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A Learning Model of a Periodic Locomotor Pattern by the Central Pattern Generator

JUN NISHII
Yamaguchi University, Japan

Many basic locomotor patterns of living bodies are rhythmic, and oscillatory components of physical systems effectively contribute to the generation of the movement. The control signals for the basic locomotor patterns are generated by the central pattern generator (CPG), which is composed of collective neural oscillators, and the activity of the CPG is tightly synchronized with the movement of the physical systems. That is, appropriate locomotor patterns are realized by mutual. synchronization between the physical system and the neural system. In this article a simple learning model is proposed to acquire an appropriate parameter set, the intrinsic frequency of the CPG, and the interaction between the CPG and the physical system, in order to obtain a desired locomotor pattern. The performance of the proposed learning model is confirmed by computer simulations and an adaptive control experiment of a one-dimensional hopping robot.

keywords: CPG, nonlinear oscillator, locomotion, associative learning, adaptive control.

1 INTRODUCTION

The central pattern generator (CPG), which generates control signals for basic rhythmic locomotor patterns such as swimming, crawling, and walking, is composed of coupled neural oscillators, and the legs or the segments of the body are controlled by the component oscillators (Pearson, 1976; Pearce and Friesen, 1988; Grillner et al., 1991). The CPG receives sensory feedback signals which show the bending or movement of the body, and the firing pattern of the CPG is strongly affected and entrained by these signals (Grillner, 1985; McClellan and Sigvardt, 1988). That is, the activity of the CPG is synchronized with the movement of a locomotor system such as a leg, which is a physical oscillator, by which the CPG can send control signals to muscular systems at an appropriate time in a cycle of the movement.

In order to generate a desired locomotor pattern, (1) the intrinsic frequency of the CPG, and (2) the interactions between the CPG and the muscular system must be appropriately determined. If the intrinsic frequency of the CPG is much different from that of the physical system, the synchronization between the two becomes difficult and much energy is consumed in controlling the physical system. If the interactions are not well organized, the control signals are not sent at an appropriate time in the cycle. Neurophysiological experiments have been reported suggesting that the isolated CPG itself can produce a firing pattern to generate the basic locomotor pattern (Wallen and Williams, 1984). This suggests that the CPG itself has acquired an appropriate parameter set for a basic locomotor pattern. The appropriate parameters might be given inherently, but the parameters should be tuned to improve the performance of the locomotion according to changes in the physical dynamics of the body due to body growth, injury, and so on.

Two situations are possible for acquiring these parameters.

1. The higher motor centers or the reflex systems generate an explicit desired firing pattern which the CPG should produce, and the parameters are acquired so that the firing pattern of the CPG becomes similar to the teacher signal.

JN: Dept. of Physics, Biology, and Informatics, Faculty of Science, Yamaguchi University, 1677-1 Yoshida, Yamaguchi 753-8512, Japan. nishii@bcl.sci.yamaguchi-u.ac.jp

2. The desired signal is not explicitly given, but higher centers evaluate the performance of the locomotion and send error signals to the CPG. The appropriate parameters are acquired in accordance with these signals.

The learning model proposed by Ermentrout and Kopell (1994) is concerned with the first case. In their model, the intrinsic frequencies of the component oscillators of the CPG are fixed, and coupling weights between oscillators are acquired according to the difference between the output signal of each oscillator and the desired signal. The learning rule for the coupling weights was derived for a specific neural oscillator model. The learning rule proposed by Nishii (in press) also relates to the first case, in which a simple phase oscillator is used as a component oscillator. The desired firing pattern entrains the component oscillators, and the intrinsic frequencies and the coupling weights are tuned according to the effects of the input signals. In these models, the method by which higher centers obtain the desired signal has not been elucidated.

The second situation corresponds to the case in which the parameters of the CPG are tuned according to an evaluation of the results of the locomotion, such as velocity, stability, and energetic efficiency. Doya and Yoshizawa (1992) have proposed a learning rule to acquire appropriate coupling weights between a specific neural oscillator model and a physical system with one-degree freedom based on the evaluation. But the proposed learning rule was derived only for the specific neural oscillator model, and the intrinsic frequency of the CPG was fixed.

In this article, we consider the second situation and propose a simple learning model for acquiring a desired parameter set, the intrinsic frequency of the CPG, and the coupling weights between a physical system and the CPG, by which a desired locomotor pattern is achieved in accordance with the error signal of the obtained locomotion. We consider a simple phase oscillator model as the CPG in which the dynamics take the general form derived from many classes of nonlinear oscillators. The conditions for successful learning are analytically discussed, and the performance of the proposed learning rule is confirmed by computer simulations and a control experiment of a one-dimensional hopping robot.

2 AN ADAPTIVE LEARNING MODEL FOR THE CPG

In this article, we consider only one-degree freedom rhythmic locomotor patterns. We assume that the phase dynamics of the CPG and the physical system showing periodic movement take the following form by defining their phases, $\theta \in S^1$ and $\tilde{\theta} \in S$, respectively.
Thus:

$$\begin{cases} \dot{\theta} = \omega + \sum_{l=1}^{L} w^l R\left(\phi - \psi^l\right) \\ \tilde{\theta} = \Omega + \in_f F(-\phi) \end{cases} \tag{1}$$

where $\phi \equiv \tilde{\theta} - \theta$ is the phase difference, ω and Ω are the intrinsic frequencies of the CPG and the physical system, respectively, $R(\phi)$ shows the effect of feedback signals from the physical system to the CPG, $F(\phi)$ shows the effect of the control signal from the CPG to the physical system, and $\in_f << 1$ is a constant showing the strength of the control signal. Various phase-delayed couplings of sensory feedback signals to the CPG are assumed, φ^l $(l = 1,\dots,L)$ and $\sum_l^L w^l << 1$ represent the phase delay and coupling weight of each coupling, respectively, and L is the number of the phase-delay. These phase-delayed effects occur when different cells in a neural oscillator receive a feedback signal and when various feedback signals, such as displacement, velocity, and acceleration are obtained. Ω and $\in_f F$ depend on the properties of the physical system, and these values are assumed to be unknown. The above phase equations are approximately obtained by transformations from many nonlinear oscillators when the attraction to the limit cycle is strong enough (Ermentrout and Kopell, 1991).

The performance characteristics of the physical system, such as the locomotion velocity and hopping height, depend on the timing of control signals received from the CPG, i.e., the phase difference ϕ between the CPG and the physical system, as mentioned in the Introduction. Here we propose the following learning rule to acquire an appropriate phase relation between the CPG and the physical system to achieve a desired locomotion with turning parameters ω and ω^l:

$$\begin{cases} \dot{\omega} = \varepsilon \sum_{l=1}^{L} w^l \mathrm{R}\left(\phi - \psi^l\right) \\ \dot{w}^i = \varepsilon\gamma E(\phi) \cdot \mathrm{R}\left(\phi - \psi^i\right), \end{cases} \quad (2)$$

where $E(\phi)$ is an error function of the performance of the physical system, and $\varepsilon << 1$ and $\gamma << 1$ are constants determining the learning rate of the frequency and the weight. Therefore, the parameters change much more slowly than the phase difference ϕ, and the coupling weight ω^l changes much more slowly than the frequency ω. The above learning rule implies that the intrinsic frequency ω is modulated according to the sum of the effects of the input signals to the CPG so as to adapt the current frequency. The coupling weight ω^l is modulated according to the correlation between the error function and the effect of the feedback signal. When the error function and the effect of the feedback signal have the same sign, the coupling weight is enforced, and when they have the opposite signs, the weight is reduced. If the above learning rule successfully converges, $E(\phi = 0)$ and $\sum_l w^l \mathrm{R}\left(\phi - \psi^l\right) = 0$ are obtained; that is, a desired phase relation which makes the error function zero, provided that $\forall \phi \in \mathrm{S}, \exists i, \mathrm{R}\left(\phi - \psi^i\right) \neq 0$. Note that the above learning rule does not contain the variables concerning the physical system Ω and F. Using this learning rule, the following theorem is obtained.

Theorem $E(\phi) = 0$ is obtained in the equation (1) by the learning rule (2), if the following conditions are satisfied.

1. A stable solution always exists in the phase difference space $\phi \in \mathrm{S}$, and the learning velocity is sufficiently slow $\varepsilon << 1$ so that the phase difference ϕ is always at steady state, i.e., $\dot{\phi}_i \cong 0$ is satisfied during the learning.
2. There exist more than two phase-delayed feedback signals to the CPG, which give the different zero points of the interaction effect $\mathrm{R}\left(\phi - \varphi^l\right)$, i.e., $\forall \phi \in \mathrm{S} \sum_{l=1}^{L} \left(\mathrm{R}\left(\phi - \psi^l\right)\right)^2 \neq 0$ is satisfied.
3. A C^1 function $g : \mathrm{S} \to \mathrm{S} \forall \phi \in \mathrm{S}\, g'(\phi) > 0$ exists such that $E(\phi)$ and $\sin 2\pi\, \mathrm{g}(\phi)$ have the same sign in $\phi \in \mathrm{S}$.
4. For all $\mathrm{w} \equiv \left(w^1, ..., w^L\right) \neq (0, ..., 0)$, there exists a C^1 function $h_w : \mathrm{S} \to \mathrm{S}$, $\forall \phi \in \mathrm{S}, h_w'(\phi) > 0$ such that $\sum_{l=1}^{L} w^l \mathrm{R}\left(\phi - \psi^l\right)$ and $\sin 2\pi h_{\mathrm{w}}(\phi)$ have the same sign in $\phi \in \mathrm{S}$.

Conditions 3 and 4 indicate that the functions $R(\phi)$ and $E(\phi)$ should be periodic and have both positive and negative domains. Examples of their simple expressions are $\mathrm{R}(\phi) = \sin 2\pi\phi$ and $\mathrm{E}(\phi) = \sin 2\pi\phi$.

Proof: The dynamics of the phase difference OE takes the following form from eq. (1),

$$\dot{\phi} = \Omega - w + \varepsilon_f \mathrm{F}(-\phi) - \sum_{l=1}^{L} w^l \mathrm{R}\left(\phi - \psi^l\right) \quad (3)$$

The proof is carried out under the assumption that the above equation has a stable point and remain continuously in steady state (Condition 1) in the manner shown by Pineda (1987). At the stable point ϕ, we have:

$$f + a > 0 \quad (4)$$

from Equation 1, where

$$f = \varepsilon_f F'(-\phi), \quad a = \sum_{l=1}^{L} w^l \mathrm{R}'\left(\phi - \psi^l\right) \quad (5)$$

From Equation 3 and condition 1, the following relation is obtained.

$$0 = -1 - (f + a)\frac{\partial \phi}{\partial \omega}$$

Therefore, we have

$$\frac{\partial \phi}{\partial \omega} = -\frac{1}{f + a} \quad (6)$$

Consider the following Liapunov functions.

$$V_1 = \frac{1}{\pi}\sin^2 \pi h w(\phi), \quad V_2 = \frac{1}{\pi}\sin^2 \pi\, \mathrm{g}(\phi)$$

Concerning V1 , we have

$$\begin{aligned} \dot{V}_1 &= h_w'(\phi)\sin 2\pi h_w(\phi) \cdot \frac{\partial \phi}{\partial w}\dot{w} \\ &= -\varepsilon h_w'(\phi)\sin 2\pi_w(\phi) \cdot \frac{\sum_l w^l \mathrm{R}\left(\phi - \psi^l\right)}{f + a} \leq 0. \end{aligned}$$

where we used Equation 4, 6, and Condition 4, and the assumption that the change in coupling weight ω^l is small ($\gamma << 1$) during the learning of the frequency ω. The equality is established on the points satisfying $\sin 2\pi h_{\mathbf{W}}(\phi(\omega, \mathbf{w})) = 0$ or $w = 0$. Because $w = 0$ is not a equilibrium point of the learning rule (2) by the second Condition when $E(\phi) \neq 0$, we obtain $E(\phi) = 0$ or the following relation after sufficient time.

$$\sin 2\pi h_w(\phi) = 0, \sum_l w^l \mathrm{R}(\phi - \psi^l) = 0, \dot{\omega} = 0 \qquad (7)$$

Note that the points satisfying $h_w = (\phi(\omega, w)) = 0$ are stable, because they are the zero points of the Liapunov function V_1, i.e., we obtain:

$$a > 0 \qquad (8)$$

at steady state, and the points satisfying $h_W(\phi(\omega, \mathbf{w})) = 1/2$ are unstable. (The proof of the instability of the points is omitted but can be obtained in similar way to that shown above by using the Liapunov function $V = 1/\pi \sin^2 \pi(h_\omega(\phi) - 1/2)$.)

Then, we will show $\dot{V}_2 \leq 0$. Because the learning velocity of the coupling weight ω^l is much slower than that of the intrinsic frequency ω, we assume that ω is in steady state, i.e., Equation 7 is established, during the learning of the weight ω^l. From the second equation in (7), the phase difference ϕ can be regarded as a function of the coupling weight ω^l, and we obtain:

$$\frac{\partial \phi}{\partial w^l} = -\frac{\mathrm{R}(\phi - \psi^l)}{a} \qquad (9)$$

The time derivative of V_2 takes the form:

$$\begin{aligned}\dot{V}_2 &= \mathrm{g}' \sin 2\pi\, \mathrm{g}(\phi) \cdot \sum_l \frac{\partial \phi}{\partial w^l} \dot{w}^l \\ &= -\varepsilon\gamma\, \mathrm{g}' \sin 2\pi\, \mathrm{g}(\phi) \cdot E(\phi) \cdot \sum_l \frac{\left(\mathrm{R}(\phi - \psi^l)\right)^2}{a} < 0\end{aligned}$$

where we used Equation 8 and 9, and Conditions 2 and 3. Hence, we obtain:

$$E(\phi) = 0$$

Note that the points satisfying $g(\phi) = 0$ are stable because they are the zero points of the Liapunov function V_2, and the points satisfying $g(\phi) = 1/2$ are unstable. (The proof of the instability of the points is omitted but can be obtained in a similar way to that shown above by using the Liapunov function $V_2 = \frac{1}{\pi} \sin^2 \pi\left(\mathrm{g}(\phi) - \frac{1}{2}\right)$.) We can therefore expect to obtain the phase relation satisfying $g(\phi) = 0$ through the learning. Q.E.D

We assumed that the functions R, F and E in Equation 1 are functions of the phase difference ϕ. The proposed learning rule can also be applied to a more general case.

Consider the following dynamics of the CPG and the physical system:

$$\begin{cases}\dot{\theta} = \omega + \sum_{l=1}^{L} w^l\, \mathrm{R}(\theta, \tilde{\theta} - \psi^l) \\ \dot{\tilde{\theta}} = \Omega + \varepsilon_f F(\tilde{\theta}, \theta)\end{cases} \qquad (10)$$

When the above system has a phase-locked solution, the following approximated form is obtained by applying the averaging theory (Guckenheimer and Holmes, 1983):

$$\begin{cases}\dot{\theta} = \omega + \sum_{l=1}^{L} w^l\, \overline{\mathrm{R}}(\phi - \psi^l) \\ \dot{\tilde{\theta}} = \Omega + \varepsilon_f \overline{F}(-\phi)\end{cases} \qquad (11)$$

where $\overline{R}$ and $\overline{F}$ are the time-averaged functions over one period which is equivalent to the forms (Ermentrout and Kopell, 1991):

$$\overline{\mathrm{R}}(\varphi) = \int_0^1 \mathrm{R}(\theta, \theta + \varphi)\, \mathrm{d}\theta, \quad \overline{\mathrm{F}}(\varphi) = \int_0^1 \mathrm{F}(\theta, \theta + \varphi)\, \mathrm{d}\theta \qquad (12)$$

$E(\tilde{\theta}, \theta)$ can also be transformed to the function of phase difference $\overline{E}(\phi)$ in the same manner. Because Equation 11 has a form similar to Equation 1, we can apply the learning rule (2), that is, we obtain the learning rule:

$$\begin{cases}\dot{\omega} = \varepsilon \sum_{l=1}^{L} w^l\, \overline{\mathrm{R}}^l \\ \dot{w}^i = \varepsilon\gamma \overline{E} \cdot \overline{\mathrm{R}}^i\end{cases} \quad \overline{\mathrm{R}}^l \equiv \overline{\mathrm{R}}(\phi - \psi^l) \qquad (13)$$

3 EXPERIMENTAL RESULTS

In this section we will show the results of computer simulations to obtain a desired phase relation between

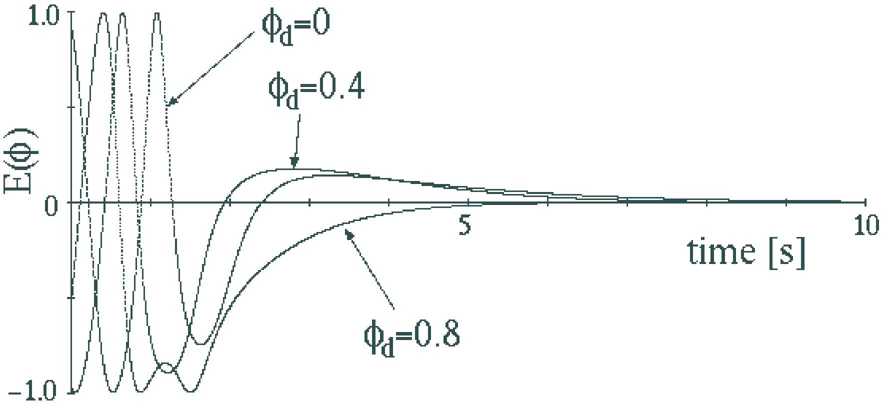

Figure 1. The time profile of the error function $E(\phi)=\sin 2\pi(\phi-\phi_d)$. Desired phase differences $\phi_d = 0, 0.4, 0.8$ were achieved in a few cycles. Parameters: $\Omega = 2.0\,[Hz]$, $(\varphi_1,\varphi_2) = (0, 0.2)$, $\varepsilon = 1.0$, $\gamma = 1.0$. Initial condition: $(\theta(0), \tilde{\theta}(0)) = (0.5, 0.7)$, $(w^1(0), w^2(0)) = (0.1, -0.1)^t$, $\omega(0) = 1.0$ [Hz].

two phase oscillators. We will then show the experimental results to apply the proposed learning rule to the adaptive control of a one-dimensional hopping robot.

3.1 Control of the phase difference between oscillators

Assuming that the phase dynamics of the CPG and the physical system follow Equation 1, we give the functions as:

$$\varepsilon_f(\phi) = -0.1\sin 2\pi\phi, \quad R(\phi) = \sin 2\pi\phi$$

The learning rule (2) was examined for the following two error functions.

$$E_1(\phi) = \sin 2\pi(\phi-\phi_d), \quad \phi_d = 0,0.4,0.8 \quad (14)$$

$$E_2(\phi) = \sin 2\pi(\phi-K_d), \quad K_d = -0.4,0.3.1.0 \quad (15)$$

Figures 1 and 3 show the time course of the error functions E_1 and E_2, respectively, during learning. In both cases, the value of the error function became zero by the learning despite the two oscillators not synchronizing with each other in the initial state, violating the Condition 1 in the theorem. The parameter $K_d = 1.0$ in E_2 does not satisfy Condition 3 in the theorem because $\forall\phi,\ E_2(\phi) \le 0$ in this case, but it was shown that the desired parameter set is successfully acquired by the proposed learning rule in this simulation even in such a case. **Figure 2** shows the phases of the oscillators and the phase difference between them during learning mode and in recalling mode for E_1 and $\phi_d = 0.8$. The desired phase difference $\phi = \phi_d$ was obtained by the learning in a few cycles, and the learned phase relation was immediately obtained in the recalling mode after acquiring an appropriate parameter set. The same results were obtained from the other initial conditions.

3.2 Computer simulation of the adaptive control of a hopping robot

The robot is composed of a trunk with a mass and a leg which has a spring component, a damping component, and a thruster (**Figure 4**). The thruster generates a force between the trunk and the toe according to the phase of the CPG. The CPG receives the normalized velocity $\hat{v}$ of the trunk of the robot as a sensory feedback signal, and its dynamics takes the form:

$$\dot{\theta} = \omega + \sum_{l=1}^{L} w^l P\left(\theta - \psi^l\right)\hat{v} \quad (16)$$

where $P(\theta) = \sin 2\pi\theta$ is the function showing the effect of the input signal on the dynamics of the CPG. The normalized velocity of the robot $\hat{v}$ is given by:

$$\hat{v} = \dot{x}_0/\bar{v}_0, \quad \tau_0\dot{\bar{v}}_0 = -\bar{v}_0 + |\dot{x}_0| \quad (17)$$

where x_0 is the position of the trunk of the robot, and $\tau_0 = 5.0$ [s] is a time constant. The phase equation (16)

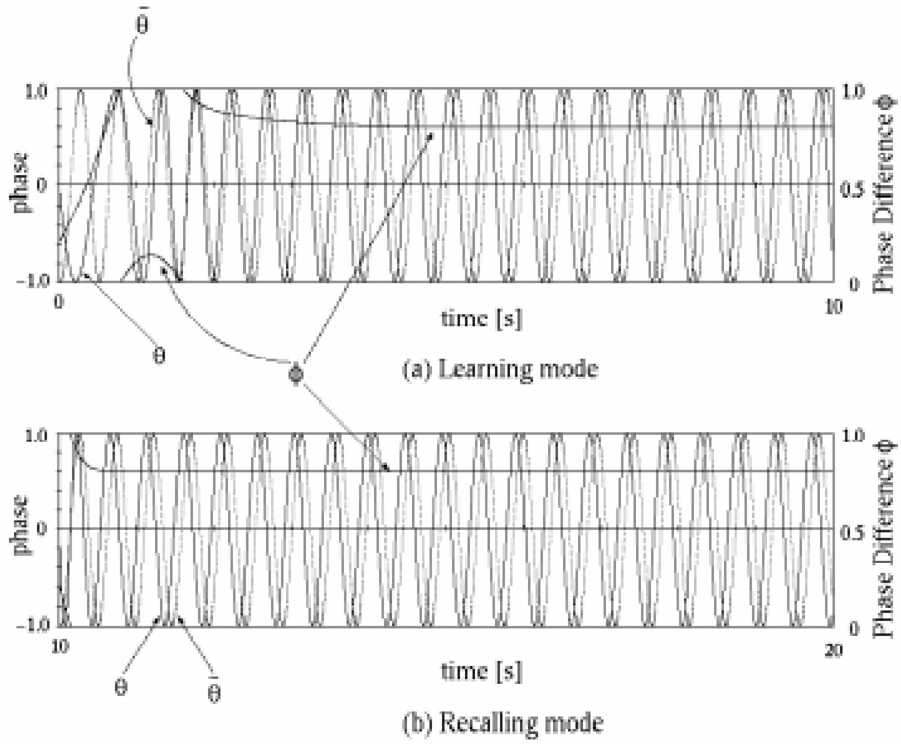

Figure 2. The time profile of the phases of oscillators, $y = \sin 2\pi\theta$ (solid line) and $y = \sin 2\pi\tilde{\theta}$ (dotted line), and the phase difference, $\phi = \tilde{\theta} - \theta$. (a) Learning mode (first 10 seconds). Two oscillators were synchronized, and the desired phase relation $\phi_d = 0.8$ was acquired within a few cycles by learning. (b) Recalling mode (10-20 seconds). At t=10 [s], the learning was stopped, and the learned phase difference was immediately regenerated from a random initial phases.

is obtained 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 (Nishii et al., 1994). The dynamics of the robot is shown in the appendix.

3.2.1 Learning a desired hopping height.

First, the simulation results for learning a desired hopping height are shown. The error function is given by:

$$E = x_d - \bar{x}_0 \tag{18}$$

where x_d is the desired height and $\bar{x}_0$ is the time-averaged height of the trunk of the robot x_0; that is:

$$\tau \dot{\bar{x}}_0 = -\bar{x}_0 + x_0 \tag{19}$$

where $\tau = 5.0/\omega$ is the time constant. The learning rule (13) is applied, and the time-averaged function $\bar{R}^i$ is obtained by:

$$\tau \dot{\bar{R}}^i = -\bar{R}^i + P(\theta - \psi^i) \tag{20}$$

Figure 5 shows the simulation results. One period of hopping is about one second in a steady state. No learning was carried out in the first ten seconds so that a steady relation between the CPG and the robot could be achieved. The desired heights, $x_d = 0.6, 0.7, 0.8, 0.9$ [m], were obtained within 100 seconds. **Figure 6** shows the time course of the hopping height after the acquisition of the desired parameters for $x_d = 0.9$ [m], which indicates that the learned height was immediately acquired. In this simulation, learning failed for larger and smaller target heights $(x_d \le 0.5$ and $x_d \ge 1.0)$ and for ini-

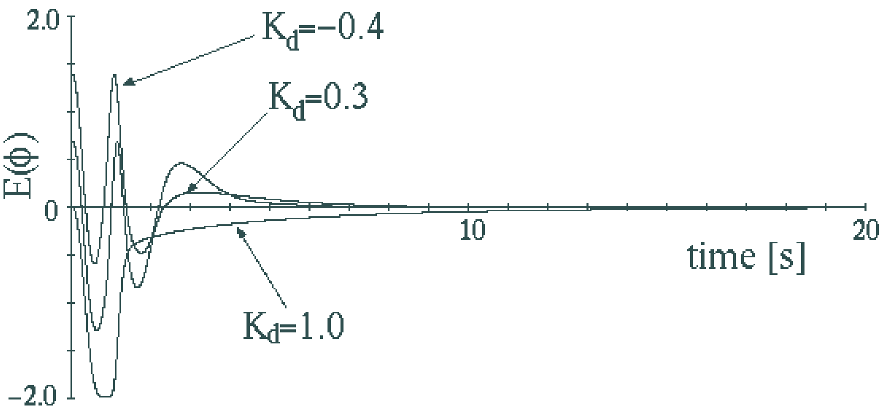

Figure 3. The time profile of the error function $E_2(\phi) = \sin 2\phi - K_d$. The error function became zero within 10 seconds by learning for each parameter, $K_d = -0.4, 0.3, 1.0$. The parameters and initial condition are the same as those shown in Fig.1.

tial parameters which desynchronized the CPG and the robot.

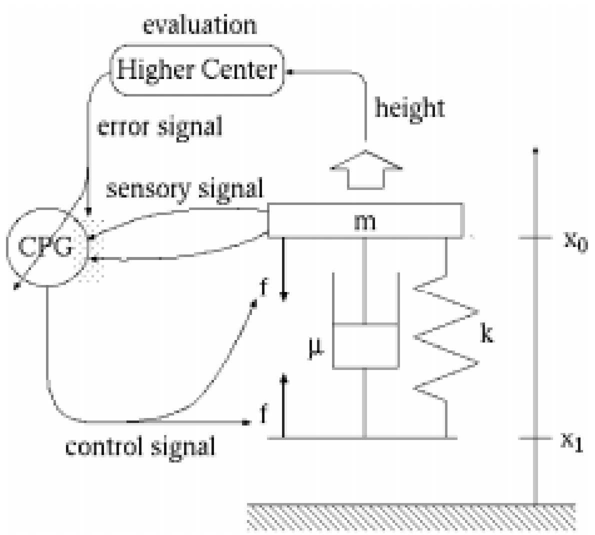

Figure 4. One-dimensional hopping robot. The robot consists of a trunk with mass *m* and a leg which has a spring component (elastic coefficient : *k*), a damping component (damping coefficient μ), and a thruster. The CPG sends a control signal to the thruster which generates the force *f* between the trunk and the toe and receives a sensory feedback signal from the robot. Based on the error for the hopping performance, the intrinsic frequency of the CPG and the weights of the sensory feedback are learned.

3.2.2 Learning a maximum hopping height.

Although it was shown that the desired parameter set can be learned by an error function, it is difficult to obtain the maximum value allowed by the physical system, such as maximum hopping height, because the desired value is unknown in such a case. Even if the desired value is known, the appropriate parameter set might not be obtained by the error function given by the error between the actual value and the desired value because such an error function does not satisfy Condition 3 in the theorem.

In these cases the learning can be done by setting the error function as:

$$E(\phi) = -c\frac{\partial z}{\partial \phi} \tag{21}$$

where c is a positive constant and $z(\phi)$ is the variable which we want to maximize. With this error function, z becomes maximum if $z'(\phi)$ changes its sign twice in $\phi \in S$ like the function $\sin 2\pi\phi$.

Based on this consideration, we set the following error function instead of Equation 21 to obtain the maximum hopping height in the simulation experiment of the adaptive control of the hopping robot:

$$E(\phi) = -\frac{\Delta x_{max}}{\Delta \phi_{max}} \tag{22}$$

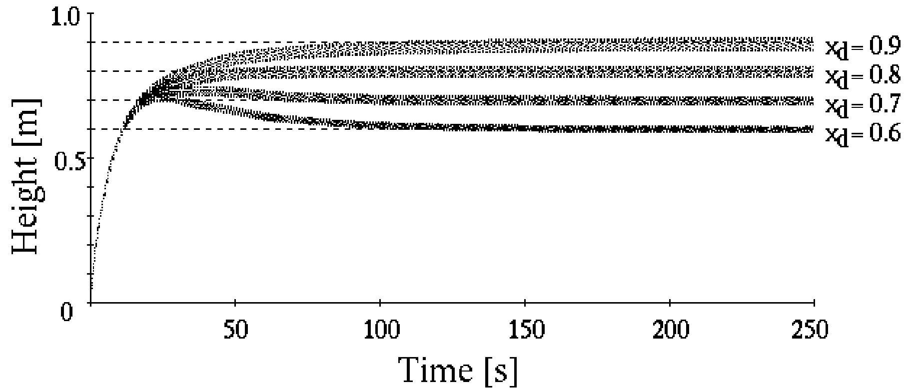

Figure 5. The time profile of the time-averaged height $\bar{x}_0$ of the trunk of the robot. Desired hopping heights x_d = 0.6, 0.7, 0.8 0.9 were adaptively achieved. Parameters are given as $(\varphi_1, \varphi_2) = (0, 0.8)$, $\varepsilon = 0.3$, *and* γ 1/3. As an initial condition, we put $\theta(0) = 0.5$, $(w^1(0), w^2(0)) = (1.0, -1.0)$, $\omega(0) = 1.0$ [Hz], $x_1(0) = 0.1$ [m], $x_0(0) = x_x(0) + l = 0.8$ [m]. The lines look thick because of the small high-frequency changes in the height $\bar{x}_0$.

where $\Delta\phi_{\max}$ is the change in the maximum height $x_{\max}$ between each new hop from the previous hop, and $\Delta\phi_{\max}$ is the change in phase difference between the robot and the oscillator since the previous hop. By defining the phase of the robot as zero when the robot reaches maximum height, $\phi_{\max}$ is given by $\phi_{\max} = -\theta_{max}$, where $\theta_{\max}$ is the phase of the oscillator at the moment. Small random values are added to the coupling weights during learning to avoid a stagnation in learning by the eventually obtained value $\Delta x_{\max} \cong 0$. **Figure 7** shows the time-averaged height of the robot $\bar{x}_0$, which indicates that $\bar{x}_0 \cong 0.95$ [m] was obtained by the learning. The obtained value was almost same as the maximum value obtained in the previous simulation (Figure 5). This value would be the maximum height allowed by this physical system.

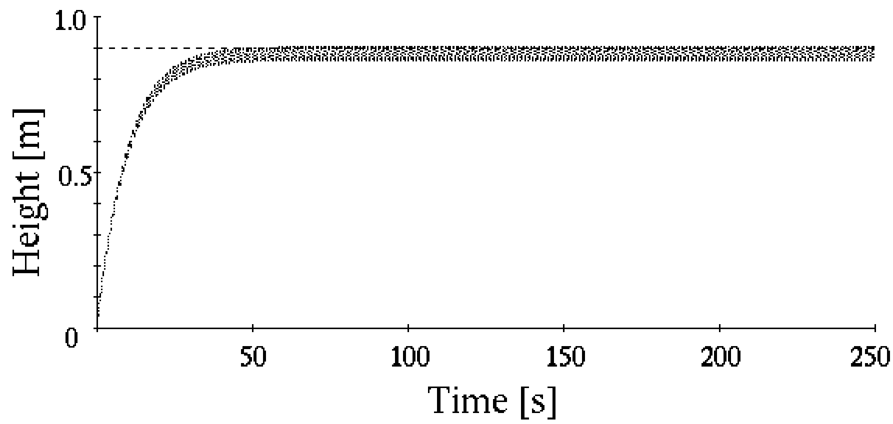

Figure 6. The time profile of the time-averaged height $\bar{x}_0$ of the trunk of the robot after learning. The memorized hopping height x_d = 0.9 [m] was achieved.

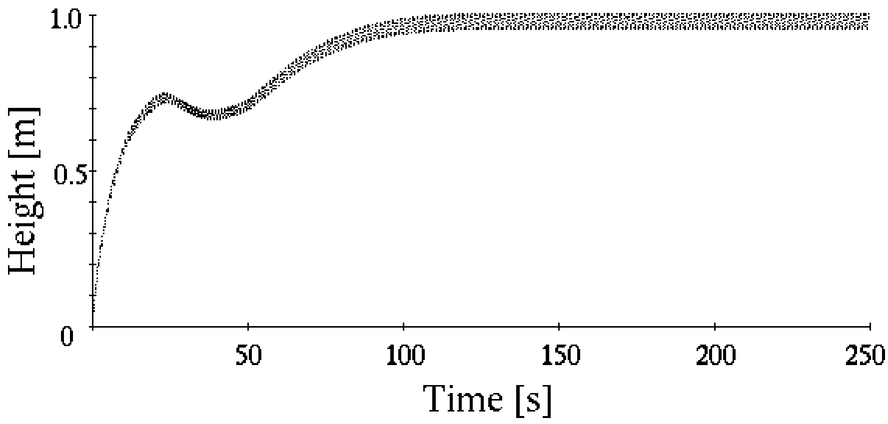

Figure 7. The time profile of the time-averaged height $\bar{x}_0$ of the trunk of the robot in learning the maximum height hopping. Almost the same value as the maximum value obtained in the previous simulation (Figure 5) was obtained.

3.3 Control experiment of a hopping robot

The proposed learning rule was applied to the control of an actual one-dimensional hopping robot (**Figure 8**). **Figure 9** shows an overview of the robot. The robot moves along two vertically situated poles. A DC-motor on the trunk makes a force on the table through arms which consist of a crank system. Because a spring is fixed under the table, the robot can continue hopping if the arms push the table at an appropriate time in a hopping cycle. The angle of the arm θ is measured by a potentio-meter, and the acceleration of the table a is obtained by an acceleration sensor.

Because the motor speed $\dot{\theta}$ is approximately proportional to the current I applied to the motor in steady state, i.e., $\dot{\theta} \propto I$, we regard the average of the current I_0 and the angle of the arm as the scaled intrinsic frequency and the phase of the CPG, respectively, and give the current I to the DC motor as:

$$\dot{\theta} \sim I = I_0 + \sum_{i=1}^{2} w^i a \sin 2\pi\left(\theta - \varphi^i\right) \qquad (23)$$

The parameters I_0 and w^i change according to the learning rule (13). The time-averaged term was given in the same way in the previous simulation. The error function is given by:

$$E = a_d - \overline{|a|} \qquad (24)$$

that is, the purpose of this learning is to approach the time average of absolute value obtained by the acceleration sensor $\overline{|a|}$ to the desired value a_d. The reason we used an absolute value is that the time average of the acceleration is zero for an arbitrary height hopping. **Figure 10** shows the time course of $\overline{|a|}$ during learning. The frequency of the hopping was about 2Hz and the desired value was obtained in about one minute.

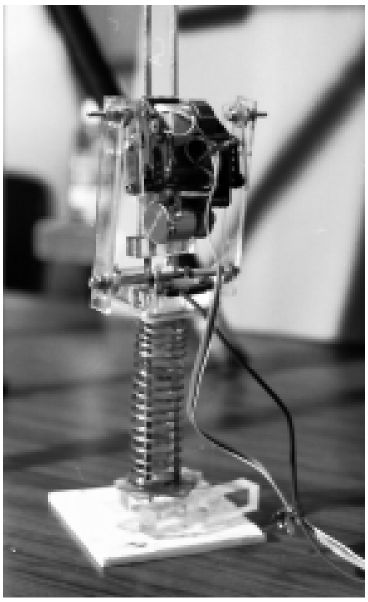

Figure 8. The one-legged hopping robot.

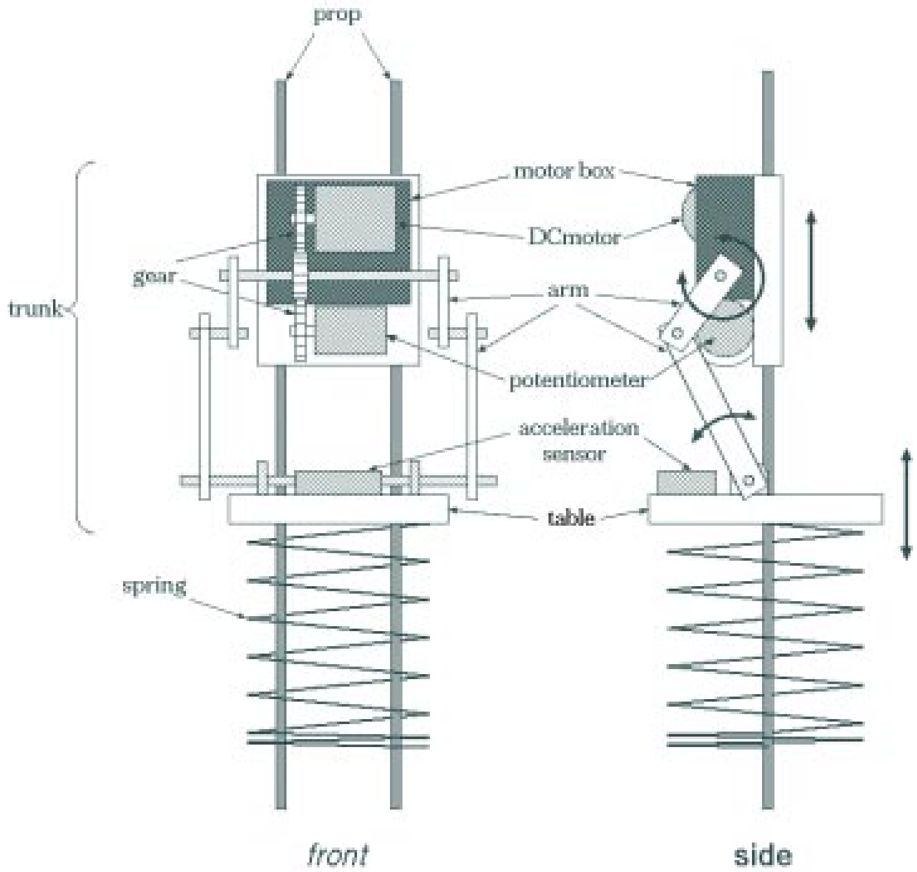

Figure 9. Schematic representation of the one-legged hopping robot.

Although we demonstrated the result of obtaining the desired value of a time-averaged absolute acceleration, we could obtain the desired hopping height as shown in the simulation if the hopping height of the robot was provided.

4 CONCLUSION

In most traditional control methods in the engineering field, methods to enforce the controlled object to trace the pre-determined trajectory have been discussed, and the physical properties of the object are eliminated by compensations in control systems. On the other hand, it has been suggested that locomotor systems in living bodies might utilize an oscillatory factor, such as elastic components of the physical system, to achieve highly efficient locomotion (Cavagna et al., 1977; Alexander et al., 1980; Heglund et al., 1982; Blickhan and Full, 1993) and that the CPG would not enforce the pre-determined trajectory on physical system but compensate for movement to obtain a desired performance (Raibert and Hodgins, 1992). Control models of human locomotion and control methods for legged robots have been proposed based on such ideas. Taga et.al. (1991,1995a,1995b) have proposed control models of human locomotion with neural oscillators and have shown that stable walking patterns emerge in response to small changes in environment and small disturbances under fixed control parameters. Raibert and his colleagues have developed many legged robots utilizing the elastic components of legs (Raibert, 1986; Raibert and Hodgins, 1992) and have shown that dynamic walking can be stabilized even with no sensors (Ringrose, 1997) if the control parameters and physical parameters of a legged system are appropriately given. We proposed a simple learning model for acquiring the desired

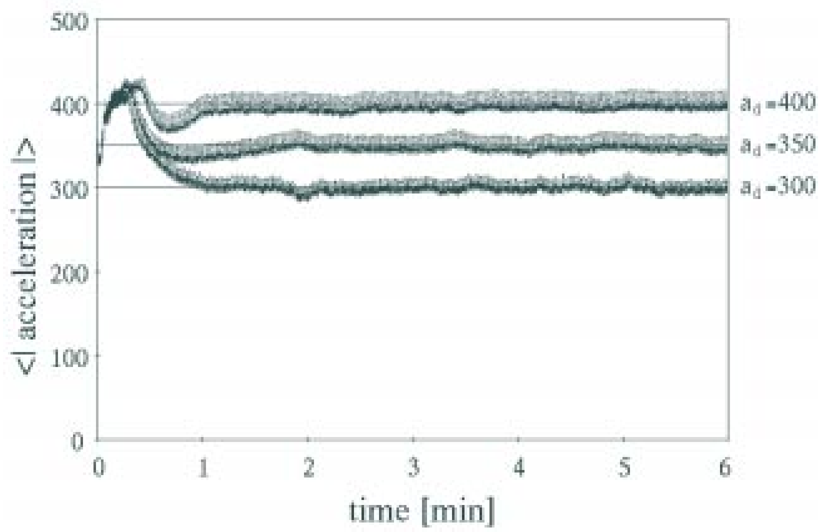

Figure 10. The time profile of the time averaged absolute value of the acceleration of the robot. The desired values a_d = 300, 350, 400 were obtained within a minute. The value of the acceleration indicates the value obtained by the acceleration sensor.

control parameters for such periodic locomotion.

Using the proposed learning model, an appropriate locomotor pattern can be achieved by tuning the phase difference between the physical system and the CPG based on the feedback signals to the CPG. Although the learning rule for the amplitude of the control signal should also be considered, tuning the control signal is generally difficult without any knowledge of the controlled object. It has been reported that feedback signals to the CPG from sensory systems strongly affect the activity of the CPG, as mentioned in the Introduction. In living bodies, a desired locomotor pattern might be acquired by tuning the effects of the feedback signals in the first stage of the development of locomotion, creating an internal model of the dynamics of the controlled object, and the control signals might be tuned for precise control after acquiring the internal model.

In this paper, we considered a simple case using a physical system with one-degree freedom and a phase oscillator. We are studying a learning model for multi-oscillators based on error functions (Nishii, 1997b), and the relation between the proposed learning rule and the learning rule for neural oscillators (Nishii, 1997a).

NOTES

[1]Here, we define **S** = **R**, (mod 1).

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APPENDIX

Dynamics of the one-dimensional hopping robot in the computer simulation

When the robot is jumping and not on the ground, the dynamics is given by the form:

$$\begin{cases} m\ddot{x}_0 &= -mg \\ 0 &= k(x_0 - x_1 - l) + \mu(\dot{x}_0 - \dot{x}_1) + f, \end{cases} \tag{25}$$

where $m = 0.1$ [kg] is the mass of the trunk of the robot, x_0 and x_1 are the position of the toe and the trunk, respectively, $\kappa = 7.0$ [N/m] and $\mu = 0.05$ [N/(m/s)] are the elastic coefficient and the damping coefficient of the leg, respectively, $l = 0.7$ [m] is the resting length of the spring, $f = f_{max} \sin 2\pi\theta$ is the force generated by the thruster, and $f_{\max} = 0.2$ [N] is its maximum force. When the robot is on the ground $(x_1 = 0 \text{ and } N > 0)$, where N is the ground reaction force, the dynamics take the form:

$$\begin{cases} m\ddot{x}_0 &= -mg - k(x_0 - x_1 - l) - \mu(\dot{x}_0 - \dot{x}_1) - f \\ 0 &= k(x_0 - l) + \mu\dot{x}_0 + f + N \\ \dot{x}_1 &= 0. \end{cases} \tag{26}$$

ABOUT THE AUTHOR

Jun Nishii

Jun Nishii received his M.E.in 1992 and his Ph.D.in 1996 in Mathamatical Engineering and Information Physics from the University of Tokyo, Japan. He has been a research associate at the University of Tokyo from 1992 to 1996, and Special Postdoctoral Fellow in RIKEN from 1996 to 1998. Since 1999, he has been an Associate Professor in the Department of Physics, Biology, and Informatics at Yamaguchi University. He is interested in learning and control mechanisms of locomotor systems and the analysis of the optimality of the locomotor patterns.