15

Basic Concepts of the Control and Learning Mechanism of Locomotion by the Central Pattern Generator

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1. Introduction

Basic locomotor patterns of living bodies, such as walking and swimming, are produced by a central nervous system that is referred to as the CPG (central pattern generator). In vertebrates, the CPG is located in the spinal cord and a burst signal from the brainstem induces a periodic activity in the CPG. The firing pattern of the CPG is strongly affected by sensory feedback signals from the musculoskeletal system; with the help of these feedback signals, the CPG synchronizes with body movement and accordingly send motor commands to motor neurons at an appropriate time in a movement cycle. Although it has been known that higher centers are also involved in the control of locomotion, particularly in higher vertebrates such as cats (Takakusaki et al., 2004), some experiments on spinal animals have revealed that only the CPG in the spinal cord can generate a basic motor command (Kandel et al., 2000). Although the neural circuit of the CPG would be genetically determined at a significant level, some studies such as those on spinal cats suggest the existence of a learning mechanism in the CPG (Rossignol & Bouyer, 2004).

How does the CPG learn and generate proper motor signals for locomotor patterns? Considering the answer for this question would not only help the understanding of learning control system of living bodies but also bring a hint to make legged robots. In fact, some studies using computer simulation and legged robots have indicated the robustness of locomotion by using the concept of the CPG (Taga et al., 1991; Fukuoka et al., 2003). In this chapter, we introduce basic concepts of the control and learning mechanism of locomotor patterns produced by the CPG.

2. CPG and physical system

The CPG generates a periodic activity on receiving a burst signal from the brainstem. Therefore, the CPG is often modeled as an oscillatory network that translates the spatio-pattern from higher centers (supraspinal centers) to a periodic pattern. Let us begin modeling the CPG from the most simple mathematical form: a phase oscillator model,

$$\dot{\theta} = \omega, \tag{1}$$

Source: Bioinspiration and Robotics: Walking and Climbing Robots, Book edited by: Maki K. Habib
ISBN 978-3-902613-15-8, pp. 544, I-Tech, Vienna, Austria, EU, September 2007

where θ and ω are the phase and intrinsic frequency of the oscillator, respectively. A locomotor pattern is generated as a result of interaction between the CPG and a physical system. In the case of walking, a leg has its intrinsic frequency and exhibits a periodic movement. Therefore, the physical system can also be regarded as an oscillator based on which the dynamics of the CPG and the physical system can be modeled as

$$\begin{cases} \dot{\theta} = \omega + \varepsilon R(\theta, \tilde{\theta}) \\ \dot{\tilde{\theta}} = \Omega + \varepsilon_f F(\tilde{\theta}, \theta), \end{cases} \tag{2}$$

where $\tilde{\theta}$ and Ω denote the phase and intrinsic frequency of the physical system, respectively. $R(\theta, \tilde{\theta})$ indicates the effect of sensory signals on the phase dynamics of the CPG, $F(\tilde{\theta}, \theta)$ signifies the effect of the control signal from the CPG on the physical system, and $\varepsilon, \varepsilon_f << 1$ indicate the coupling strength. When the dynamics of the CPG can be transformed to the Poincare's normal form for Hopf bifurcation and the attraction to the limit cycle is strong, the above phase dynamics of the oscillator can be approximated as follows:

$$\dot{\theta} = \omega + \varepsilon P(\theta) Q(\tilde{\theta}), \tag{3}$$

where $P(\theta) \approx a \sin(\theta + \phi)$ (a, ϕ: constants) indicates the effect of an input signal on the phase dynamics of the oscillator, and $Q(\tilde{\theta})$ is a sensory feedback signal from the physical system to the oscillator (Nishii & Suzuki, 1994).

3. Control parameters of the CPG

Which parameters of the CPG must be coordinated in order to realize a target motion? First, the intrinsic frequency of the CPG must be tuned in order to synchronize the firing pattern of the CPG with the physical system. This is because it is difficult to synchronize the CPG and the physical system if there is a considerable difference between their intrinsic frequencies; consequently a significant amount of energy is required to control the physical system.

Second, the phase difference between the CPG and the physical system should be coordinated in order that the CPG fires and sends signals to motor neurons at a proper time within a period of the movement. Then, how can the phase difference be adjusted? In living bodies, feedback signals from the musculoskeletal system have large effects on the central nervous system, and a variety of feedback signals exist, e.g., information of muscle length and tension. Therefore, the phase difference between the CPG and the physical system can be coordinated by a combination of these feedback signals. The dynamics of the CPG with such feedback signals can be modeled by

$$\dot{\theta} = \omega + \sum_i w_i P(\theta) Q_i(\tilde{\theta}), \tag{4}$$

where $Q_i(\tilde{\theta})$ and $w_i << 1$ indicate a sensory feedback signal from a physical system and the connection weight of the i-th signal, respectively (Fig. 1(a)). When different cells in a neural oscillator receive a feedback signal (Fig. 1(b)), we obtain the following phase dynamics:

$$\dot{\theta} = \omega + \sum_i w_i P(\theta - \varphi_i) Q(\tilde{\theta}), \tag{5}$$

where φ_i is the phase delay of the effect of the i-th feedback signal. When $Q_i(\tilde{\theta}) = Q(\tilde{\theta} + \varphi_i)$ in eq. (4), eq. (4) and (5) take the same following form by applying the averaging method (Guckenheimer & Holmes 1983):

$$\dot{\theta} = \omega + \sum_i w_i R(\phi - \varphi_i), \tag{6}$$

where $\phi = \theta - \tilde{\theta}$, and $R(\phi)$ is the correlation function between $P(\theta)$ and $Q(\tilde{\theta})$. Therefore, eq. (4) and (5) are equivalent in the time averaged form, and we use eq. (4) in the following sections.

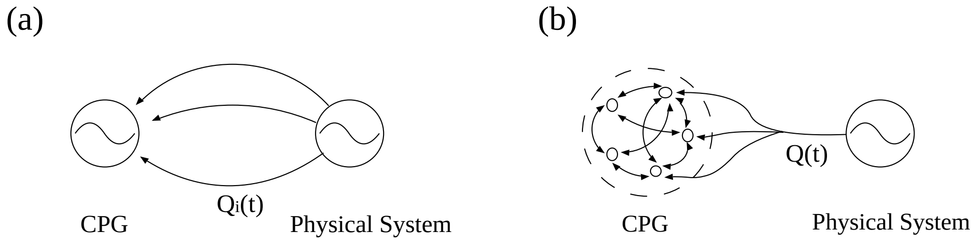

Figure 1. Feedback signals from a physical system to the CPG

4. Learning models of the CPG

There are two possible cases for the learning of a proper parameter set of the CPG. In the first case, the CPG receives an explicit desired firing pattern $T(t)$ that it should produce, and the parameters of the CPG—such as intrinsic frequency and coupling weights between the CPG and physical system—are coordinated so that the firing pattern produced by it approaches the teacher signal $T(t)$ (Fig. 2(a)). In this case, the phase dynamics of the CPG, the learning rule of the intrinsic frequency, and the coupling weights can take the following form (Nishii, 1998):

$$\dot{\theta} = \omega + \sum_i w_i P(\theta) Q_i(\tilde{\theta}) + P(\theta) T(t),$$

$$\begin{cases} \dot{\omega} = \varepsilon_\omega \{ \sum_i w_i < P(\theta) Q_i(\tilde{\theta}) > + < P(\theta) T(t) > \} \\ \dot{w}_i = \varepsilon < P(\theta) Q_i(\tilde{\theta}) > \cdot < P(\theta) T(t) >, \end{cases} \tag{7}$$

where $\varepsilon << 1$ and $\varepsilon_\omega << 1$ are the learning rates, and $<>$ denotes the time average.

In the second case, instead of a desired firing pattern, the CPG receives error signals based on the evaluation of the performance of the physical system (Fig. 2(b)). In this case, the phase dynamics of the CPG and the learning rule can take the following form:

$$\dot{\theta} = \omega + \sum_i w_i P(\theta) Q_i(\tilde{\theta}),$$

$$\begin{cases} \dot{\omega} = \varepsilon_\omega \{ \sum_i w_i < P(\theta) Q_i(\tilde{\theta}) > \} \\ \dot{w}_i = \varepsilon < P(\theta) Q_i(\tilde{\theta}) > \cdot < E(t) >, \end{cases} \tag{8}$$

where $E(t)$ is an error function of the performance of the physical system (Nishii, 1999(a)).

In both the cases, the learning rules imply that the intrinsic frequency ω is modulated according to the sum of the effects of the input signals on the CPG so as to adapt the current frequency (Fig. 3(a)). The coupling weight w_i is modulated according to the correlation of the effect of the feedback signal from the physical system with the teacher signal in the first case, and with the error function in the second case (Fig. 3(b)). In other words, when the effects of the teacher signal and the feedback signal have the same signs in the first case, the coupling weight is enforced, while the weight is reduced when they have opposite signs. It was mathematically proved that these learning rules enable the acquisition of a proper parameter set of the CPG, provided that a stable solution always exists in the phase difference between the CPG and the physical system and each function in eq. (7) and (8) satisfies some conditions. The learning rule eq. (7) can be applied not only for coupled two oscillators but also for an oscillatory network when each oscillator receives the teacher signal (Nishii, 1998). The learning rule of the intrinsic frequency was also applied in the study by Righetti et al. (2006).

The validity of these learning rules was confirmed by computer simulations and the learning control of a hopping robot (Nishii, 1998, 1999(a), 1999(b)). Figure 4 is an example of the simulations using two coupled oscillators and Fig. 5 shows a result of the learning. It is shown that the phase difference approaches the desired phase difference as learning proceeds. After the learning, the memorized phase difference was recalled from a random phase pattern.

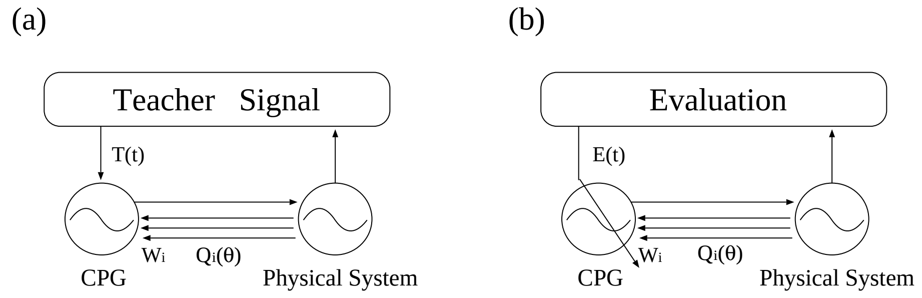

Figure 2. Learning model of the CPG

The learning rules can also be rewritten as a learning rule for a neural cell that composes a neural oscillator (Nishii, 1999 (b)). Figure 6 shows a simulation experiment of the adaptive control of a one-dimensional hopping robot by a neural oscillator. The thruster of the robot generates a force between the trunk and toe when an oscillator fires and sends a control signal. As a result, the desired hopping heights were successfully achieved by the learning rule (Fig. 7).

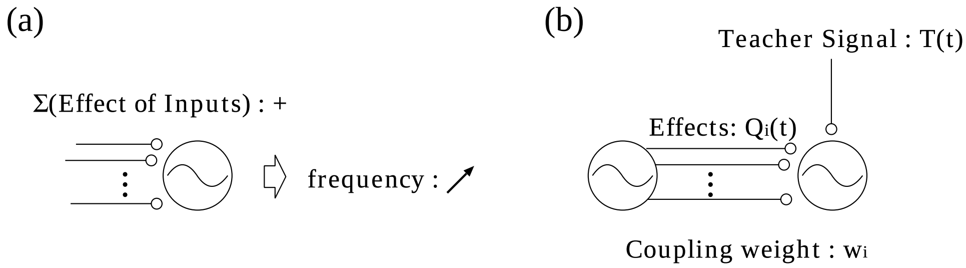

Figure 3. Learning rules for coupled oscillators. (a) The intrinsic frequency ω changes according to the sum of the effects of input signals. (b) The coupling weight w_i changes according to the correlation between the input signal Q_i and the teacher signal $T(t)$

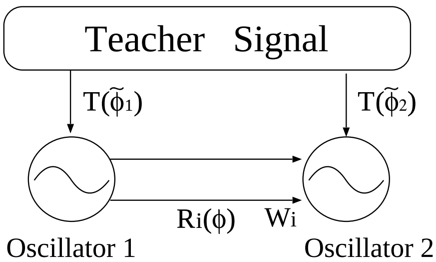

Figure 4. Coupled oscillators forced by teacher signals with the desired frequency and phase. $T(\phi)$ denotes the effect of the teacher signal; $R_i(\phi)$ and w_i are the i -th effect and the connection weight, respectively, of the signal from oscillator 1 to oscillator 2; $\phi = \theta_2 - \theta_1$, $\tilde{\phi}_1 = \theta_1 - \tilde{\theta}_1$, $\tilde{\phi}_2 = \theta_2 - \tilde{\theta}_2$ are the phase differences, and $\tilde{\theta}_1$ and $\tilde{\theta}_2$ are the phases of teacher signals for oscillator 1 and oscillator 2, respectively. This expression is obtained by using the averaging theory for eq. (7)

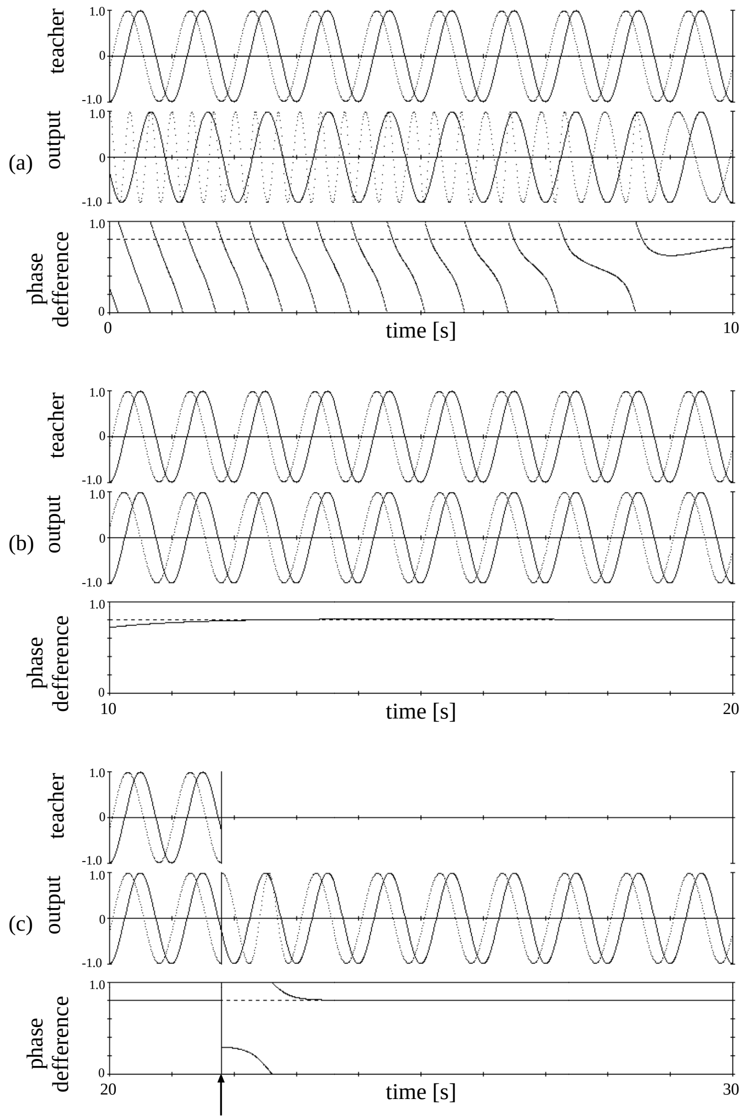

Figure 5. Time profile of the phases in learning a phase difference between two oscillators, each of which receives a teacher signal. Each figure shows the phases of the teacher signals for oscillator 1 (solid line) and oscillator 2 (dotted line) (top), the outputs of the oscillators (center), and the phase difference between the two oscillators (bottom). (a) and (b) are learning modes, and (c) is the recalling mode. The effect of oscillator 1 on oscillator 2 is set as $R_i(\phi) = \sin 2\pi\phi$, and the effect of the teacher signal is set as $T(\phi) = \sin 2\pi\phi$, where ϕ is the phase difference between the two oscillators. The arrow indicates when the learning stopped (Nishii, 1998)

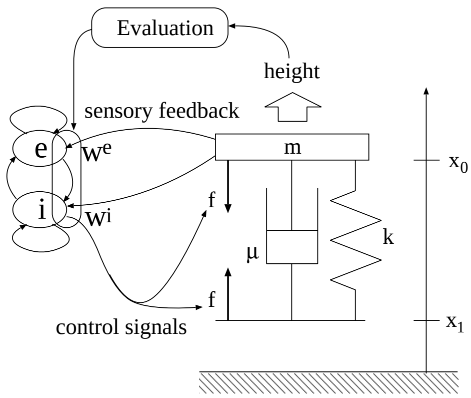

Figure 6. One-dimensional hopping robot. The robot consists of a trunk with mass m and a leg with a spring component (elastic coefficient: k), a damping component (damping coefficient: μ), and a thruster. The oscillator sends control signals to the thruster that generates a force f between the trunk and the toe and receives the sensory feedback signals from the robot (Nishii, 1999(b))

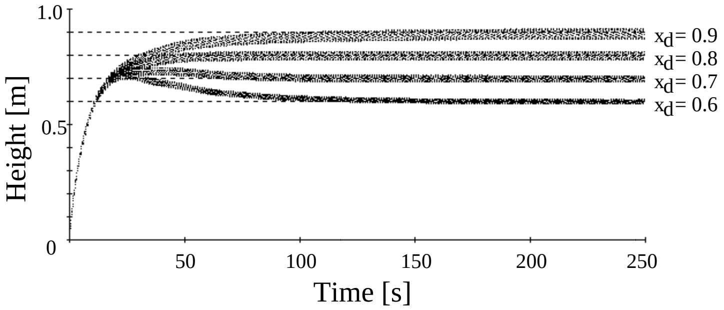

Figure 7. Time profile of the time averaged heights of the trunk of the hopping robot. In this simulation, the evaluation function is set as $E = x_d - < x_0 >$, where x_d = 0.6, 0.7, 0.8, 0.9 [m] are the desired hopping heights, and $< x_0 >$ is the time averaged height of the trunk (Nishii, 1999(b))

5. Learning control model of the CPG and higher centers

We have introduced simple learning models for coupled oscillators in previous sections. When we apply these models to the learning control of a robot with multi-degree of freedom using coupled oscillators, we must solve some problems: how the evaluation signals or the teacher signals for the oscillators are obtained and how the amplitude of the motor command is tuned. During the learning of a locomotor pattern, the evaluation of the locomotion would be expressed by some indexes such as stability and energy cost. However, it would be difficult to specify how each of the phase differences between oscillators affects the evaluation; this makes it difficult to apply the learning rules for oscillators. Then, how do living bodies acquire adequate parameters of the CPG? In this section, we introduce a hierarchical learning model that is a model of the mechanism to acquire the teacher signal for the CPG.

5.1 Hierarchical learning model of the CPG and higher centers

It has been known that the legged locomotion of animals is controlled by not only the CPG in the spinal cord but also higher centers such as the cerebellum and motor cortex (Kandel et al., 2000). It appears that these higher centers play important roles in the realization of locomotion, e.g., monitoring and controlling the activity of the CPG, particularly for reacting to perturbation and avoiding obstacles. If we assume that the higher centers evaluate the performance of locomotion and learn control signals for the component oscillators of the CPG by some learning mechanisms such as reinforcement learning, the control signal can serve not only for tuning the activity of the oscillators but also as a teacher signal for the learning of the CPG. Some experimental studies have also reported the existence of some projections from higher centers, such as motor cortex, to the spinal cord, which affect the activity of motor neurons (Takakusaki et al. 2004). Although it would be difficult to independently modulate the period, phase relation, and amplitude of the firing pattern of coupled neural oscillators by tuning the parameters within the oscillators, the modulation would become easier if higher centers control the amplitude.

The above considerations led to the concept of the hierarchical learning model proposed by Miyazaki et al. (2007) (Fig. 8). This model consists of a physical system, a higher center, the CPG, and motor neurons. In this model, the higher center monitors the activity of the CPG and the result of locomotion through sensory feedback signals. It also learns the control signals to the CPG, such as a reset signal that induces an immediate firing of component oscillators of the CPG and a suspend signal that delays the firing, according to the states of the physical system and the CPG. The CPG coordinates its intrinsic frequency and the weights of connections from sensory feedback signals so as to decrease the effect of control signals from the higher center by eq. (7); thus, the CPG can itself produce the desired signal without the control signal after learning. The higher center also learns and controls the amplitude of motor command.

This model was again applied to the learning control of a one-dimensional hopping robot (Fig. 6). In this application, an actor-critic architecture of reinforcement learning was used for the learning of the higher center. As learning progressed, the robot was able to hop at the target heights. Figure 9 shows the activity of the higher center and the amplitude of the force both during and after learning. Shortly after the beginning of learning, many control signals were sent to the CPG and the amplitude of the force continued to change, since the higher center explored the control signals for the desired hopping. After learning, the robot hopped at the target height, and the higher center sent no signal to the CPG, and the force amplitude attained a constant value.

Figure 10 shows the time profile of the height of the trunk of the robot, the control signals from the higher center, and the amplitude of the force when a mechanical perturbation was applied to the robot after learning. It is shown that the higher center sent control signals and tuned the amplitude of the force in response to the perturbation. When the hopping of the robot was perturbed, the hopping was sometimes stopped. The recovery obtained by using the multiple controls from both the CPG and the higher center exhibited a higher success rate and a shorter average time than that obtained by using only the control from the CPG.

These results indicate that this multiple control system comprising the CPG and higher centers is more robust than that based only on the CPG. Although we introduced the simulation result for the control of a physical system having only one degree of freedom, the proposed learning model can be applied to the learning of a physical-system with multi-degree of freedom by using coupled oscillators and the learning rules described in section 4.

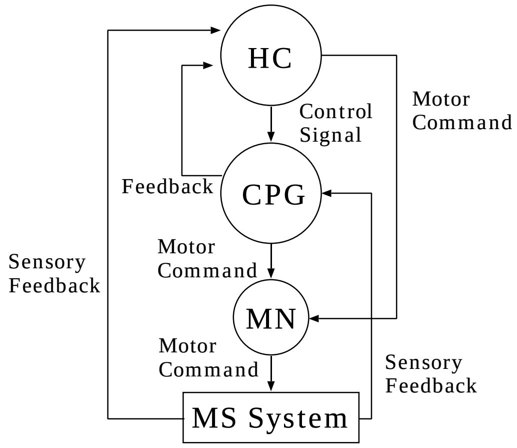

Figure 8. Schematic representation of the hierarchical learning model of the CPG and higher centers. A control signal generated by a higher center is sent to a motor neuron through the CPG. In this figure, HC denotes a higher center; MN, a motor neuron; and MS, the musculoskeletal system (Miyazaki et al., 2007)

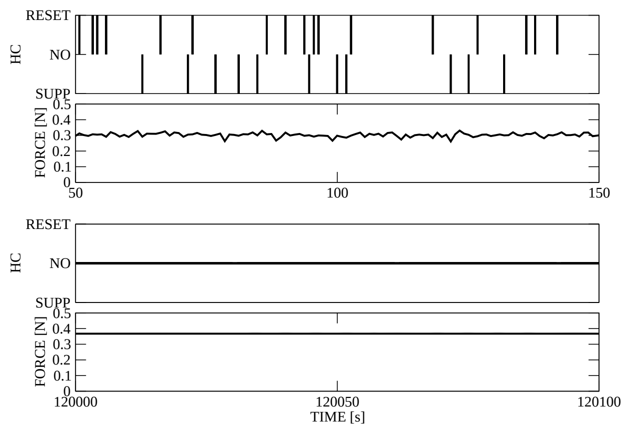

Figure 9. Simulation result of the learning control of the hopping robot by the hierarchical learning model of the CPG and higher centers. The activity of the higher center and the amplitude of the force during learning (the upper two figures) and after learning (the lower two figures) are shown. The target height was set as 1.0 [m]. The first figure in each pair shows the control signals of the higher center—the vertical lines above and below the abscissa indicate the reset and suspend signals from the higher center to the CPG, respectively. The second figure in each pair shows the amplitude of the force (Miyazaki et al., 2007)

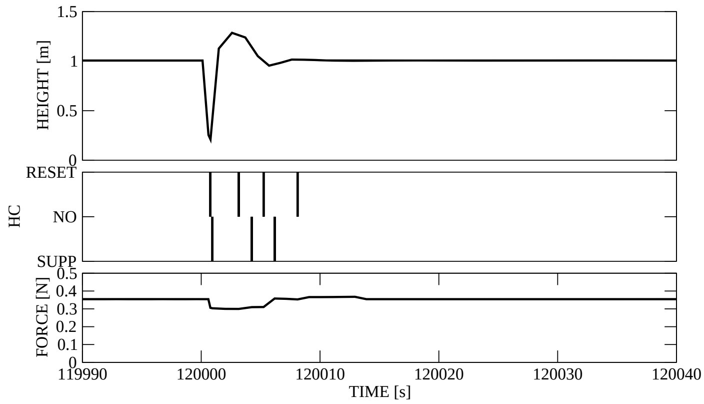

Figure 10. Response to a perturbation of the hopping robot controlled by the hierarchical learning model. The time profile of the height of the trunk of the robot (top), the control signal of the higher center (middle), and the amplitude of the force (bottom) when a mechanical perturbation was applied after learning. The target height was set as 1.0 [m] (Miyazaki et al., 2007)

5.2 Coordination of the waveform of the motor command

Many studies concerning walking patterns have suggested that many locomotor parameters such as the stance length and period of leg swing and swing trajectory are optimized for each locomotion speed based on energy cost (Donelan et al., 2001; Minetti & Alexander, 1997; Nishii, 2000, 2006; Nishii & Nakamura, 2005; Zarrugh & Radcliffe, 1978). These results suggest that the waveform of the motor command is well designed to realize efficient locomotion. How can the coupled oscillators of the CPG design the waveform of a motor command? In living bodies, motor neurons receive the output signals from the component neurons of the CPG, which fire at a variety of phases, and as mentioned in the previous section, it is suggested that higher centers modulate the activities of motor neurons.

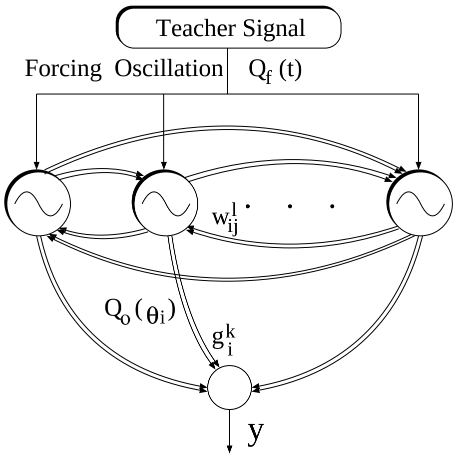

Figure 11. Structure of the oscillator network proposed by Nishii & Suzuki (1994)

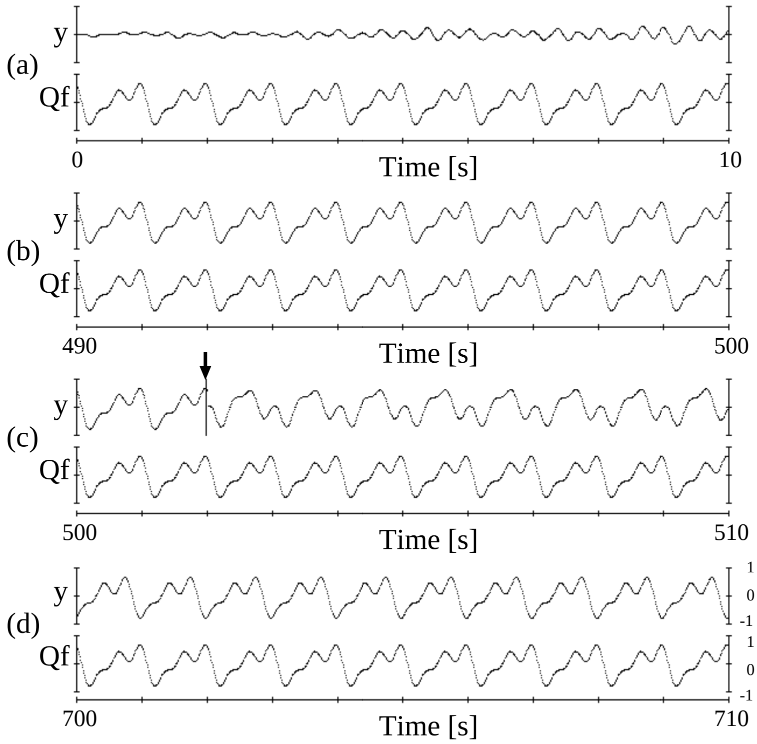

Figure 12. Output of the oscillator network during and after learning. y is the output of the network and Q_f is the teacher signal. (a) and (b) correspond to the learning phase. (c) and (d) correspond to the recalling phase. The arrow indicates the time when the learning is stopped and the network begins to recall the desired signal from random initial phases (Nishii & Suzuki, 1994). In this simulation, $Q(\theta) = (\cos 2\pi\theta + \cos 4\pi\theta + \cos 6\pi\theta) / 3$, $Q_0 = \cos 2\pi\theta$, $P(\theta) = \sin 2\theta$, $Q_f(t) = (\cos 2\pi(t + 0.2) + (\cos 4\pi t + \cos 6\pi t) / 2) / 2$

From these considerations, Nishii and Suzuki (1994) proposed an oscillatory network that is composed of a layer of mutually coupled oscillators and an output cell (Fig. 11). The phase dynamics of each oscillator are given by eq. (7); the output cell receives signals $Q_o(\theta)$ from oscillators and outputs the sum of a linear combination of the signals, i.e., the output y is given by

$$y = \sum_{i,l} g_i^l Q_o(\theta_i - \psi_i^l) , \tag{9}$$

where ψ_i^l and g_i^l are the phase delay and the weight of each connection, respectively. In a learning mode, all the oscillators receive a desired rhythmic pattern from a higher center, and the intrinsic frequencies of component oscillators and connections between them are changed according to the learning rule eq. (7). The connections from each oscillator to the output cell are modulated in order to minimize the square error E between the output of the network y and the teacher signal Q_f, i.e.,

$$E = \frac{1}{2}(y - Q_f)^2,$$

$$\dot{g}_i^k = -\varepsilon \frac{\partial E}{\partial g_i^k} = -\varepsilon (y - Q_f) Q_0 (\theta_i - \psi_i^k), \quad (10)$$

where ε is the learning rate. Figure 12 shows the simulation result. The output of the network converges to the desired signal in the learning phase, and the desired signal is recalled after learning from random initial phases of oscillators. In this model, each intrinsic frequency of the component oscillators of the CPG converges to a component frequency of the teacher signal. Although there is no evidence that the desired waveform of a motor pattern in living bodies is decomposed into component frequencies, a desired waveform of motor command would be obtained by the linear sum of the outputs from the component neurons of the CPG which fire with a variety of phases and duration, and the proposed learning rule in this section could be applied.

6. Conclusion

In this chapter, we introduced the basic concepts of the control and learning mechanism to realize a desired locomotion by the CPG. As introduced in section 5.1, the control system of locomotion in living bodies assumes a hierarchical structure in which the CPG synchronizes with a physical system and generates motor signals to motor neurons, and higher centers learn a desired motor signal from the performance of locomotion and control the CPG. The control signal from higher centers can also function as a teacher signal for the CPG to acquire neural parameters in the CPG. The concept that the higher centers acquire a motor command appears to be a natural assumption because higher centers such as the motor cortex sends motor commands in order to respond to sensory stimulus, e.g., avoiding obstacles. Such hierarchical and multiple control system by higher centers and the CPG also contribute to acquire robust control, as shown in the simulation result in section 5.1. The concept of this model with learning rules for coupled oscillators that send signals to each actuator can be applied to a robot with multi-degree of freedom. However, in order to consider the learning system for locomotion, we should consider the learning mechanism not only for the CPG but also for higher centers. For instance, it appears that higher centers play an important role in shaping the motor command that is generated by the CPG, as mentioned in section 5.2. Another important problem is the explosion of the search space of a motor command, e.g., as the number of actuators increases, that is, as the degree of freedom of a robot increases, the search space for the desired motor command becomes vast. Therefore, it is important to consider an efficient learning mechanism for higher centers to find a desired motor command for each actuator from the performance of locomotion. It has been suggested that locomotor patterns of living bodies are well optimized on energy cost; as mentioned in section 5.2; therefore, the minimization of energy cost would be a constraint to design a locomotor pattern. Such a constraint would contribute to narrow the search space for the desired motor command. Recent studies have also revealed that human walking is generated by some base set of muscle activities (Ivanenko et al., 2004), which suggests the existence of a good base of motor commands for locomotion. The understanding of an efficient system in living bodies to find a desired motor command or a base set for a motor command under some criterion would be a challenging problem for revealing the intelligence of living bodies.

7. Reference

Donelan, J.; Kram, R. and Kuo, A. (2001). Mechanical and metabolic determinants of the preferred step width in human walking, *Proceeding of the Royal Society of London B*, Vol. 268, pp. 1985-1992.

Fukuoka, Y.; Kimura, H. and Cohen, H. (2003). Adaptive dynamic walking of a quadruped robot on irregular terrain based on biological concepts, *International Journal of Robotic Research*, Vol. 22, No. 3-4, pp. 187-202.

Ivanenko, Y.; Poppele, R. and Lacquaniti, F. (2004). Five basic muscle activation patterns account for muscle activity during human locomotion, *Journal of Physiology*, Vol. 556, No. 1, pp.267-282.

Guckenheimer, J. and Holmes, P. (1983). *Nonlinear oscillations, dynamical systems, and bifurcations of vector fields*, New York: Springer-Verlag, ISBN 0387908196.

Kandel, E.; Schwartz, J. and Jessell, T. (2000). Locomotion, In: *Principles of neural science Fourth Edition*, pp. 737-755, McGraw-Hill Companies, ISBN 0838577016.

Minetti, A. and Alexander, R. (1997). A theory of metabolic costs for bipedal gaits, *Journal of Theoretical Biology*, Vol. 186, pp.467-476.

Miyazaki, Y.; Maeda, H.; Hioki, T. and Nishii, J. (2007). A hierarchical learning control model of locomotor patterns of legged animals, *Proceeding of 2nd International Symposium on Mobiligence*, pp. 295-298.

Nishii, J. and Suzuki, R. (1994). Oscillatory network model which learns a rhythmic pattern of an external signal, *Proceeding of IFAC symposium*, pp. 501-502.

Nishii, J. (1998). A learning model for oscillatory networks, *Neural Networks*, Vol. 11, pp. 249-257.

Nishii, J. (1999). (a) . A learning model of a periodic locomotor pattern by the central pattern generator, *Adaptive Behavior*, Vol. 7, No. 2, pp. 137-149.

Nishii, J. (1999). (b) . Learning model for coupled neural oscillators, *Network: Computation in Neural Systems*, Vol. 10, pp. 213-226.

Nishii, J. (2000). Legged insects select the optimal locomotor pattern based on energetic cost, *Biological Cybernetics*, Vol. 83, No. 5, pp. 435-442.

Nishii, J. and Nakamura, M. (2005). A determinant of the leg swing trajectory during walking, *Proceeding of 3rd international symposium on adaptive motion in animals and machines*, CD-ROM.

Nishii, J. (2006). An analytical estimation of the energy cost for legged locomotion, *Journal of Theoretical Biology*, Vol. 238, pp. 636-645.

Righetti, L.; Buchli, J. and Ijspeert, A. (2006). Dynamic Hebbian learning in adaptive frequency oscillators, *Physica D*, Vol. 216, No. 2, pp. 269-281.

Rossignol, S. and Bouyer, L. (2004). Adaptive mechanism of spinal locomotion in cats, *Integrative and Comparative Biology*, Vol. 44, No. 1, pp. 71-79.

Taga, G.; Yamaguchi, Y. and Shimizu, H. (1991). Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment, *Biological Cybernetics*, Vol. 65, pp. 147-159.

Takakusaki, K.; Saitoh, K.; Harada, H. and Kashiwayanagi, M. (2004). Role of basal ganglia-brainstem pathways in the control of motor behaviors, *Neuroscience Research*, Vol. 50, pp. 137-151.

Zarrugh, M. and Radcliffe, C. (1978). Predicting metabolic cost of level walking, *European Journal of Applied Physiology*, Vol. 38, No. 3, pp. 215-223.