A design principle of adaptive neural controllers for realizing anticipatory behavior in reaching movement under unexperienced environments

Toshiyuki Kondo[1] and Koji Ito[2]

[1]Department of Computer, Information and Communication Sciences,
Tokyo University of Agriculture and Technology,
2-24-16 Naka-cho, Koganei, Tokyo 184-8588, Japan
tkondo@ieee.org
http://www.livingsys.lab.tuat.ac.jp/
[2] Department of Computational Intelligence and Systems Science,
Tokyo Institute of Technology,
4259 Nagatsuta, Midori, Yokohama, 226-8502, Japan
ito@dis.titech.ac.jp
http://www.ito.dis.titech.ac.jp/

Abstract. Regardless of complex, unknown, and dynamically-changing environments, living creatures can recognize situated environments and behave adaptively in real-time. However it is impossible to prepare optimal motion trajectories with respect to every possible situations in advance. The key concept for realizing the environmental cognition and motor adaptation is a context-based elicitation of constraints which are canalizing well-suited sensorimotor coordination. For this aim, in this study, we propose a polymorphic neural networks model called CTRNN+NM (CTRNN with neuromodulatory bias). The proposed model is applied to two dimensional arm-reaching movement control under various viscous force fields. Simulation results indicate that the proposed model inherits high robustness even though it is situated in unexperienced environments, which have similar rotation, but different size of viscous force, because it evolved "how to adapt" instead of "how to move."

1 Introduction

Living creatures are information structuring systems which have enormous sensorimotor degrees of freedom (DOF). External environments can be recognized based on spatiotemporal integration of their sensorimotor information (e.g. vision, tactile, somatosensory stimulus). Given a task goal in addition to the environmental cognition, smooth limb movements are immediately planned, and executed in spite of huge DOF of our musculoskeletal systems. However the detail mechanisms of the cognition and motor adaptation are still open questions[1].

Due to this, not a few computational models for the cognition and motor adaptation have been proposed. Most of them are based on *internal model* theory in which an adequate inverse model (i.e. sensorimotor mapping or controller) would be selected according to a prediction derived from forward models (e.g. [2]). In these *localist* models, a novel pattern can be incrementally learned by allocating an additional module. But owing to this, they have less ability for dealing with unknown environments without the additional learning process.

In contrast, recently much attention has been focused on *dynamical systems* (or *distributed*) approach to the cognition and motor adaptation problem [3–7]. In the approach, the state prediction and motor generation are represented in accordance with the concept of attractors in dynamical systems theory.

On the other hand, recent neurophysiology has revealed that those environmental cognition and real-time adaptation can be observed in real nervous systems of insects and crustaceans. It is known that a variety of chemical substances called neuromodulators (NMs) play crucial roles to regulate the dynamic characteristics of the neural networks (e.g. activating/blocking/changing of synaptic connections)[9–11].

Based on the physiological findings, a number of connectionist models of neuromodulation has been proposed[12–17]. In [13], a polymorphic neural networks with self reconfigurable ability was proposed, and it was applied to real robot control. In their work, it was argued that the neuromodulatory neural networks evolved in a computer simulation can be seamlessly applicable to real robot control. In [16], the homeostatic networks in which the ability of neural plasticity is the target to be evolved was proposed. In [17], *GasNet* model was proposed, which is the first model considered the spatiotemporal distribution of neuromodulators, and reported that it could show highly evolutionary performance compared with NoGas model.

In this paper, we would explore a possible neuronal mechanism of environmental cognition and motor adaptation in unknown (i.e. unexperienced) environments. For this aim, we develop a polymorphic neural networks model called CTRNN+NM (CTRNN with neuromodulatory bias). The proposed model is applied to two dimensional arm-reaching movement control in various viscous curl force fields, and the robustness of the proposed neural controller has been evaluated.

2 Proposed Method

2.1 CTRNN with NM bias

In this study, a polymorphic neural networks model has been proposed. As the proposed model is based on a continuous time recurrent neural networks (CTRNN)(e.g. [5]), it is named CTRNN+NM (CTRNN with NM bias).

Fig.1 schematically shows the proposed model. The network basically consists of fully-connected hidden neurons, and each of which has following dynamics (i.e. leaky-integrator model).

$$T_i \frac{ds_i(t)}{dt} = -s_i(t) + \sum_{j=1}^{N_h} w_{ij} h_j(t) + \sum_{k=1}^{N_s} w_{ik} I_k(t) \tag{1}$$

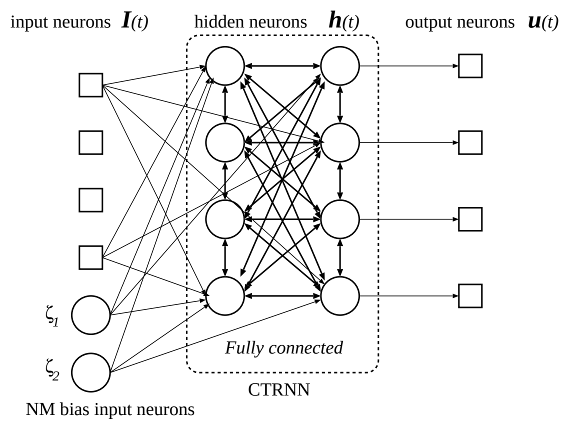


Fig. 1. CTRNN with NM bias.

$$h_j(t) = \frac{1}{1 + \exp\left[-\left(s_j(t) - \theta_j\right)\right]} \tag{2}$$

where $s_i(t)$ and $h_i(t)$ are the internal state and output of the neuron i, respectively. N_s and N_h are the number of sensors and hidden units. T_i is the time constant of the neuron, w_{ij} and w_{ik} are the synaptic weights, and θ_j is the threshold of the neuron. These parameters ($[\boldsymbol{T}, \boldsymbol{w}, \boldsymbol{\theta}]$) are the target to be optimized.

As can be seen in the figure, the proposed model has additional bias inputs named NM bias, ζ_i. The characteristics of the CTRNN can be altered by modulating the NM bias ζ_i just like RNNPB (recurrent neural networks with parametric bias) proposed by Tani[6].

In general, in those neuromodulation model, the crucial point to be noted is how the NM bias can be regulated.

2.2 Diffusion of NM

In contrast to existing hierarchal network models, the regulation of the NM bias is controlled by the identical network itself (i.e. a monolithic network) proposed in [12]. The behavior analysis of the neuromodulatory neural networks can be seen in [13].

As schematically shown in Fig.2, each hidden neuron has the capability to diffuse its specific (i.e. genetically-determined) type of NM ($\lambda_j = \{1, 2, \cdots, M\}$) in accordance with its activity and the diffusing function given by Eq.(3), it is also genetically-determined.

$$\zeta_i(t) = \exp\left(\frac{(h_j(t) - \mu_j)^2}{2\sigma_j^2}\right) \tag{3}$$

In this example, the instance hidden neuron (shaded in the figure) can diffuse NM2 with the concentration ζ_2 depending on its activity.

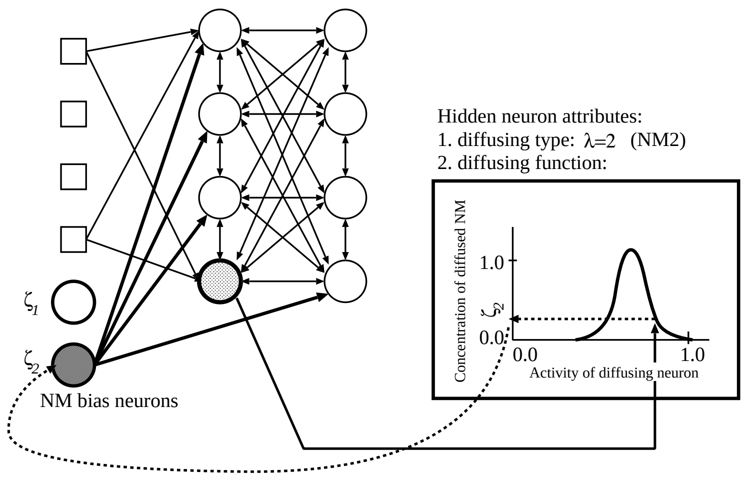


Fig. 2. diffusion of NMs.

The parameters for NM diffusion ([$\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$]) are also the target to be optimized.

2.3 Evolution of CTRNN with NM bias

In this study, the parameters to be optimized (i.e. [$\boldsymbol{T}$, $\boldsymbol{w}$, $\boldsymbol{\theta}$, $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$]) are evolutionally determined by using a genetic algorithms.

In the evolutionary process, each parameter is encoded as real number with the range $[0, 1]$. On the contrary in the decoding process, each parameter can be linearly transformed into the corresponding (i.e. defined) range (Table.1).

The other simulation conditions are listed in Table.2.

3 Experiments

3.1 Arm-reaching movement in various force fields

To investigate the validity of the proposed model, it is applied to two dimensional arm-reaching movement control in various viscous curl force fields. Fig.3 schematically illustrates the task. As shown in the figure, human arm can be modeled as a planar two-link manipulator.

Table 1. Parameter range.

Time constant:	$T_j \in [0.01, 2.0]$
Synaptic weights (intra-neuron):	$w_{ij} \in [-5.0, 5.0]$
Synaptic weights (sensor neuron):	$w_{ik} \in [-5.0, 5.0]$
Threshold of neuron:	$\theta_j \in [-1.0, 1.0]$
NM type:	$\lambda \in \{1, 2\}$
NM diffusing function (center):	$\mu \in [0.0, 1.0]$
NM diffusing function (width):	$\sigma \in [0.01, 0.1]$

Table 2. Simulation conditions.

Generations:	100000
Population (Elitist strategy):	50
Crossover rate (Uniform crossover):	0.5
Mutation rate:	0.04

The equations of motion of the two link arm are described by,

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}}) = \boldsymbol{\tau} + \boldsymbol{J}(\boldsymbol{q})^T \boldsymbol{f}_{Env} \tag{4}$$

where $\boldsymbol{q}$, $\boldsymbol{M}(\boldsymbol{q})$, $\boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}})$, $\boldsymbol{J}(\boldsymbol{q})^T$ are joint angle vector, inertia matrix, Coriolis' force, Jacobian matrix in joint coordinate, and $\boldsymbol{f}_{Env}$ is external force in Cartesian coordinate, respectively.

In this model, the joint torque $\boldsymbol{\tau}$ can be derived from activities of antagonist muscles, and each muscle is contracted based on motor command $\boldsymbol{u}$ which corresponds to the output of the CTRNN (See Eq.(12)).

$$\boldsymbol{\tau} = \boldsymbol{G}^T \cdot diag\,[F_1, F_1, F_2, F_2] \cdot \boldsymbol{u} \tag{5}$$

$$\boldsymbol{G} = \begin{bmatrix} 0.04 & -0.04 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.025 & -0.025 \end{bmatrix}^T \tag{6}$$

$$F_j = 1 - k(q_j - q_j^{(0)}) - b\dot{q}_j \tag{7}$$

where $\boldsymbol{G}$ and $\boldsymbol{F}$ are matrix of the moment arm and the maximum force of each muscle, respectively. This equation implies that shoulder muscles have higher gains than elbow.

In this reaching experiments, we can simulate arbitrary external force in the hand coordinate as environmental changes. For instance, $\boldsymbol{f}_{Env}$ described by Eq.(9) is a viscous curl force field (hereafter VF), in which the hand suffers an orthogonal force in proportion to the hand velocity $\dot{\boldsymbol{X}}$ (See Fig.4). In the study, the

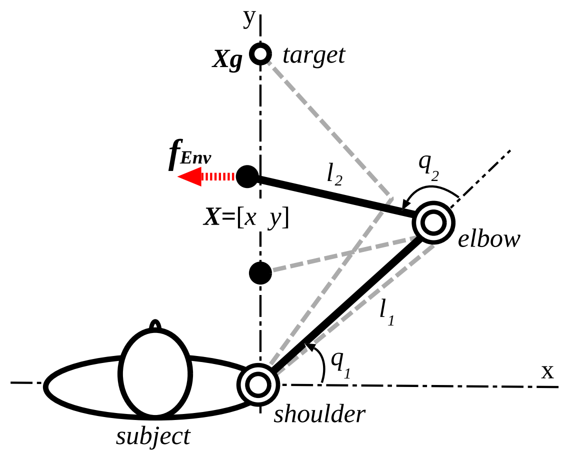


Fig. 3. Reaching task.

two-link arm dynamics are numerically calculated using open dynamics engine (ODE) provided by R.Smith[18].

In order to develop robust neural controller which has "how to adapt" instead of "how to move", we assumed two different force fields (i.e. $\boldsymbol{f}_{Env_1}$ and $\boldsymbol{f}_{Env_2}$) as the training environments in the evolutionary optimization experiments [8]. Here, $\boldsymbol{f}_{Env_1}$ is a null field (hereafter NF), in other words n=0.0 in Eq.(10). On the other hand, $\boldsymbol{f}_{Env_2}$ corresponds to VF, and also n=5.0.

$$\boldsymbol{f}_{Env} = B\dot{\boldsymbol{X}} \tag{8}$$

$$\dot{\boldsymbol{X}} = [\dot{x} \quad \dot{y}]^T \tag{9}$$

$$B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} = n \begin{pmatrix} 0.0 & -1.0 \\ 1.0 & 0.0 \end{pmatrix} \tag{10}$$

3.2 Neural controller

The sensory inputs to the neural controller is $\boldsymbol{I}$, and the outputs of the controller is motor command $\boldsymbol{u}$. In Eq.(11) and (12), SH, EL, f, and e represent $Shoulder$, $Elbow$, $flexor$, and $extensor$, respectively. The other parameters for the CTRNN+NM model used in the following experiments are listed in Table.3

$$\boldsymbol{I} = [q^{SH} \ q^{EL} \ \tau^{SH} \ \tau^{EL} \ \zeta_1 \ \zeta_2]^T \tag{11}$$

$$\boldsymbol{u} = [u_f^{SH} \ u_e^{SH} \ u_f^{EL} \ u_e^{EL}]^T \tag{12}$$

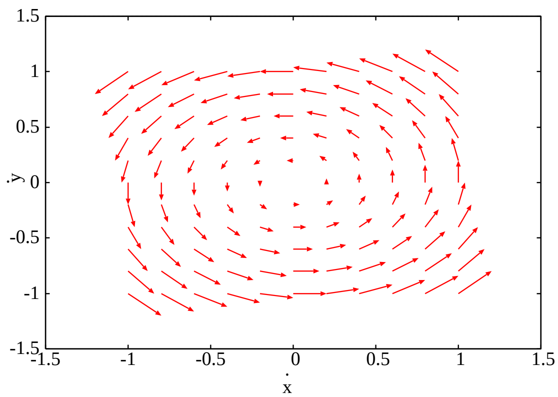


Fig. 4. Viscous curl force field.

Table 3. Parameters for CTRNN+NM.

# of sensor neuronsN_s:	4
# of hidden neuronsN_h:	10
# of NM type:	2

3.3 Evaluation criteria

The evaluation criteria for arm-reaching control task is given by following equations:

$$E = E_1 + E_2, \tag{13}$$

$$E_1 = \frac{1}{T}\int_T \exp\left[\frac{(\boldsymbol{X}_g - \boldsymbol{X})^T(\boldsymbol{X}_g - \boldsymbol{X})}{2\sigma_g^2}\right] dt \tag{14}$$

$$E_2 = \frac{1}{T}\int_T \frac{1}{1 + \boldsymbol{u}^T\boldsymbol{u}} dt \tag{15}$$

where $\boldsymbol{X}$ and $\boldsymbol{X}_g$ are hand and target positions, respectively. In the following experiments, the start position and target position are fixed ($\boldsymbol{X}_g = [0.0 \quad 0.5]^T$). Therefore, the criterion E_1 represents averaged position errors, and E_2 indicates the averaged energy consumptions of muscles.

4 Results

Because we are interested in robustness of the optimized CTRNN+NM-based controller, it should be compared with a normal CTRNN-based controller.

As has been noted, firstly the neural controllers (i.e. (a) CTRNN and (b) CTRNN+NM) are optimized under both of two different environments (i.e. NF(n=0.0) and VF(n=5.0)) using genetic algorithms (GA) with the above mentioned evaluation criteria (i.e. Eq.(13)).

After the optimization, the evolved neural controllers are evaluated in the following four environments, i.e. n=0.0, 2.5, 5.0, and 7.5 in Eq.(10). Here, n=0.0 and n=5.0 are the training environments. In contrast, n=2.5 and n=7.5 are unexperienced (i.e. unknown) environments.

Fig.5 (a) and (b) demonstrate the resultant hand trajectories in the four kinds of viscous curl force fields. Also Fig.5 (c) and (d) illustrate the resultant hand velocity curves in the four environments.

For further investigation of the robustness of the trained neural controllers, we measured the performance (i.e. E) of them (i.e. CTRNN and CTRNN+NM) while the viscous parameters (b_{12} and b_{21} in Eq.(10)) are exhaustively changed in a range ($b_{12} \in [-3.0, -7.0]$, $b_{21} \in [3.0, 7.0]$). Fig.6 shows the results of the exhaustive evaluation experiments.

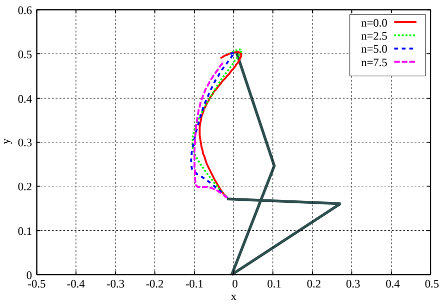
5 Discussions

In this paper, a possible neuronal mechanism of environmental cognition and motor adaptation in unknown (i.e. unexperienced) environments has been investigated.

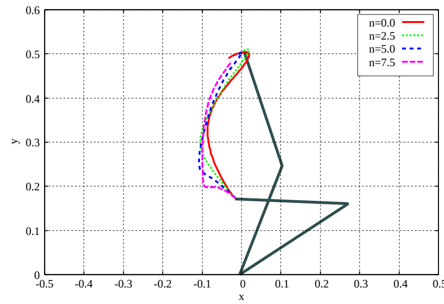
Based on the physiological findings, we proposed a polymorphic neural networks model with self-reconfigurable feature, called "CTRNN with NM bias." The proposed neural networks model was applied to a planar two-link arm-reaching movement control in various (e.g. partly unexperienced) viscous curl force fields.

As can be seen in Fig.5 (a) and (c), the neural controller based on a normal CTRNN learned different trajectories and hand velocity curves with respect to environmental changes. This is because the normal CTRNN has to store them as different dynamics in a monolithic neural networks.

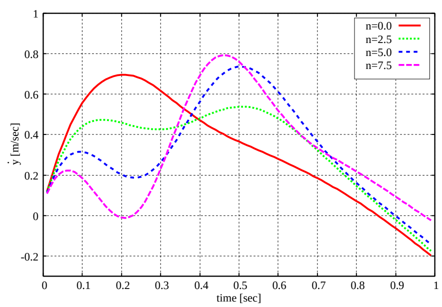
On the contrary, the Fig.5 (b) and (d) are indicating that the proposed CTRNN+NM model can recognize environmental change via its sensorimotor feedback, and it can appropriately modulate sensorimotor mapping so as to keep an optimal hand velocity curves (i.e. bell-shape) in spite of environmental changes. The crucial points to be noted here is the diffusing conditions of the NM bias are dependent on neurons' state vector in the identical neural networks. There are self-referential loops with wide variety of time constant. These multiple feedback loops would contribute to a real-time adaptation ability through continuing interactions with infinite environments.



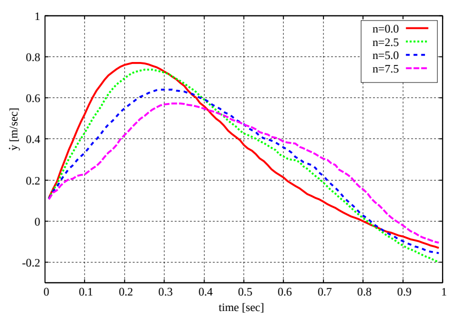
(a) CTRNN



(b) CTRNN+NM



(c) CTRNN

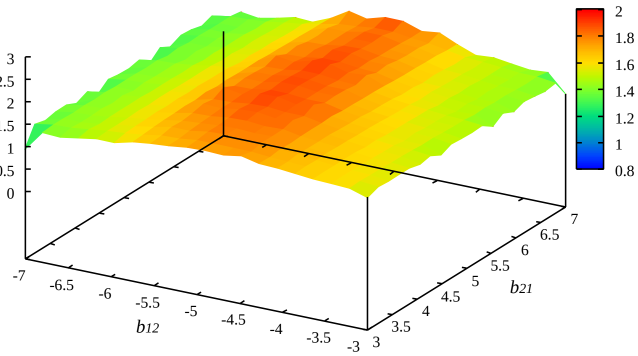


(d) CTRNN+NM

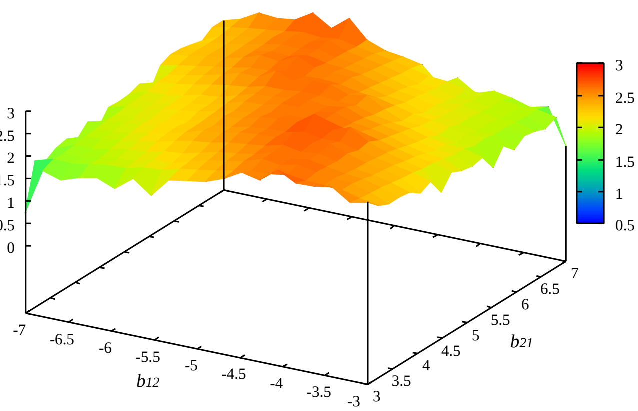
Fig. 5. Resultant hand trajectories and velocity curves in different size of viscous curl force fields. Here n=0.0 and n=5.0 are the training environments, in contrast, n=2.5 and n=7.5 are unexperienced (i.e. unknown) environments. (a), (c) In case of CTRNN, the neural controller learned different trajectories and velocity curves with respect to environments, since it has to store different sensorimotor mappings in the monolithic neural networks. (b), (d) On the other hand, CTRNN+NM can recognize environmental change via its sensorimotor feedback loop, and it can appropriately modulate sensorimotor mapping so as to keep the optimal trajectory in spite of environmental changes.

According to verification experiments (Fig.6), the neural controller based on the CTRNN showed brittleness against b_{12} changes. Because y-directional component of hand velocity is dominant in the reaching movement assumed here, less robustness against b_{12} is considered fatal compared with b_{21} sensitivity.

In contrast, the CTRNN+NM demonstrates high robustness against not only b_{12}, but also b_{21}. Note that the gradation in the graph specifies different range. Especially, the diagonal line keeps high performance. This implies that the CTRNN+NM evolved “how to adapt” (i.e. sensorimotor constraints and their elicitation procedure) instead of “how to move” (i.e. an optimal sensorimotor mapping itself). Because it seems that the CTRNN+NM extracts the dynamical structure of the external environments ($\boldsymbol{f}_{Env}$), which has following form.



(a) CTRNN



(b) CTRNN+NM

Fig. 6. Robustness of the evolved controllers ((a) CTRNN and (b) CTRNN+NM) while environmental viscous parameters (b_{12} and b_{21}) are exhaustively changed. (a) In case of CTRNN, the controller shows high robustness against b_{21}, but it is brittle under b_{12} changes. (b) In contrast, CTRNN+NM demonstrates high robustness against not only b_{12}, but also b_{21} (Note that the gradation specifies different range). Especially, the diagonal line keeps high performance.

$$B = \begin{pmatrix} 0 & -\Gamma \\ \Gamma & 0 \end{pmatrix} \tag{16}$$

Due to these considerations, we confirmed that the proposed model has high robustness even though it is situated in unexperienced environmental changes. Therefore the proposed model should be a simple solution to explain the self-referential adaptation, which is essential to work out the environmental cognition and motor adaptation.

Acknowledgments

This research has been partially supported by a Grant-in-Aid for Scientific Research on Priority Areas (No.454, 2005–2010) and Young Scientists (B) (No.18700195, 2006–2007) from the Japanese Ministry of Education, Culture, Sports, Science, and Technology.

References

1. N. Bernstein, The Coordination and Regulation of Movements, Oxford: Pergamon, 1967.
2. Wolpert, D. M. and Kawato, M.: Multiple paired forward and inverse models for motor control, *Neural Networks*, vol.11, pp.1317–1329, 1998.
3. Schöner, G. and Kelso, J. A. S.: Dynamic pattern generation in behavioral and neural systems, *Science*, vol.239, pp.1513–1520, 1988.
4. Thelen, E. and Smith, L. B.: A Dynamic Systems Approach to the Development of Cognition and Action Cambridge, MA: MIT Press, 1994.
5. Beer, R. D.: Dynamical approaches to cognitive science, *Trend in Cognitive Sciences*, vol.4, no.3, pp.91–99, 2000.
6. Tani, J.: Learning to generate articulated behavior through the bottom-up and the top-down interaction processes, *Neural Networks*, vol.16, pp.11–23, 2003.
7. Paine, R. W. and Tani, J., Motor primitive and sequence self-organization in a hierarchical recurrent neural network, *Neural Networks*, vol.17, pp.1291–1309, 2004.
8. A. Karniel and F. A. Mussa-Ivaldi, Sequence, time, or state representation: how does the motor control system adapt to variable environments?, *Biological Cybernetics*, vol.89, no.1, pp.10–21, 2003
9. P. A. Getting, and M. S. Dekin., Tritonia swimming: A model system for integration within rhythmic motor systems. In A. I. Selverston (ed.), Model neural networks and behavior, pp.3–20, Plenum Press, New York., 1985.
10. P. Meyrand, J. Simmers and M. Moulins, Construction of a pattern-generating circuit with neurons of different networks, *NATURE*, vol.351, 2 MAY, pp.60–63, 1991.
11. M. Hasselmo, Neuromodulation and cortical function: modeling the physiological basis of behavior, *Behavioral Brain Research*, vol. 67, pp. 1–27, Elsevier Science B.V. 1995.

12. T. Kondo, A. Ishiguro, S. Tokura, Y. Uchikawa and P.Eggenberger, Realization of Robust Controllers in Evolutionary Robotics: A Dynamically-rearranging Neural Network Approach, *Proceedings of the 1999 Congress of Evolutionary Computation*, vol.1, pp.366–373, 1999.
13. T. Kondo, Evolutionary design and behavior analysis of neuromodulatory neural networks for mobile robots control, *Applied Soft Computing*, in Press.
14. P. Eggenberger, A. Ishiguro, S. Tokura, T. Kondo and Y. Uchikawa, Toward Seamless Transfer from Simulated to Real Worlds: A Dynamically-Rearranging Neural Network Approach, Lecture Notes in Computer Science, vol.1812, Springer, 2000, pp.44–60.
15. A. Ishiguro, A Fujii, and P. Eggenberger, Neuromodulated Control of Bipedal Locomotion Using a Polymorphic CPG Circuit, *Adaptive Behavior*, vol.11, no.1, pp.7-17, 2003.
16. E. A. Di Paolo, Homeostatic adaptation to inversion of the visual field and other sensorimotor disruptions, *From animals to animat 6*, MIT Press, pp.440–449, 2000.
17. T. M. C. Smith, P. Husbands, A. Philippides and M. O'Shea, Neuronal Plasticity and Temporal Adaptivity: GasNet Robot Control Networks, *Adaptive Behavior*, vol.10, no.3–4, pp.161–183, 2002.
18. Smith, R.: Open dynamics engine v0.5 user guide. (2004) http://ode.org/