Intelligent Automation and Soft Computing, Vol. 10, No. 2, pp. 185-192, 2004

DESIGN OF AN ARTIFICIAL CENTRAL PATTERN GENERATOR WITH FEEDBACK CONTROLLER

KAZUKI NAKADA, TETSUYA ASAI, AND YOSHIHITO AMEMIYA
Department of Electrical Engineering
Hokkaido University
North 13, West 8, Sapporo 060-8628, Japan
nakada@sapiens-ei.eng.hokudai.ac.jp

ABSTRACT—This paper proposes an approach to design of an artificial central pattern generator (CPG) with a feedback control loop. CPG is the biological neural network that generates rhythmic movements for locomotion of animals. A crucial point in designing of an artificial CPG controller is how to deal with sensory information on surrounding environments. Hence, we investigated the properties of an artificial CPG controller including sensory feedback. First, we analyzed the stability of the CPG controller, and then how a sensory feedback influences to the output of the controller. The results provide a realistic approach to design of an artificial CPG controller.

Key Words: Central pattern generator, feedback control loop, biologically-inspired walking robot.

1. INTRODUCTION

Central pattern generators (CPGs) are biological neural networks that generate rhythmic movements for locomotion of animals, such as walking, running, swimming and flying [1]. The rhythmic movement generated by CPG induces a coordination of physical parts. Since the degree of freedom relevant to locomotion is very high, this coordination is necessary for stable locomotion. Furthermore, it is believed that a rhythmic movement emerge as a stable limit cycle from a *global entrainment* between the neural system that includes CPG and the physical system that interacts with a varying environment [7]. As a result, high autonomous adaptation to unpredictable environments during locomotion is achieved.

In recent years, many researchers have applied such functions of CPG to locomotion control in robotics [3]-[5]. For example, Kimura et al. have developed a quadruped walking robot capable of adapting to irregular terrain using CPG dynamics [3]. Billard and Ijspeert have applied a CPG-based controller to an entertainment robot, AIBO [4]. Lewis et al. have designed and fabricated a custom CPG chip for a biped walking robot [5].

In robotics, using the CPG controller for locomotion control has the following advantages: 1) reduction of the amount of calculation required for motion control as a result of the coordination of physical parts induced by rhythmic movements, and 2) autonomous adaptation to unexpected environments caused by the *global entrainment* between the CPG controller and the physical system such as robot arms and legs.

In this paper, we propose an approach to design of an artificial CPG controller including a feedback control loop. From the point of view of the *global entrainment*, one of the key issues in the design of an artificial CPG controller is how to deal with sensory information that reflects the dynamics of the physical system and a surrounding environment. Hence, we investigate the properties of an artificial CPG controller for driving an actuator with sensory feedback control. The results provide a realistic approach to design of an artificial CPG controller.

This paper is divided into five sections. In section 2, we briefly review the neural basis of the locomotion control of animals. In section 3, we propose a CPG controller including feedback control loop for driving a simple actuator. Section 4 shows the properties of the CPG controller through several computer simulations. Finally, our work is summarized in section 5.

2. NEURAL BASIS OF LOCOMOTION CONTROL

In this section, we briefly review the neural basis of the control principles in locomotion of animals.

2.1 Central Pattern Generator

Locomotion of animals, such as walking, running, swimming and flying is based on periodic rhythmic movements generated by CPG [1]. CPG consists of sets of neural oscillators, situated in the ganglion or the spinal cord. Induced by inputs from command neurons, a CPG generates a rhythmic pattern of nerve activity automatically, resulting in a rhythmic movement for locomotion of animals. Such a rhythmic movement induces a coordination of physical parts. Since the degree of freedom relevant to locomotion is very high, the coordination of physical parts is necessary for stable locomotion. Thus, CPG can be said to play the principle role in locomotion of animals.

2.2 Global Entrainment

While not necessary for generating a rhythmic pattern of nerve activity, sensory feedback plays also important roles in locomotion control [2]. One role of sensory feedback is to regulate the frequency and phase of the rhythmic nerve activity depending on varying situations. Another is to entrain between the rhythmic pattern of nerve activity and the actual motion of the limbs interacting with the external environment. Based on the biological findings, Taga et al. have proposed that a rhythmic movement emerges as a limit cycle generated through a *global entrainment* between the neural pattern generator and the physical system that interacts with the environment [7]. As a result of the *global entrainment*, autonomous adaptation to the unpredictable events is achieved. Figure 1 shows a conceptual illustration of the *global entrainment*.

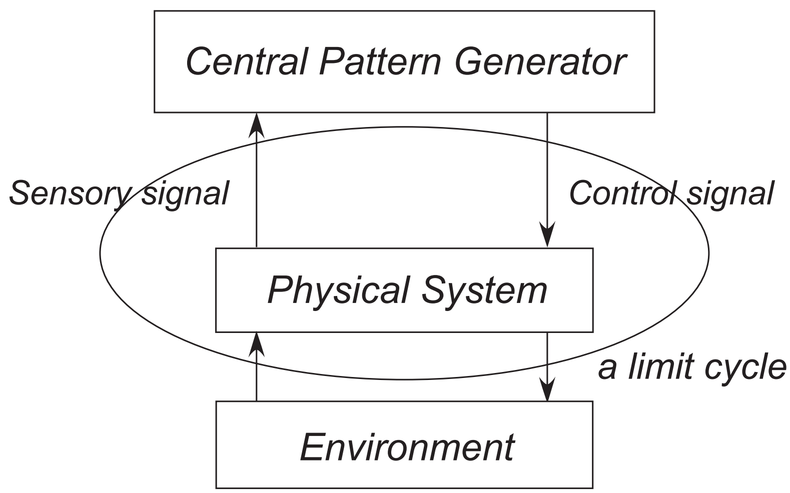


Figure 1. Conceptual illustration of the global entrainment.

3. CPG CONTROLLER

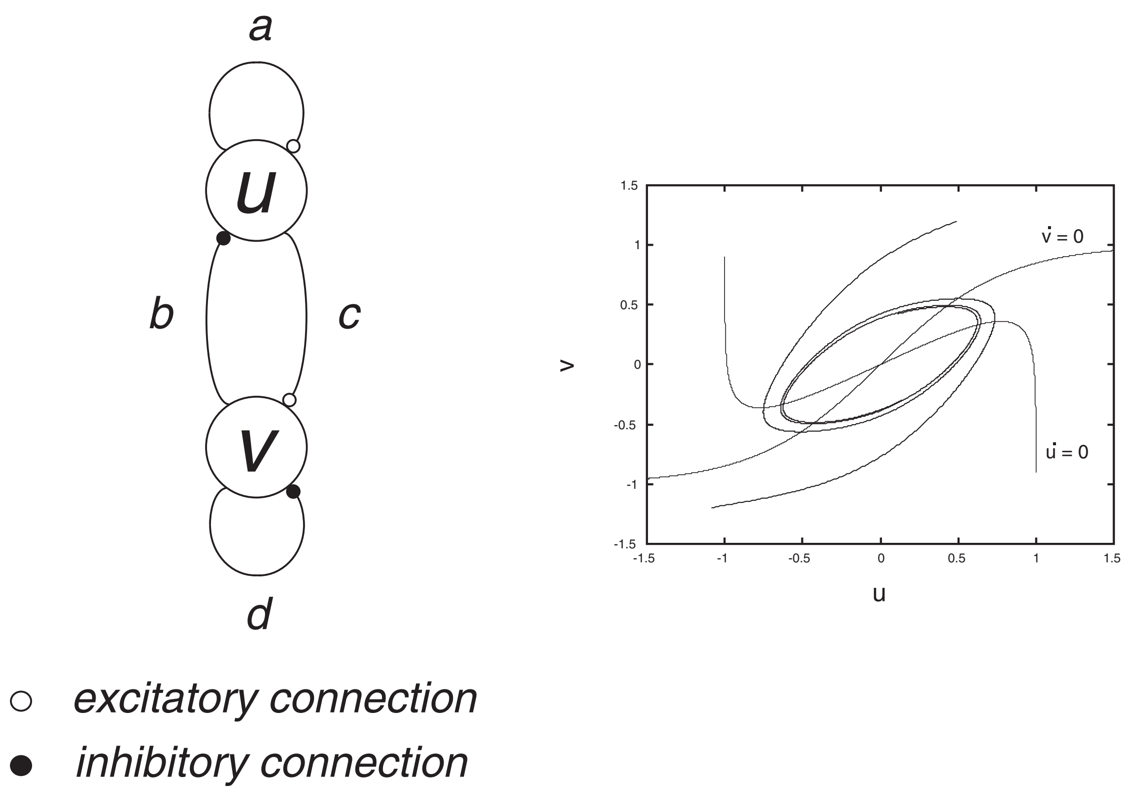
In this section, we propose an artificial CPG controller including a feedback control loop. First, we are going to explain a CPG model underlying the CPG controller. Second, a physical system driven by the CPG controller is described, and the feedback control loop of the CPG controller.

3.1 CPG Model

In the past a great number of CPG models have been proposed [6]-[8]. Most of these have been constructed with coupled nonlinear oscillators. In the present paper, we propose a CPG model based on the Wilson-Cowan neural oscillator [9], which consists of a population of excitatory neurons and inhibitory neurons with reciprocal synaptic connections (Fig. 2(a)). The neural oscillator is described by the following equations:

$$\begin{cases} \dfrac{du}{dt} = -u + f_\mu(au - bv + S_u) \\ \dfrac{dv}{dt} = -v + f_\mu(cu - dv + S_v) \end{cases} \quad (1)$$

where *u* and *v* express the activities of the population of the excitatory and inhibitory neurons, respectively. The parameters *a* through *d* express the synaptic strength between the populations of neurons, S_u and S_v the external inputs such as the bias current and the sensory inputs, τ_u and τ_v the time constants. The transfer function $f_\mu(x) = \tanh(\mu x)$ and μ is its gain parameter. Depending on all the parameters, the Wilson-Cowan neural oscillator shows various oscillatory behaviors. For instance, Figure 2(b) shows limit cycles for stable oscillation in the *u*-*v* phase plane. Because of its differentiable transfer function, the stability of the Wilson-Cowan neural oscillator can be easily analyzed. Figure 3 shows the stable region of the periodic solutions. As driven by an external input, the neural oscillator shows more complex behaviors such as bursting and damping. Such dynamic behaviors of the Wilson-Cowan neural oscillator have been investigated in detail [10].



(a) **(b)**

Figure 2. The Wilson-Cowan neural oscillators. (a) Configurations. (b) Phase-plane portrait.

We constructed a CPG network model from the Wilson-Cowan neural oscillators. The dynamics of the network model is described by the following equations:

$$\begin{cases} \dfrac{du_i}{dt} = -u_i + f_\mu\left(\sum_j a_{ij} u_j - \sum_j b_{ij} v_j + S_{ui}\right) \\ \dfrac{dv_i}{dt} = -v_i + f_\mu\left(\sum_j c_{ij} u_j - \sum_j d_{ij} v_j + S_{vi}\right) \end{cases} \quad (2)$$

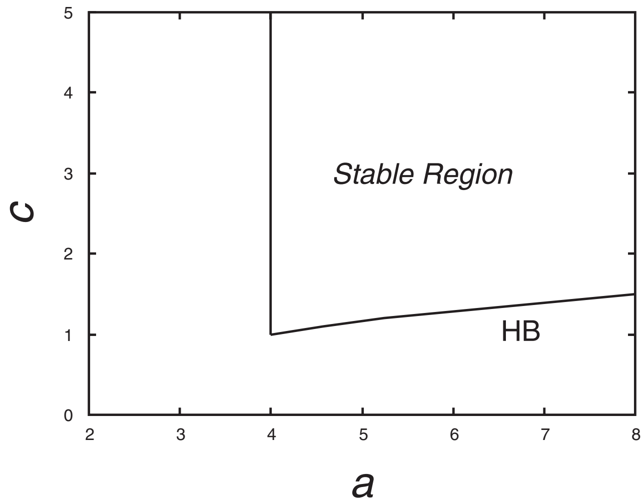


Figure 3. Bifurcation diagrams of the Wilson-Cowan neural oscillator, where we set parameters as follows: $a = b$, $d = 0$, $\mu = 0.5$, $\tau_u = \tau_v = 0.1$ and $S_u = S_v = 0$, and HB represents Hopf bifurcations.

where u_i and v_i express the activities of the i-th population of the excitatory and inhibitory neurons, respectively. Depending on the parameters a_{ij} through d_{ij} and the external inputs S_{ui} and S_{vi}, the CPG network model has various periodic solutions. We can utilize such periodic solutions for controlling of rhythmic movements in locomotion robots.

3.2 Joint Actuator and PD Controller

In the following, we assumed that one neural oscillator drives an actuator connected with a joint of a robot. The dynamics of the joint actuator is given as follows:

$$M\ddot{\theta} + k\dot{\theta} + h\theta = \tau \tag{3}$$

where θ is the joint angle, M the moment of inertia of the joint actuator, k the stiffness parameter, h the damping and τ the driving force. By using a simple proportional differential (PD) controller, the driving force is given as follows:

$$\tau = K_P(\theta_o - \theta) - K_D\dot{\theta} \tag{4}$$

where θ_o is the equilibrium angle. θ and $\dot{\theta}$ can be measured quite accurately. K_P and K_D express the proportional and differential parameter, respectively. The output of the neural oscillator gives the equilibrium angle expressed as follows:

$$\theta_o = g(u - v) \tag{5}$$

where g is the proportional gain. By using the PD controller, the motion of the joints can be stabilized. The physical system including the PD controller is the standard second-order system, which is given by the following equation:

$$G(s) = \frac{K\omega_n^2}{s^2 + 2\varsigma\omega_n s + \omega_n^2} \tag{6}$$

where ω_n is the natural angular frequency of the system, ζ the damping and K a constant. The dynamic characteristics of the system depend on these parameters. We should determine ω_n and ζ in order to get a sufficient quick response of the controller, especially, ω_n should be sufficiently large compared with the natural angular frequency of the neural oscillator. The other parameters K_P, K_D, K and g will be determined thorough the following equations, once ω_n and ζ are given:

$$2\varsigma\omega_n = \frac{K_D + h}{M},\ \omega_n^2 = \frac{K_P + k}{M},\ K\omega_n^2 = \frac{K_P g}{M} \tag{7}$$

where the constant K decides the dynamic range of the joint angle θ. In the following section, we assumed that M=1.0, ω_n =25.0, ζ=1.5 and K =0.5.

3.3 Feedback Controller

One of the key issues in the design of a CPG controller is how to give a sensory feedback to the controller since it might influence the stability of the system. Hence, we should consider the stability of the whole system by examining the following equations, which is taking into account sensory information:

$$\begin{pmatrix} \tau_u \dot{u} \\ \tau_v \dot{v} \\ \dot{\theta} \\ M\dot{\omega} \end{pmatrix} = \begin{pmatrix} -u + f_\mu(au - bv + S_u(\theta, \dot{\theta})) \\ -v + f_\mu(cu - dv + S_v(\theta, \dot{\theta})) \\ \omega \\ K_P g(u-v) - (K_P + k)\theta - (K_D + h)\omega \end{pmatrix} \tag{8}$$

where S_u and S_v are the functions of the sensory information about the joint of the states θ and $\dot{\theta}$. Since the nonlinear function of the Wilson-Cowan neural oscillator is differentiable, the Jacobian matrix of the above system is easily obtained. Therefore, the stability of the system with any reasonable sensory feedback function can be analyzed. Based on the results, we can determine the parameters of the CPG controller including a sensory feedback control.

4. RESULTS

In this section, we show the properties of the CPG controller through computer simulations.

4.1 Stability Analysis

We analyzed the stability of the CPG controller including the feedback control (Figure 4). By computer simulation, we investigated bifurcations of periodic solutions of the Wilson-Cowan neural oscillator with two types of sensory feedback such as follows:

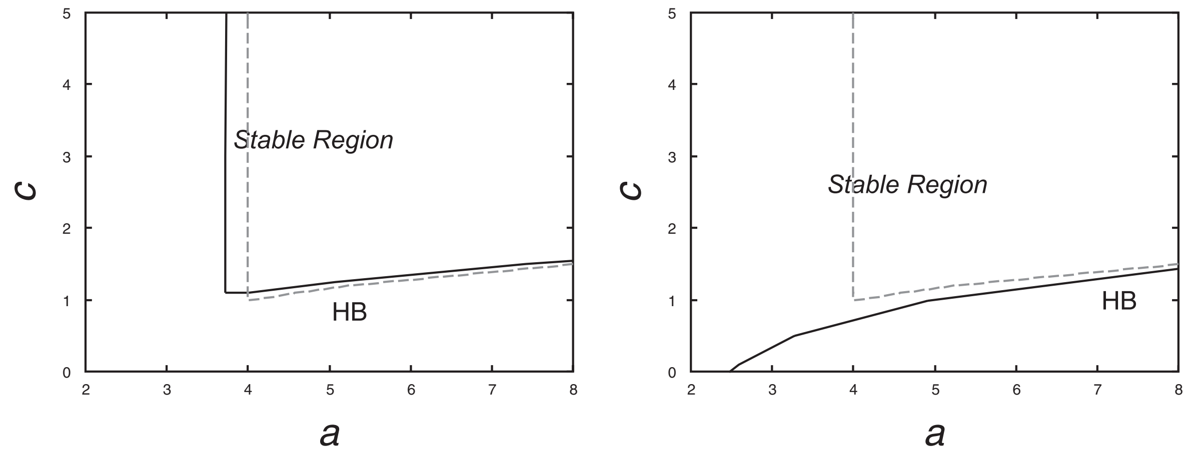
$$S_u(\theta, \dot{\theta}) = \eta\theta \ \ or \ \ \eta\dot{\theta}, \quad S_v(\theta, \dot{\theta}) = 0 \tag{9}$$

where η is the feedback gain. The following results were obtained by using AUTO [12], which is an application for bifurcation analysis of ordinary differential equations. Figures 4(a) and (b) show the bifurcation diagrams of the control system, where HB represent the Hopf bifurcation. By introducing both of the sensory feedback $\eta\theta$ and $\eta\dot{\theta}$, the stable region of periodic solutions is found to be extended (see Figure 3).

4.2 Frequency and amplitude modulation

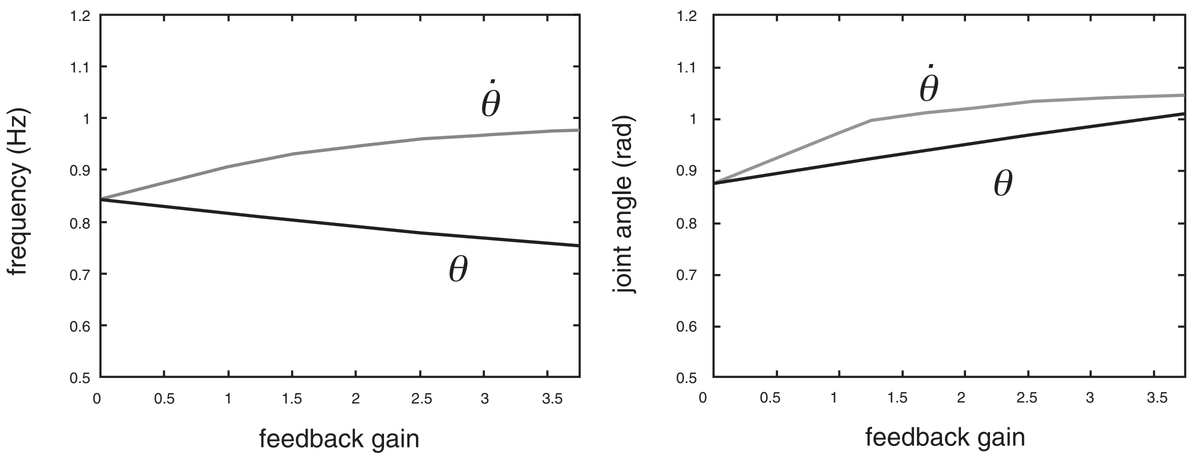
Williamson investigated the frequency entrainment between the neural oscillator proposed by Matsuoka [6] and the joint actuator modeled by (15) [11]. We also investigated the frequency and amplitude modulation of our controller by changing the feedback gain. In the following, we set parameters as follows: a=b=5.5, c = 2.5, d=0, μ=0.5, and τ_u= τ_v =0.1. Figure 5(a) shows the oscillatory frequency of the controller with the sensory feedback $\eta\theta$ and $\eta\dot{\theta}$. Depending on the type of the feedback and its gain, different responses were observed. Figure 5(b) shows the amplitude of the periodic solution that corresponds the joint angle at the same conditions.

As the joint angle $\dot{\theta}$ is used for sensory feedback, its sensory feedback gain increases the amplitude of the periodic solution with decreasing the frequency of the periodic solution. By using the angular velocity



(a) (b)

Figure 4. Bifurcation diagrams of the system including feedback control. (a) $S_u = \eta\theta$ and (b) $S_u = \eta\dot{\theta}$.



(a) (b)

Figure 5. Frequency and amplitude modulation of the system.

for sensory feedback, we can increase the frequency of the controller with increasing the amplitude. Based on the results, we can make use of the feedback function given by the following equation for regulating the amplitude and frequency of the system independently (Figure 6):

$$S_u(\theta,\dot{\theta}) = \varsigma\theta + \eta\dot{\theta} \tag{10}$$

where ζ is the feedback gain. If we implement our CPG controller as an analog circuit, this feedback function should be useful for controlling rhythmic patterns generated by the circuit. According to the physical system driven by the CPG controller, we can construct a suitable feedback function.

5. SUMMARY

In the present paper, we propose an approach to design of an artificial CPG controller including a feedback control loop. Our controller is based on a CPG model constructed from the Wilson-Cowan neural oscillator. In order to achieve stable locomotion, we introduced the PD controller into the individual

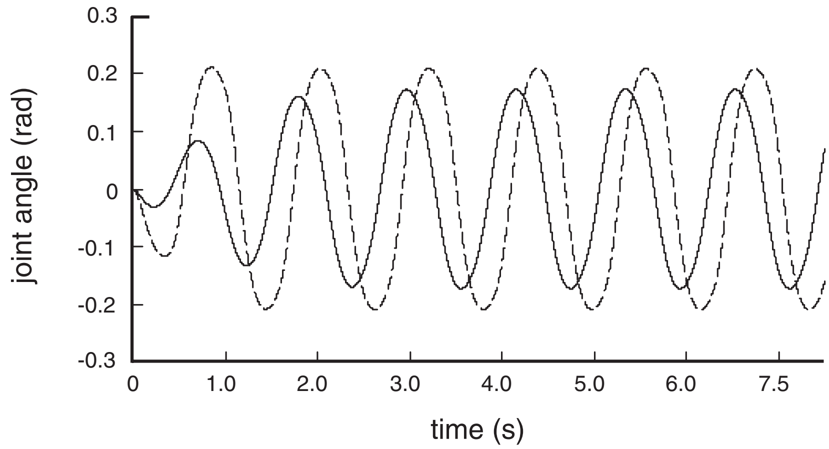


Figure 6. Waveforms of joint angle, where $\zeta = \eta = 0.0$ (bold line) and $\zeta = 3.5$, $\eta = 1.2$ (solid line).

oscillator that drives each of the joints, and used the sensory information about the joint states as a feedback to the CPG controller. By several computer simulations, we investigated the properties of the CPG controller. First, we analyzed the stability of the periodic solutions of the controller. As a result, it is shown that the stable region is extended further by introducing the feedback control. Second, we investigated how the sensory feedback and its gain modulate the frequency and amplitude of the joint angle driven by the controller. Thus, it is also shown that the feedback function combining the joint angular and the angular velocity can regulate the frequency and the amplitude independently. These results provide useful information to design a CPG controller. In future, it is hoped, we will be able to implement the CPG controller for a biologically-inspired walking robot.

REFERENCES

1. F. Delcomyn. 1980. "Neural basis of rhythmic behaviour in animals", *Science*, vol. 210, pp. 492-498.
2. F. Delcomyn. 1997. *Foundations of Neurobiology*, New York: W.H. Freeman and Co.
3. H. Kimura, Y. Fukuoka, and K. Konaga. 2001. "Adaptive dynamic walking of a quadruped robot by using neural system model", *ADVANCED ROBOTICS*, Vol. 15, No. 8, pp.859-876.
4. A. Billard and A. J. Ijspeert. 2000. "Biologically inspired neural controllers for motor control in a quadruped walking robot", *in proc. IEEE-INNS International Joint Conference on Neural Networks*, Italy.
5. M. A. Lewis, M. J. Harttmann, R. Etienne-Cummings, and A. H. Cohen. 2001. "Control of a robot leg with an adaptive aVLSI CPG chip", *Neurocomputing,* vol. 38-40, pp. 1409-1421.
6. K. Matsuoka. 1987. "Mechanism of frequency and pattern control in the neural rhythm generators", *Biol. Cybern.*, vol, 56, pp.345-353.
7. G. Taga, Y. Yamaguchi, and H. Shimizu. 1991. "Self-organaized control of bipedal locomotion by neural oscillators in unpredictable environment", *Biol. Cybern.*, vol. 65, pp.147-159.
8. H. Nagashino, Y. Nomura, and Y. Kinouchi. 2001. "Generation and transitions of phase-locked oscillations in coupled neural oscillators", *in proc. the 40h SICE Annual Conference*, Nagoya, Japan.
9. H. R. Wilson and J. D. Cowan. 1972. "Excitatory and Inhibitory interactions in localized populations of model neurons", *Biophys., J.*, Vol. 12, pp.1-24.
10. F. C. Hoppensteadt and E. Izhikevich. 1997. *Weakly Connected Neural Networks*, Springer-Verlag.
11. M. Williamson. 1998. "Neural control of rhythmic arm movements", *Neural Networks, special issue on neural control of movement*, pp.1379-1394.
12. E. Doedel, X. Wang, and T. Fairgrieve. 1994. "Auto94: Software for continuation and bifurcation problems in ODEs", *Appl. Math. Technical Report*, California Inst. of Technology.