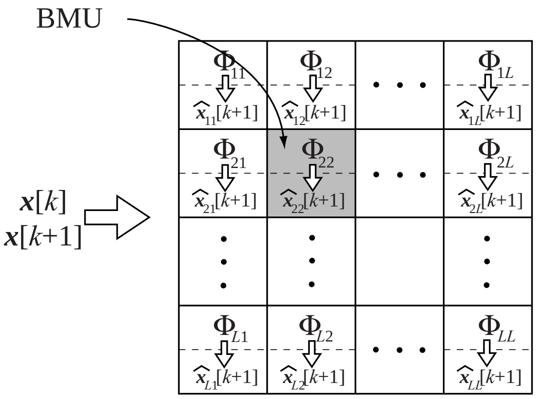

Figure 1: Calculation of the best matching unit

Step2 From the input signal $\boldsymbol{x}[k]$ at time k, unit U_{ij} yields the estimation $\widehat{\boldsymbol{x}}_{ij}[k+1]$ of $\boldsymbol{x}[k+1]$ at the next time step $k+1$ as follow.

$$\widehat{\boldsymbol{x}}_{ij}[k+1] = \boldsymbol{x}[k] + \Phi_{ij}\boldsymbol{\theta}(\boldsymbol{x}[k]) \tag{7}$$

where $\boldsymbol{\theta}(\boldsymbol{x}[k])$ consists of the power of the element of $\boldsymbol{x}[k]$ same as shown in equation (6).

Step3 By using the real signal $\boldsymbol{x}[k+1]$ at time step $k+1$, the BMU U^b is selected as follows (refer to Figure 1).

$$U^b = \underset{U_{ij}}{\arg}\min_{ij} J_{ij} \tag{8}$$

$$J_{ij} = \gamma_d \left(\sum_{q=k-k_0+1}^{k} \|\boldsymbol{x}[q+1] - \widehat{\boldsymbol{x}}_{ij}[q+1]\| \right) + \gamma_p \left(\sum_{q=k-k_0+1}^{k} \frac{(\Delta\boldsymbol{x}[q])^T \Delta\widehat{\boldsymbol{x}}_{ij}[q]}{\|\Delta\boldsymbol{x}[q]\|\,\|\Delta\widehat{\boldsymbol{x}}_{ij}[q]\| + \varepsilon} \right) \tag{9}$$

$$\Delta\boldsymbol{x}[q] = \boldsymbol{x}[q+1] - \boldsymbol{x}[q] \tag{10}$$

$$\Delta\widehat{\boldsymbol{x}}_{ij}[q] = \widehat{\boldsymbol{x}}_{ij}[q+1] - \boldsymbol{x}[q] \tag{11}$$

where $\gamma_d > 0$ and $\gamma_p > 0$ are weighting parameters. $\varepsilon > 0$ is a small number to prevent the denominator being zero. The first term in the right hand side of equation (9) evaluates the difference of the estimation and real signal, the second term evaluates the consistency of the direction of the two vectors. Because $\boldsymbol{x}[k]$ is a multi-dimensional vector and the norm of $\boldsymbol{x}[k]$ is different according to the time steps, these two evaluations are necessary.

Step4 Using the proximity function $h^b_{ij}[k]$ in equation (B.9), each unit learns Φ_{ij} by the following equations. This learning method is based on the on-line least square method of obtaining Φ in equation (A.5)

$$\Phi_{ij} \leftarrow \Phi_{ij} + h^b_{ij}[k] X \frac{\boldsymbol{\theta}^T(\boldsymbol{\eta}_q) P_{ij}}{1 + \boldsymbol{\theta}^T(\boldsymbol{\eta}_q) P_{ij} \boldsymbol{\theta}(\boldsymbol{\eta}_q)} \tag{12}$$

$$X = \boldsymbol{x}[k+1] - \Phi_{ij}\boldsymbol{\theta}(\boldsymbol{\eta}_q) \tag{13}$$

$$P_{ij} \leftarrow \frac{1}{\alpha^2}\left(P_{ij} - h^b_{ij}[k] \frac{P_{ij}\boldsymbol{\theta}(\boldsymbol{\eta}_q)\boldsymbol{\theta}^T(\boldsymbol{\eta}_q) P_{ij}}{1 + \boldsymbol{\theta}^T(\boldsymbol{\eta}_q) P_{ij} \boldsymbol{\theta}(\boldsymbol{\eta}_q)}\right) \tag{14}$$

where α ($0 < \alpha \leq 1$) is a forgetting parameter. $\boldsymbol{\eta}_q$ ($q = 1, 2, \cdots, \rho$) are around $\boldsymbol{x}[k]$ as shown in Figure 2. For one $\boldsymbol{x}[k]$, iterate from equation (12) to equation (14) by ρ times, which means the units learn the vector field around $\boldsymbol{x}[k]$. Equation (12) means the hard learning around BMU

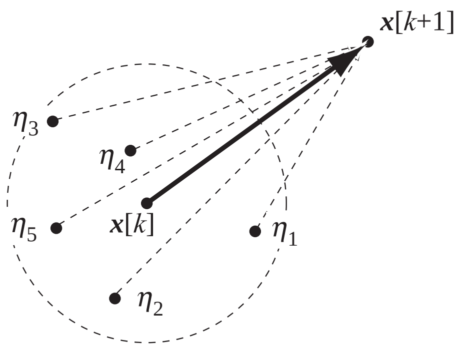

Figure 2: Calculation of Φ

($h^b_{ij}[k] \simeq 1$) and the soft learning in other units ($h^b_{ij}[k] \simeq 0$) as shown in Figure 3.

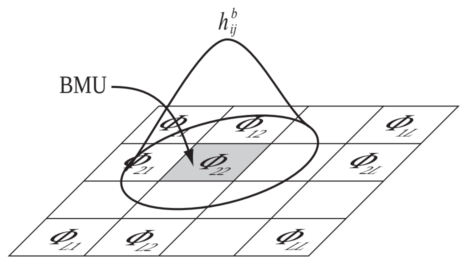

Figure 3: Learning of DBSOM

Step5 For the next input $\boldsymbol{x}[k+1]$, iterate the procedure from Step2.

4 Symbol acquisition from the whole body motion data

4.1 Humanoid robot and the whole body motion

In this section, the proposed DBSOM is adapted to the humanoid whole body motion and evaluate the symbol acquisition by the self-organizing way and the motion emergency based on the symbols. Consider the humanoid robot shown in Figure 4. This robot has 20 joints and its configuration is same as

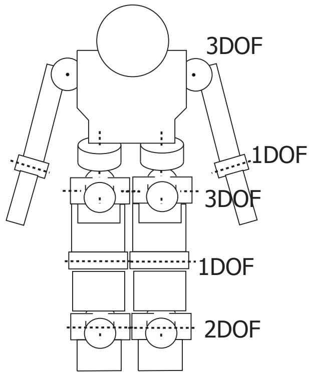

Figure 4: Humanoid robot

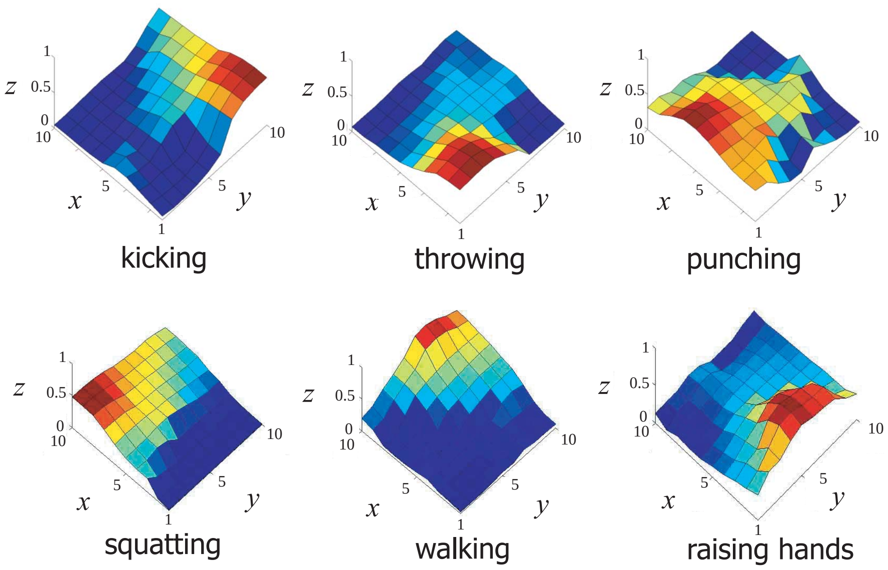

Figure 5: Activation index of the designed DBSOM for the learned motions

HOAP-1 produced by FUJITSU Co. We set "kicking", "throwing", "punching", "squatting", "walking" and "raising hands" motions that are designed from the motion capture data of a human. Because it requires hard and long calculation to design the dynamics in 20 dimensional space, the humanoid motions are reduced to 4 dimensional space by the motion reduction method based on the principal component analysis [6]. The DBSOM has a 10×10 array.

4.2 Symbol acquisition, motion recognition and generation

Setting the forgetting parameter $\alpha = 0.99$, we design the DBSOM, where the degree of the polynomial in equation (4) is set as $\ell = 2$. Figure 5 shows the activation of each unit for the input signals. x and y

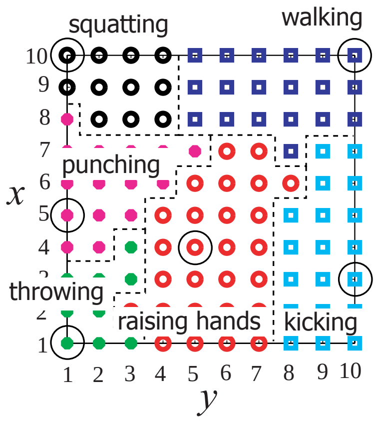

Figure 6: Activation map of the designed DBSOM

axes mean the number of array. z axis shows the activation index σ_{ij} that is defined as

$$\sigma_{ij} = \frac{1}{1 + \sum_{q=k-k_0+1}^{k} \|\boldsymbol{x}[q+1] - \widehat{\boldsymbol{x}}_{ij}[q+1]\|} \tag{15}$$

When the activation index is large, the unit yields the correct estimation of the input signal, which

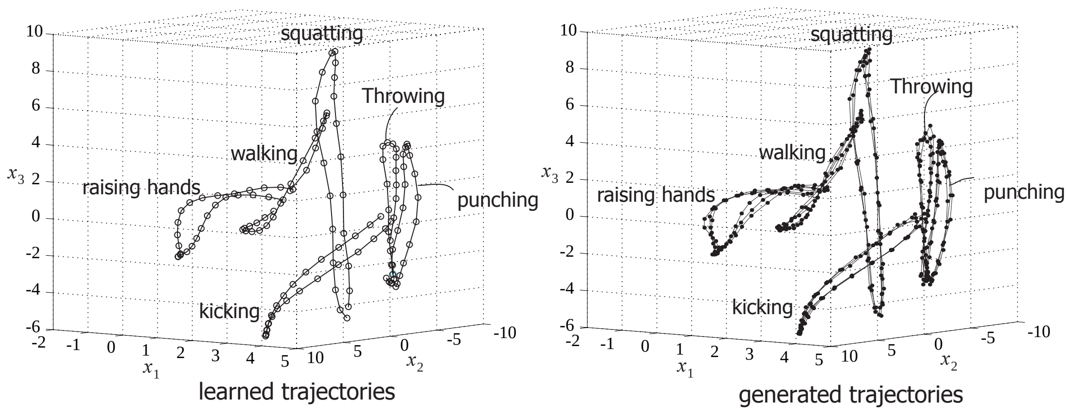

Figure 7: Learned trajectories and generated trajectories

means that the unit memorizes the corresponding motion. Because the input signal is time sequence data, the activation index changes dynamically, however, the change is small and Figure 5 shows the index of representative time. Figure 6 shows the classification of the DBSOM based on which motion the units yield high activation for. The unit with a mark ◯ yields the highest activation in each region. The units of the DBSOM are classified to corresponding motions. Based on the dynamics parameter Φ_{ij} in each unit, the humanoid whole body motions are generated, which means the motion generation using symbols. Figure 7 shows the closed curved lines of the reference motions and trajectories of the dynamics obtained from the DBSOM. Though the dynamics has 4 dimensional state vector, Figure 7 shows three of them. From this result, the reference trajectories are learned and we obtain the learned motion from each unit. Figure 8 shows the "kicking", "punching", "walking" and "raising hands" motions. By using the dynamics with Φ_{ij} from other units, the stable motions are not obtained. This is because it is difficult to set the conditions that the dynamics in equation (4) has attractors, and arbitrary Φ does not yield the attractor. For functionality of symbols, it is desirable for all units to have corresponding attractor, which requires not only set of the neighborhood function $h^b_{ij}[k]$ or forgetting parameter α but also another design method of dynamics.

Figure 8: Generated motion of the humanoid robot

Figure 9 shows the activation of the DBSOM for unlearned inputs. The "humanoid walking" is designed so that the dynamic constraints of the humanoid body are satisfied. That is different from "walking" in Figure 8. The "bending forward" is obtained from the motion capture data. The activation of the DBSOM is shown in Figure 10. Because "humanoid walking" is similar to "walking" in Figure 5, the activation pattern of the DBSOM is similar to corresponding motion pattern. Because "bending forward" is similar to "raising hand" from the joint angles time pattern point of view, which means the base link is not fixed, the similar activation pattern is generated. These results show the design of symbol map with phase conservation.

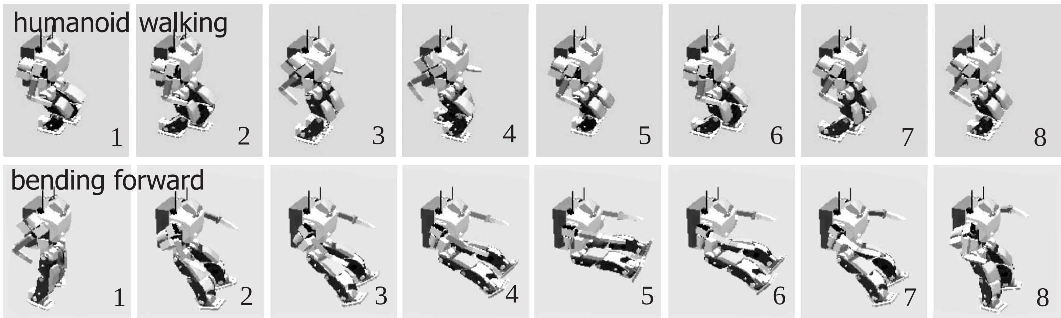

Figure 9: Unlearned motions

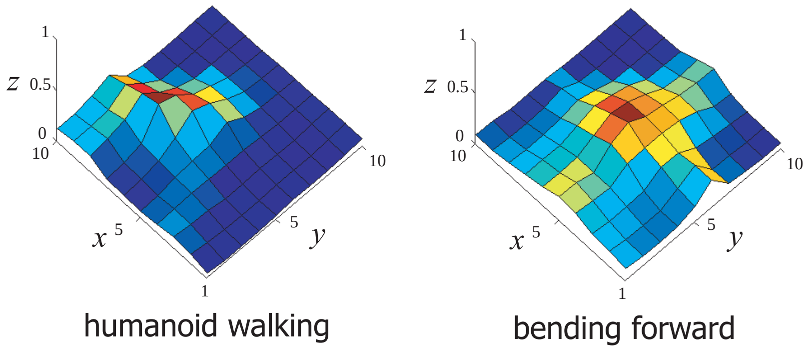

Figure 10: Activation map for unlearned motion

5 Conclusions

In this paper, we design the symbol acquisition system by self-organizing way based on time sequence data. The results of this paper are as follows.

1. Using the dynamics-based information processing system, we propose dynamics-based recurrent self-organizing map (DBSOM) modifying the recurrent self-organizing map (RSOM). This system has an array structure, classifies the motion patterns based on the similarity, and generates the corresponding motion pattern using the parameter in the unit.

2. We make the DBSOM learn some humanoid whole body motions and evaluate the motion recognition and generation functions of the DBSOM. The motions are classified based on the similarity and some units in the DBSOM generate the learned motion.

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Appendix A Design method of the dynamics

In this section, we show the design method of dynamics in equation (3). Consider that $\boldsymbol{f}(\boldsymbol{x}[k])$ in equation (3) represents the vector flow in $\boldsymbol{x}[k]$-space. By the functional approximation, we obtain $\boldsymbol{f}(\boldsymbol{x}[k])$ defining the vector field so that the closed curved line C is an attractor. By setting $\boldsymbol{\eta}$ around $\boldsymbol{\xi}[k]$, we define the vector at $\boldsymbol{\eta}$ as follow.

$$\boldsymbol{f}(\boldsymbol{\eta}) = \boldsymbol{\xi}[k+1] - \boldsymbol{\eta} \tag{A.1}$$

which means the point around $\boldsymbol{\xi}[k]$ goes to $\boldsymbol{\xi}[k+1]$ in the next time step. For $\boldsymbol{\xi}[k]$ $(k = 1, 2, \cdots, m)$, we define some points $\boldsymbol{\eta}_i$ and obtain the some sets of $\boldsymbol{\eta}_i$ and $\boldsymbol{f}(\boldsymbol{\eta}_i)$. We approximate $\boldsymbol{f}(\boldsymbol{\eta})$ by the ℓth-order polynomial function of $\boldsymbol{\eta}$. $\boldsymbol{f}(\boldsymbol{\eta})$ is represented by

$$\boldsymbol{f}(\boldsymbol{\eta}) = \Phi\theta(\boldsymbol{\eta}) \tag{A.2}$$

where Φ is the parameter matrix consisting of the coefficient of polynomial, $\theta(\boldsymbol{\eta})$ consists of power of $\boldsymbol{\eta}$. By extending equation (A.2), we obtain

$$F = \left[\ \boldsymbol{f}(\boldsymbol{\eta}_1) \quad \boldsymbol{f}(\boldsymbol{\eta}_2) \quad \boldsymbol{f}(\boldsymbol{\eta}_3) \quad \cdots\ \right] \tag{A.3}$$

$$\Theta = \left[\ \theta(\boldsymbol{\eta}_1) \quad \theta(\boldsymbol{\eta}_2) \quad \theta(\boldsymbol{\eta}_3) \quad \cdots\ \right] \tag{A.4}$$

and Φ is calculated by the least square method.

$$\Phi = F\Theta^{\#} \tag{A.5}$$

When equation (A.5) gives the good approximate accuracy, the dynamics in equation (3) that has attractor on the closed curved line C is obtain by equation (3).

Appendix B Recurrent self-organizing map (RSOM) [5]

The RSOM has a two dimensional space with $L \times L$ array configuration and each unit U_{ij} has a weighting parameter $\boldsymbol{w}_{ij} \in \boldsymbol{R}^N$, the accumulated error vector $\boldsymbol{y}_{ij} \in \boldsymbol{R}^N$ and the coordinate value $\boldsymbol{r}_{ij} = (i,\ j)$. By defining the input signal to RSOM in time step k as $\boldsymbol{x}[k] \in \boldsymbol{R}^N$, the accumulated error vector $\boldsymbol{y}_{ij}[k]$ of each unit is represented by

$$\boldsymbol{y}_{ij}[k+1] = (1-\alpha)\boldsymbol{y}_{ij}[k] + \alpha(\boldsymbol{x}[k] - \boldsymbol{w}_{ij}[k]) \tag{B.6}$$

where $0 < \alpha \leq 1$ means the forgetting parameter. We define the best matching unit (BMU) as

$$U^b_{ij} = \underset{U_{ij}}{\arg}\min_{ij} \|\boldsymbol{y}_{ij}[k]\| \tag{B.7}$$

that minimizes the accumulated error, and update the weighting parameter $\boldsymbol{w}_{ij}$ around BMU as

$$\boldsymbol{w}_{ij}[k+1] = \boldsymbol{w}_{ij}[k] + \gamma h^b_{ij}[k]\boldsymbol{y}_{ij}[k] \tag{B.8}$$

where γ means the learning efficiency, $h^b_{ij}[k]$ is the neighborhood function that takes maximum value 1 around BMU and becomes smaller according to farther from BMU as follow

$$h^b_{ij}[k] = \exp\left(-\frac{\|\boldsymbol{r}_{ij} - \boldsymbol{r}^b\|^2}{\sigma[k]^2}\right) \tag{B.9}$$

where $\boldsymbol{r}^b$ is the coordinate value $\boldsymbol{r}_{ij}$ of BMU U^b_{ij} and $\sigma[k]$ is the monotonically decreasing function of time step k. From these calculations, assuming that the same unit is selected to BMU, the parameter $\boldsymbol{w}$ of that unit converges to

$$\lim_{k\to\infty} \boldsymbol{w} = \frac{\sum_{i=1}^{k}(1-\alpha)^{k-i}\boldsymbol{x}[i]}{\sum_{i=1}^{k}(1-\alpha)^{i}} \tag{B.10}$$

that is a constant value.

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