Symbolic Memory of Motion Patterns by an Associative Memory Dynamics with Self-organizing Nonmonotonicity

Hideki Kadone and Yoshihiko Nakamura

Department of Mechano-Informatics
Graduate School of Information Science and Technology
University of Tokyo
7-3-1, Hongo, Bunkyoku, Tokyo, Japan
{kadone, nakamura}@ynl.t.u-tokyo.ac.jp

Abstract. We previously proposed a memory system of motion patterns [4] using an assotiative memory model. It forms symbolic representations of motion patterns based on correlations by utilizing bifurcations of attractors depending on the parameter of activation nonmonotonicity. But the parameter had to be chosen appropreately to some degree by manual. We propose here a way to provide the paremeter with self-organizing dynamics along with the retrieval of the associative momory. Attractors of the parameter are discrete states representing the hierarchical correlations of the stored motion patterns.

1 Introduction

Symbols are important for intelligent systems. Extracting important information from specific memories and experiences and memorizing them as abstract symbols enable one to apply the acquired information to other different situations. Based on this point of view, the authors[4] proposed a memory system for motion patterns of humanoid robots, which forms emergent abstract representations of motions and maintains the representations in abstract-specific hierarchical manner, based on the inherent global cluster structure of the motion patterns. The proposed memory system(Fig.1) consists of transforming the motion patterns into feature vectors, storing them into the connection weights by Hebb rule, and retrieval in the dynamics of the associative model parameterized by the nonmonotonicity of the activation function. Feature vectors clarify the global structure of motion patterns. Nonmonotonic associative model forms abstract representations integrating the clusters, and maintains abstract-specific hierarchy by bifurcations of attractors depending on the parameter of nonmonotonicity(Fig.2). The integrating dynamics was originally discussed by [1] and then by other researches[2],[6],[8] for sigmoid networks. In [5], the authors gave a mathematical explanation of the above nonmonotonic associative memory dynamics. However, the nonmonotonicity parameter had to be chosen appropriately to some degree by manual. We propose here a way to provide the

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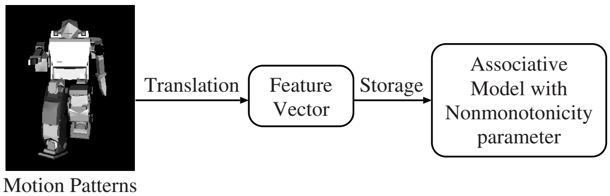

Fig. 1. Memory system for motions of humanoid robots

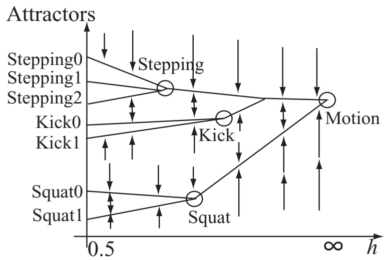

Fig. 2. Representation of hierarchy by bifurcations of attractors and basins proposed in our previous research

parameter with self-organizing dynamics along with the retrieval of the associative memory. The system automatically finds out the hierarchy of the correlations in the stored data, and forms attractors at the centers of clusters. The attractors of the nonmonotonicity parameter are discrete states representing the discrete levels of hierarchical correlations in the stored patterns. We will show the simulation results when feature vectors of motion patterns are stored, where symbolic attractors of motions and attractors of nonmonotonicity parameter are formed according to the initial values of the nonmonotonicity parameter.

There are some related researches. Okada et al.[10] proposed a model for self-organizing symbol acquisition of motions by combining Kohonen's self organizing map[7] and a polynomial dynamical system. Since Kohonen's map uses elements distributed on grids, the map is restricted in low dimensional spaces as the computational cost increases exponentially with the dimension of the map space. Sugita et al.[14] proposed a system that connects symbols and robot motions by connecting two recurrent neural networks using a parameter called parametric bias, which self-organizes to represent the connection structure. However the use of BPTT would restrict the number of neurons to small ones. Shimozaki et al.[13] proposed a model that self-organizes spatial and temporal information using nonmonotonic associative memory, where it is needed to tune the connection weights. Omori et al.[11] proposed PATON, which forms symbols as orthogonal patterns from nonorthogonal physical patterns. Oztop et al.[12] proposed HHOP, which suppresses the effects of correlations in the stored data by incorporating three body interactions between the neurons, and applied it to imitation learning by a robotic hand. These methods were not capable of representing the hierarchy of stored data by parameters.

2 Hierarchical Associative Memory with Self-organizing Nonmonotonicity

2.1 Model

We use an associative memory model in continuous space and time. N is the number of neurons, u_i is the states of each neuron, y_i is the output of each neuron, f is the activation function and g is the output function. f is the nonmonotonic function described by the following equation[9], in nonmonotonic networks.

$$f_h(u_i) = \frac{1-\exp(-cu_i)}{1+\exp(-cu_i)} \frac{1+\kappa \exp(c'(|u_i|-h))}{1+\exp(c'(|u_i|-h))} \tag{1}$$

The activation function f is parameterized by (κ, h) as shown in Fig.3 and approximates sigmoid as $\kappa \to 1$ or $h \to \infty$. Here, we fix $\kappa = -1$. h is shown to be the parameter of f, by the suffix. The output function g is a sign function.

The dynamics of the associative memory model is

$$\tau \dot{\boldsymbol{u}} = -\boldsymbol{u} + W \boldsymbol{f}_h(\boldsymbol{u}) \tag{2}$$

$$\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{u}) \ , \tag{3}$$

where $\boldsymbol{u} \in R^N$ is the state vector composed of u_i and $\boldsymbol{y} \in R^N$ is the output vector composed of y_i. $W \in R^{N \times N}$ is the connection weight matrix and τ is the time constant. $\boldsymbol{f}_h$ and $\boldsymbol{g}$ are defined as vector functions calculating (1) and g for each element of the vector respectively.

W is determined by the simplest Hopfield type [3] covariance learning. When p storage patterns $\boldsymbol{\xi}_1, \boldsymbol{\xi}_2, \cdots, \boldsymbol{\xi}_p \in \{-1, 1\}^N$ are given,

$$W = \frac{1}{N} \sum_{\mu=1}^{p} \boldsymbol{\xi}_\mu \boldsymbol{\xi}_\mu^{\mathrm{T}} - \alpha I \ , \tag{4}$$

where α is a real value and I is an identity matrix.

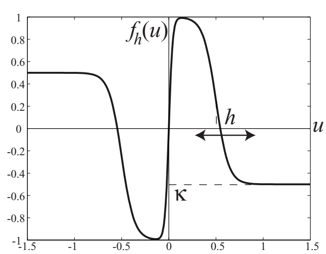

Fig. 3. Non-monotonic activation function

2.2 Hierarchically Correlated Storage Patterns and Hierarchically Bifurcating Attractors[5]

Kadone et al.[5] gave a theoretical description of the bifurcations of attractors in associative memory dynamics depending on the parameter of nonmonotonicity when storage patterns have hierarchical correlation, as an explanation of their simulations in which motion patterns are stored. We briefly summarize their results in this subsection.

Hierarchically correlated stored patterns are represented by a tree structure. Refer to Fig.6 in [5] for the image of the tree structure. Let us consider the case where a pattern at around the center of a certain cluster A in the tree structure becomes an attractor. For the storage patterns $\boldsymbol{\xi}_\mu$ and the state of neurons $\boldsymbol{u}$, a division into three is defined so as to separate the part belonging to the layer in consideration (N_a-dim), the part belonging to the upper layers (N_p-dim) and the part belonging to the lower layer (N_c-dim).

$$\boldsymbol{\xi}_\mu = [\boldsymbol{\xi}_{\mu,p}^{\mathrm{T}} \ \ \boldsymbol{\xi}_{\mu,a}^{\mathrm{T}} \ \ \boldsymbol{\xi}_{\mu,c}^{\mathrm{T}}]^{\mathrm{T}} \ , \ \boldsymbol{u} = [\boldsymbol{u}_p^{\mathrm{T}} \ \ \boldsymbol{u}_a^{\mathrm{T}} \ \ \boldsymbol{u}_c^{\mathrm{T}}]^{\mathrm{T}} \tag{5}$$

$\boldsymbol{\xi}_*^{\perp}$ is a pattern vector perpendicular to $\boldsymbol{\xi}_*$, where half of the elements of the vector is reversed. p_A is the number of storage patterns in the cluster A in consideration. With these assumptions, the following $\boldsymbol{u}^*$ is an attractor on $h \simeq \gamma^*$

$$\boldsymbol{u}^* = \begin{bmatrix} \gamma^* \boldsymbol{\xi}_{A,p} - \alpha \boldsymbol{\xi}_{A,p}^{\perp} \\ (\gamma^* - \alpha)\boldsymbol{\xi}_{A,a} \\ \gamma^* \bar{\boldsymbol{\xi}}_{A,c} - \alpha \boldsymbol{g}(\bar{\boldsymbol{\xi}}_{A,c}) \end{bmatrix} , \tag{6}$$

where

$$\gamma^* = (N_a + N_c O(1/\sqrt{p_A}))p_A/N \tag{7}$$

$$\bar{\boldsymbol{\xi}}_A = (1/p_A)\Sigma_{\mu \in A} \boldsymbol{\xi}_\mu \tag{8}$$

$$\boldsymbol{\xi}_{A,p} = \boldsymbol{g}(\bar{\boldsymbol{\xi}}_{A,p}) \tag{9}$$

$$\boldsymbol{\xi}_{A,a} = \boldsymbol{g}(\bar{\boldsymbol{\xi}}_{A,a}) \tag{10}$$

The output pattern on $\boldsymbol{u}^*$ is,

$$\boldsymbol{g}(\boldsymbol{u}^*) = [\boldsymbol{\xi}_{A,p}^{\mathrm{T}} \ \ \boldsymbol{\xi}_{A,a}^{\mathrm{T}} \ \ \boldsymbol{g}(\bar{\boldsymbol{\xi}}_{A,c})^{\mathrm{T}}]^{\mathrm{T}} , \tag{11}$$

which is at around the center of the cluster A. Also, by setting $N_c = 0, p_A = 1$, we can consider the case where the outputs from the attractors coincide with storage patterns.

2.3 Self-organizing Nonmonotonic Activation Function

In the previous subsection, we described the equilibrium points. Here, we first consider the retrieval process into the equilibrium points. In associative memory dynamics, the state is first attracted into the direction of large correlation of the storage patterns [8] with the current state, and the amplitudes of the activations become large in the subspace of large correlation. As the amplitudes of the activations become large, the output of the neurons become to be reversed by the nonmonotonic activation function. As the half number of neurons in the subspace of the large correlation are reversed, they become not to effect on the associative dynamics[5]. Then, the state is attracted into the average direction of the stored patterns in the subspace of second largest correlation with the current state, which is the direction of the center of cluster A. Therefore, by defining $\boldsymbol{u}_\gamma$ as an replacement of γ^* in the attractor (6) by a parameter γ

$$\boldsymbol{u}_\gamma = \begin{bmatrix} \gamma\boldsymbol{\xi}_{A,p} - \alpha\boldsymbol{\xi}^{\perp}_{A,p} \\ (\gamma-\alpha)\bar{\boldsymbol{\xi}}_{A,a} \\ \gamma\bar{\boldsymbol{\xi}}_{A,c} - \alpha\boldsymbol{g}(\bar{\boldsymbol{\xi}}_{A,c}) \end{bmatrix} , \tag{12}$$

the state $\boldsymbol{u}$ transits from $\boldsymbol{u}(0)$ to $\boldsymbol{u}_h$, where $\gamma = h$. Next, on $\boldsymbol{u} = \boldsymbol{u}_h$, since $W\boldsymbol{f}_h(\boldsymbol{u}_h) = \boldsymbol{u}^*$ the dynamics (2) degenerates into

$$\tau\dot{\boldsymbol{u}} = -\boldsymbol{u}_h + \boldsymbol{u}^* , \tag{13}$$

which means that there exists a flow towards $\boldsymbol{u}^*$ on $\boldsymbol{u}_h$. Therefore, the state transits from $\boldsymbol{u}(0)$ to $\boldsymbol{u}_\gamma$ and then to $\boldsymbol{u}^*$, where $\gamma = \gamma^*$ (Fig.4). Note that it does not necessarily mean that $\boldsymbol{u}^*$ is an attractor when $h \neq \gamma^*$.

From the above discussion, we can expect a pattern at the center of the cluster A in consideration to be an attractor, by estimating γ from the state $\boldsymbol{u}$ and making h to trace γ, which would bring h from $h(0)$ to γ and then to γ^*. In $\boldsymbol{u}_\gamma$ of (12), the amplitudes of the upper two rows are about γ and the amplitudes of the lower row scatters with small order since they are the average of the subspace of the small correlations by definition. Hence we determine the estimation $\hat{\gamma}$ of γ by the following

$$\hat{\gamma} = \sigma_2 \frac{\sum_{i=1}^{N} k(u_i, \sigma_1 h)|u_i|}{\sum_{i=1}^{N} k(u_i, \sigma_1 h)} , \tag{14}$$

where $k(u_i, \sigma_1 h)$ is a function that gives 1 when the absolute value of u_i is larger than $\sigma_1 h$, and 0 otherwise. σ_2 is a parameter that compensates that the second row of (12) is smaller by α than γ. The dynamics of the nonmonotonicity parameter is given by the following

$$\tau\dot{h} = -h + \hat{\gamma} , \tag{15}$$

which evolves with the associative memory dynamics (2).

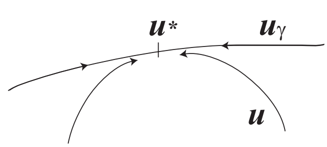

Fig. 4. Flow of the state $\boldsymbol{u}$

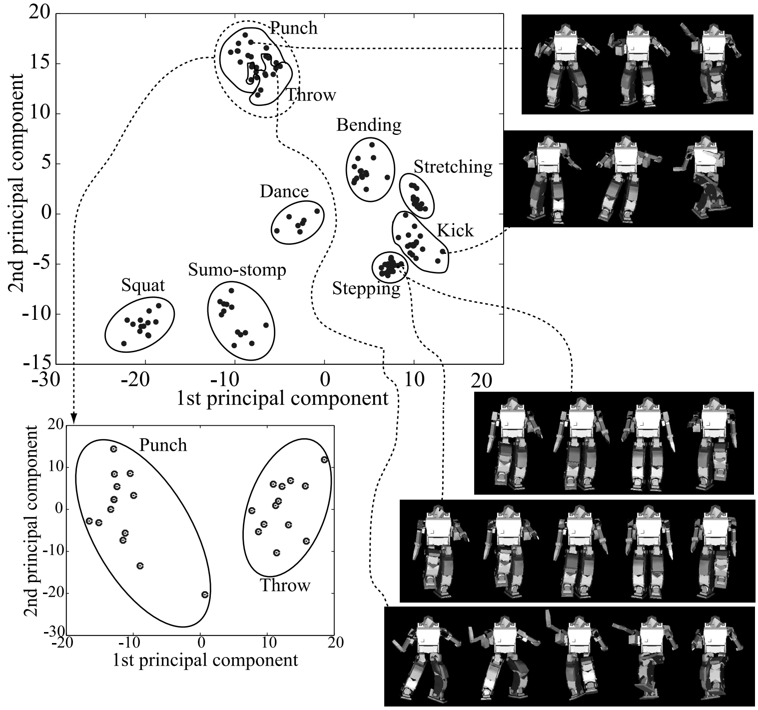

Fig. 5. Cluster structure in feature vector $\boldsymbol{m}_i$ space

3 Hierarchical Memory Integration for Motion Patterns with Self-organizing Nonmonotonicity

3.1 Feature Vectors of Motion Patterns[4]

Let $\boldsymbol{\theta}_i[k] \in R^{20}$ be the angular vector of humanoid robot motion i at time k. Motions we use are, 28 "Stepping"s, 15 "Stretching"s, 7 "Dance"s, 19 "Kick"s, 14 "Punch"s, 13 "Sumo-stomp"s, 13 "Squat"s, 13 "Throw"s, 15 "Bending"s, 137 motions in total that are obtained from motion capture. Sampling time is 0.033[ms]. Suffix i of $\boldsymbol{\theta}_i[k]$ is an index for these, for example "Stepping0".

$M_i(l) \in R^{20\times 20}$ is an auto-correlation matrix of the time sequence of $\boldsymbol{\theta}_i[k]$,

$$M_i(l) = \frac{1}{T}\sum_{k=1}^{T} \boldsymbol{\theta}_i[k]\boldsymbol{\theta}_i^{\mathrm{T}}[k-l] \tag{16}$$

Feature vector of motion i is obtained by arranging the elements of matrix $M_i(l)$ into a column vector $\boldsymbol{m}_i(l) \in R^{400}$. Fig.5 shows the plots of $\boldsymbol{m}_i(l=2)$ by principal component analysis with some samples of motion sequences. Cluster structures can be seen clearly, except for "Punch" and "Throw". This is because

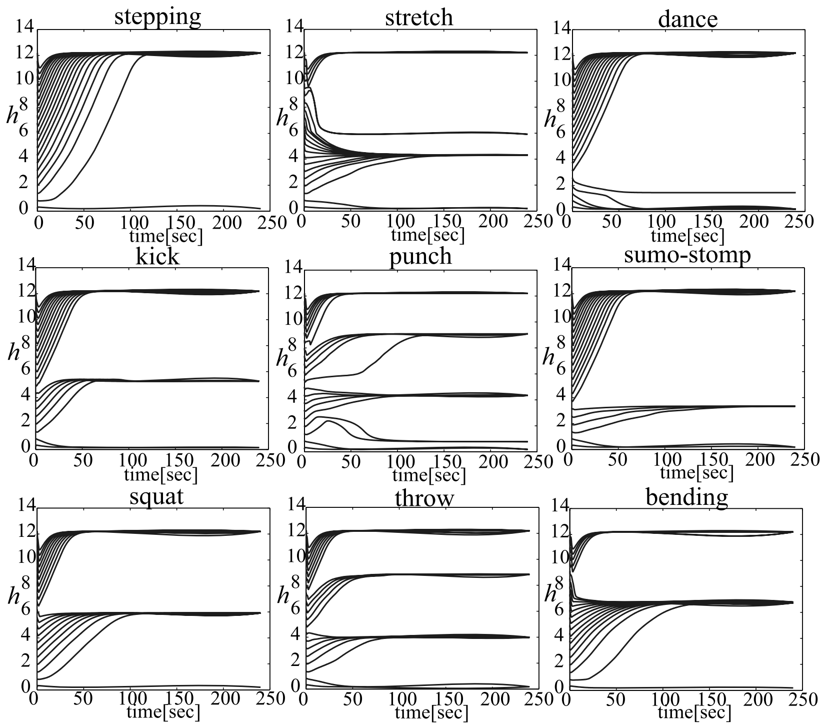

Fig. 6. Time evolution of h by (15) for representatives of each kind of motions

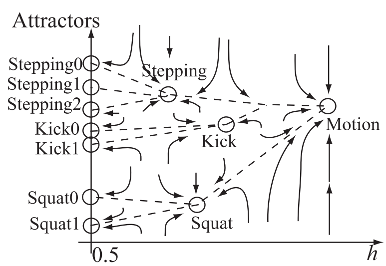

Fig. 7. Representation of hierarchy by bifurcations of attractors and basins with self-organizing nonmonotonicity, compared to Fig.2.

of executing PCA for all motions at one time. Executing PCA alone for these overlapping clusters results in clear cluster structures (Fig.5: Bottom Left).

In order to store these feature vectors into the associative networks, they are quantized into bit patterns whose elements are $\{-1, 1\}$. By quantizing $\boldsymbol{m}_i \in R^{400}$ with 10 bits for each real value, quantized pattern $\boldsymbol{\xi}_i \in \{-1, 1\}^{4000}$ is obtained. These quantized patterns have hierarchical correlations.

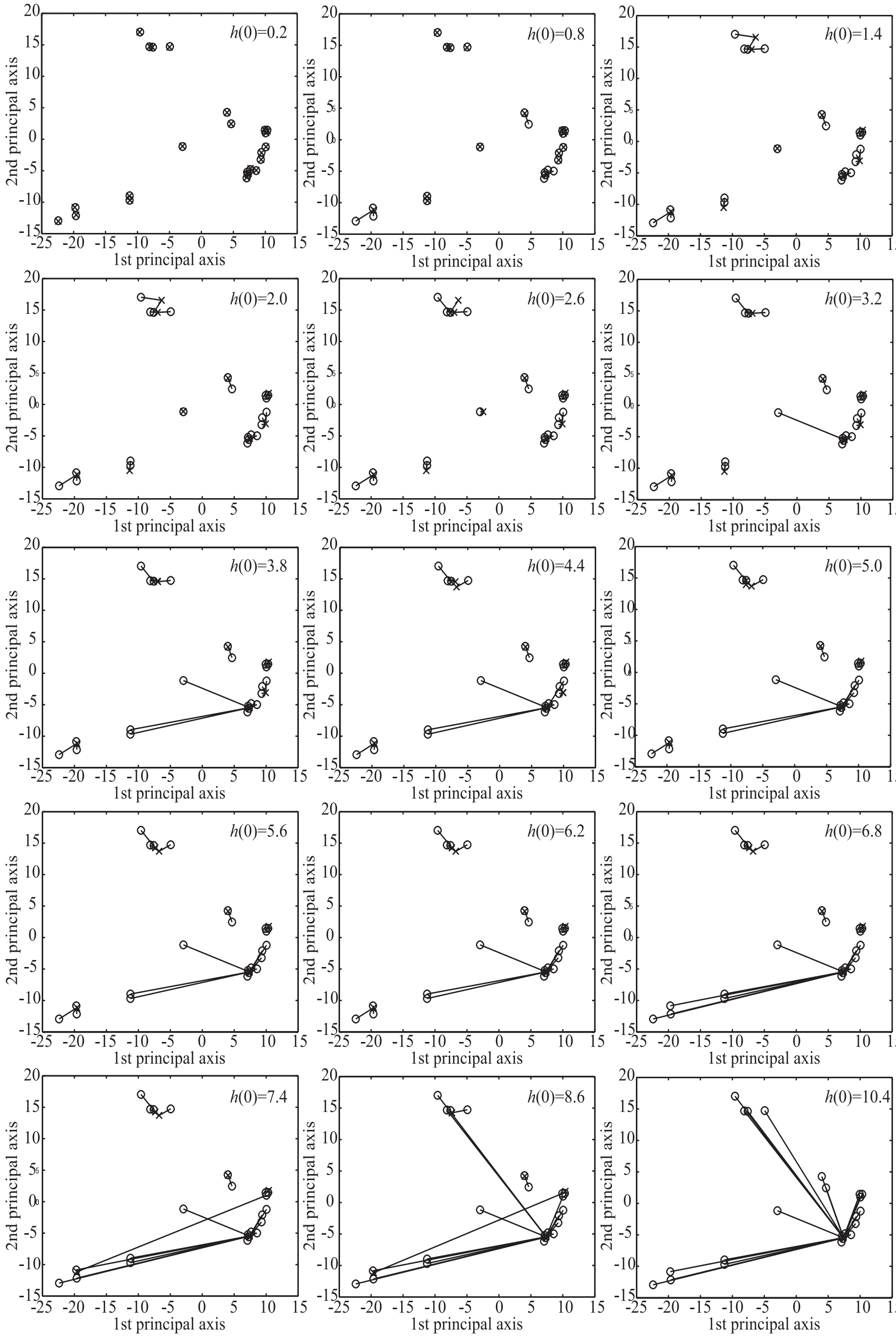

Fig. 8. Correspondences between initial states ('o') and attractors ('x') for various initial values of h, shown in the same space as Fig.5 top

3.2 Symbol Formation of Motion Patterns by Self-organizing Nonmonotonic Activation Function

The storage patterns are the quantized feature vectors of motion patterns obtained by the way described in the previous subsection. They are stored into the network by (4), and the dynamics (2)(15) are simulated to investigate the attractors. The number of neurons is $N = 4000$, the parameter of the function k of (14) is $\sigma_1 = 0.6$, and $\sigma_2 = 1.08$. σ_1 and σ_2 are chosen by some trials. Some of the storage patterns are given as the initial states of $\boldsymbol{u}$, and the initial values of h are given from 0.2 to 11.6 with the interval of 0.6. Fig.6 shows the time evolutions of h for representatives of each kind of motion. They are entrained into some discrete attractors. The time evolution of h is almost the same for the same kinds of motions. Fig.8 shows, in the same PCA space as Fig.5, the correspondences between the initial states $\boldsymbol{u}(0)$ and the attractors. Symbolic attractors are formed at $h(0) = 0.8$ for “bending” and “squat”, at $h(0) = 1.4$ for “kick”, “stretching”, “punch”, “throw” and “sumo-stomp”. At larger $h(0)$s, symbolic attractors are formed that hierarchically integrates the larger clusters.

By comparing Fig.6 and Fig8, we can see correspondences between the attractors of h and the cluster integration, an image of which is shown in Fig.7. For example “kick” in Fig.6 shows three level attractors, for $h(0)$ of (0.2,0.8), (1.4,4.4) and (5.0,10.4). In Fig.8, they correspond to retrieval of the storage patterns, the symbolic patterns integrating the same kinds of motions and the symbolic pattern integrating all the patterns. Other pattens except “stepping” have similar properties. “stepping” have two attractors in Fig.6, which correspond to retrieval of the storage patterns and the symbolic pattern integrating all the patterns.

4 Conclusion

We proposed a method to automatically find out the hierarchy of the correlations in the stored data, and form attractors at the centers of clusters, by providing the parameter of nonmonotonicity with dynamics, that evolves through time along with the retrieval in the associative dynamics. This method has its base on an estimation of the nonmonotonicity utilizing the vector fields that drives the states towards the centers of clusters when larger correlations in the upper level cluster than the one in consideration is suppressed by the nonmonotonicity, during the retrieval. Storing the feature vectors of motion patterns, it forms attractors hierarchically corresponding to the storage patterns and symbols of motions, reflecting the hierarchical correlations and clusters of motion patterns, depending on the initial values and therefore attractors of the nonmonotonicity. The attractors of the nonmonotonicity parameter are discrete states representing the discrete levels of hierarchical correlations in the stored motion patterns.

Future scope can be a connection to motion generation and control mechanisms. To generate embodied symbols by our methods, we need a motion control mechanism that generates clusters of motions in some space. Another way may include storing the pairs of motion patterns and control patterns like proposed by Oztop et al.[12]. By using our neural network, we may be able to generate motions from symbolic attractors and provide interactions between symbols and bodily situations.

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