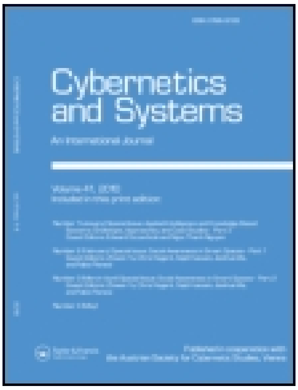

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A MATHEMATICAL MODEL THAT LEARNS AN ADAPTIVELY GENERATED NOVEL PATTERN IN QUADRUPED LOCOMOTION

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A Mathematical Model That Learns an Adaptively Generated Novel Pattern in Quadruped Locomotion

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Quadrupeds show several locomotion patterns when adapting to environmental conditions. An immediate transition among walk, trot, and gallop implies the existence of a memory for locomotion patterns. In this article, we postulate that motion pattern learning necessitates the repetitive presentation of the same environmental conditions and aim at constructing a mathematical model for new pattern learning. The model construction considers a decerebrate cat experiment in which only the left forelimb is driven at higher speed by a belt on a treadmill. A central pattern generator (CPG) model that qualitatively describes this decerebrate cat's behavior has already been proposed. In developing this model, we introduce a memory mechanism to store the locomotion pattern, where the memory is represented as the minimal point of the potential function. The recollection process is described as a gradient system of this potential function, while in the memorization process a new pattern learning is regarded as a new minimal point generation by the bifurcation from an already existing minimal point. Finally, we discuss the generalization of this model to motion adaptation and learning.

KEYWORDS adaptation, CPG, learning, mathematical modely, pattern generation, quadruped locomotion

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INTRODUCTION

Neurophysiological experiments on vertebrates' motion have revealed that assemblies of the neurons at the spinal cord generate their periodic rhythms in automatic motions such as locomotion, mastication, and respiration (Grillner 1975). In the vertebrates' locomotion, these neuronal assemblies, called a *central pattern generator* (CPG), produce an intrinsic oscillating pattern that provides limbs' extensors/flexors with the cooperative rhythms of constriction.

One challenging problem is to elucidate a control principle as well as a design criterion that produce adaptive motions such as biological systems by connecting a decentralized control structure to motor behaviors. Although sensory-based control has been investigated (Beer 1995; Paul 2005; Cruse et al. 2007), the CPG is one possible candidate for locomotion control. The CPG is modeled at different levels: the neural level (Ekeberg et al. 1991; Huss et al. 2008; Daun and Rybak 2009) and the behavior level (Holmes et al. 2006; Ijspeert 2008). In the latter cases, the phasic relation of the leg movement (Yuasa and Ito 1990; Collins and Richmond 1994; Golubitsky et al. 1999; Pinto 2007) or swimming motion (Cohen et al. 1982; Skinner et al. 1997) is sometimes described by mathematical models of the CPG. In recent engineering research on motion control, some locomotion controllers contain artificial oscillators that produce periodic rhythms of the limb motions. Taga (1995) proposed a concept of global entrainment where rhythmic interactions between the neural control system and musculoskeletal system under its environment are crucial for stable biped walk. A stable limit cycle was formed from the coupled dynamics of neural oscillator controllers and musculoskeletal mechanics to achieve stability as well as robustness of locomotion. The mechanism of entrainment has been studied not only to explain biological control mathematically (Kimura et al. 1993; Hase and Yamazaki 2002; Ishiguro et al. 2003; Tomita and Yano 2003) but has also been applied to an actual robot controller (Fukuoka et al. 2003; Inagaki et al. 2003; Nagashima 2003; Lewis et al. 2005; Righetti and Ijspeert 2006; Tsujita et al. 2007; Sproewitz et al. 2008).

The realization of actual robot walking demonstrated the effectiveness of locomotion control based on the CPG. From the designing point of view, however, this realization does not necessarily provide definitive design principles on how to construct the controller. Although the main problem there is adequate parameter selections of the oscillator dynamics embedded in the controller, this selection depends on the heuristic or trial-and-error approaches of experienced designers.

Biological systems are, on the other hand, acquiring the rhythmic patterns of the CPG by learning through the motion. Rhythm adjustments according to environmental conditions have been reported as gait pattern changes in decerebrate cat experiments (Yanagihara et al. 1993). Although motor learning on the CPG controller has been studied (Nishii 1998; Matsubara et al. 2006; Nakamura et al. 2007; Endo et al. 2008), the acquired pattern is limited to a single pattern there: the learning of multiple patterns and selective generation from them has not been treated yet. Hence, we consider this problem in a mathematical manner. Namely, we aim at constructing a conceptual model that achieves a hypothesis of the motor learning of decerebrate cats in which, if some environmental conditions are repeatedly provided, several motion patterns adequate to each condition could be learned simultaneously as different patterns. Next, we will discuss what kinds of problems arise and should be addressed when multiple patterns have to be memorized. Memorization of a new motion pattern based on the learning enables control systems to generate various motion patterns, which is expected to promote the application of the artificial intelligent systems like robots.

MOTION PATTERN LEARNING

An Adaptive Behavior of Decerebrate Cat

Yanagihara et al. (1993) made a decerebrate cat walk on the special treadmill where the belt for the left forelimb can be driven at the different speed than that of the other belts. First, all of the belts were driven at the same speed (normal condition). In this case, the cat showed the same "walk" gait as intact cats. Figure 1(a) illustrates a gait diagram of this experiment. The gait diagram expresses whether each limb is in a support phase (bold line) or not during one locomotion period that starts at the moment of touchdown of the left forelimb. LH, LF, RF, and RH denote the left hindlimb, left forelimb, right forelimb, and right hindlimb, respectively. This walk gait possesses symmetry: the duration of the support phase is almost the same in each limb and the motion is out of phase by a half-period on both sides.

Next, the belt for the left forelimb was driven 1.7 times faster than the others (disturbed condition). In the first trial (one trial contains 60–100 steps), the locomotion pattern was disturbed. In the second trial, however, a steady

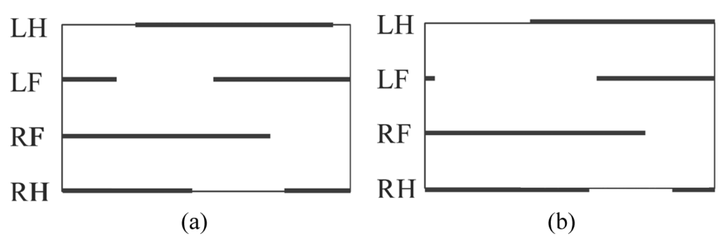

FIGURE 1 Gaits of a decerebrate cat: (a) normal gait and (b) adapted gait.

locomotion pattern was observed. In addition, the cat walked with a steady locomotion pattern at the beginning of the third trial. Figure 1(b) shows the gait pattern in this experiment.

Then this belt speed was returned to the initial condition; that is, driven at the same speed as the others again. The effect of the previous gait change remained in the beginning of this experiment: the cat regained the initial walk gait after a readaptation period.

A Hypothesis on Motion Pattern Learning

The experimental results presented in the previous section led to the following views of motor pattern learning:

- An appropriate locomotion pattern to the current environment was acquired by performing motions.
- The acquired locomotion pattern was memorized.
- Both the original walk and newly acquired gait patterns were not memorized simultaneously.

The second view is derived from the fact that the steady gait pattern emerged at the beginning of the third trial: it would have been impossible if the motion pattern had not been memorized. The last view means that readaptation was required to regain the initial walk gait.

Quadrupeds can immediately change the gait pattern among walk, trot, and gallop with respect to the environmental conditions. Furthermore, humans can utilize different motion patterns such as walk and run depending on the situation. In our opinion, such an immediate switching requires memorization of several motion patterns: they should be selectively recollected from memory to achieve instantaneous pattern transitions. This idea, however, contradicts the last view above. Why has this contradiction occurred? We inferred that training was insufficient to store two different patterns simultaneously in the decerebrate cat experiment: if both the normal and disturbed condition had been repetitively presented, the decerebrate cat would have learned both gait patterns at the same time.

Based on this consideration, we hypothesize the following regarding motion pattern learning:

> If some environmental conditions are repetitively presented, multiple motion patterns can be memorized that are appropriate to respective environmental conditions.

In the next section, we propose a scenario for multiple pattern learning by taking the decerebrate cat behaviors as an example.

Scenario on Learning of Two Gait Patterns by a Decerebrate Cat

The above hypothesis allows the decerebrate cat to simultaneously memorize two gait patterns for the normal and disturbed conditions. In order to mathematically describe the learning process of two gait patterns, we prepare the following scenario:

1. A pattern that enables cats to walk is inherently stored in memory. This pattern is never disturbed; that is, it is stored as a basic pattern.
2. A new motion pattern will be produced from the memorized motion pattern when a new environmental condition is given.
3. When the same environmental condition is repetitively presented, the pattern is newly stored as a distinct pattern.
4. If the environmental conditions are presented later, the stored pattern is selected from memory, which achieves immediate pattern recollection.

In the remainder of this article, we propose a mathematical model that realizes the above scenario. We have already proposed a CPG model for the locomotion pattern generation and its adaptation (Ito et al. 1998). In this article, we add a memorization mechanism that stores multiple motion patterns.

A LEARNING MODEL OF MULTIPLE MOTION PATTERNS

A Learning Scheme

Dealing with the learning of multiple motion patterns, the keywords are *adaptation, learning, selection*, and *recollection*. Focusing on the difference among them, we explain our scheme consisting of motion pattern memory and CPG, as shown in Figure 2. First, we describe the adaptation process that is assumed to be operated in CPG based on our previous paper (Ito et al. 1998). Next, we discuss the other process related to the motion pattern memory from the viewpoint of memorization.

Adaptive Rhythm Generation in CPG

Locomotion pattern generation

Locomotion consists of the periodic motion of each limb. Thus, one oscillator is assigned to each limb of the quadrupeds. The phase space of the oscillator is divided to two regions: the swing and the support phase. Then, the phase of the oscillator $\theta_i (i = 0, 1, 2, 3)$ is assumed to express the limb state during locomotion; that is, the swing and the support phase as shown in Figure 3.

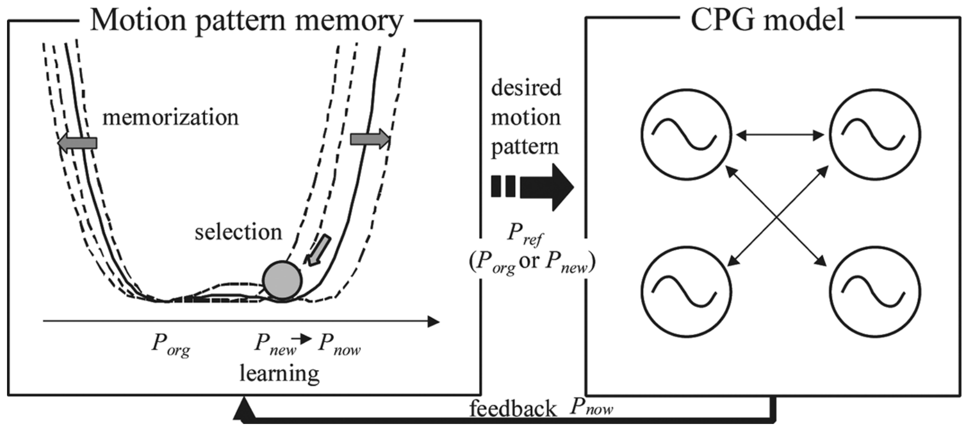

FIGURE 2 Controller containing the CPG model and gait pattern memory.

The limb is regarded as in the support phase if the following condition holds:

$$cos\theta_i > \gamma \quad (i = 0, 1, 2, 3); \tag{1}$$

otherwise, it is in the swing phase.

Gait pattern generation is achieved mainly by regulating the relative phases among oscillators to their reference values. A method based on the gradient dynamics in the relative phase space $\in$ is available for the relative phase control. According to this method, the oscillator dynamics are defined as follows:

$$\dot{\theta}_i = \omega_i + f_i \quad (i = 0, 1, 2, 3) \tag{2}$$

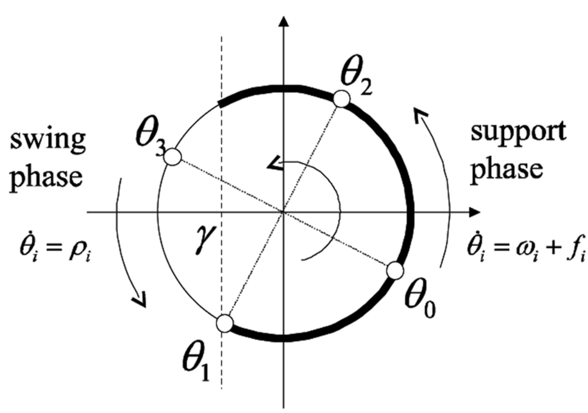

FIGURE 3 Oscillator phase divided into swing and support phases.

$$f_0 = \tau_\theta(\theta_1 + \theta_3 - 2\theta_0 - D_0 - D_1) \tag{3}$$

$$f_1 = \tau_\theta(\theta_0 + \theta_2 - 2\theta_1 + D_0 - D_2) \tag{4}$$

$$f_2 = \tau_\theta(\theta_1 - \theta_2 + D_2) \tag{5}$$

$$f_3 = \tau_\theta(\theta_0 - \theta_3 + D_1) \tag{6}$$

Here, $i = 0, 1, 2, 3$ denotes the right forelimb, left forelimb, right hindlimb, and left forelimb, in that order. ω_i are the natural frequencies of the oscillator and f_i are the interactions among the oscillators. The dynamics of the relative phases $\phi_0 = \theta_1 - \theta_0$, $\phi_1 = \theta_3 - \theta_0$ and $\phi_2 = \theta_2 - \theta_1$ are actually described in the gradient system as:

$$\dot{\phi}_i = -\frac{\partial V}{\partial \phi_i} \tag{7}$$

where the potential function V is given by

$$\begin{aligned} V = {} & \omega_0(\phi_0 + \phi_1) + \frac{1}{2}\tau_\theta(\phi_0 + \phi_1 - D_0 - D_1)^2 + \omega_1(-\phi_0 + \phi_2) \\ & + \frac{1}{2}\tau_\theta(-\phi_0 + \phi_2 + D_0 - D_2)^2 + \omega_2(-\phi_2) + \frac{1}{2}\tau_\theta(-\phi_2 + D_2)^2 \\ & + \omega_3(-\phi_1) + \frac{1}{2}\tau_\theta(-\phi_1 + D_1)^2 \end{aligned} \tag{8}$$

If all of the natural frequencies $\omega_i (i = 0, 1, 2, 3)$ are equal, these dynamics lead the relative phases ϕ_0, ϕ_1, and ϕ_2 to their desired values D_0, D_1, and D_2.

In the case of the decerebrate cat experiment, the limbs in the support phase are forced to be driven by the belt of the treadmill. Thus, the oscillator dynamics are defined separately as the forced oscillation in the support phase:

$$\dot{\theta} = \rho_i \quad (i = 0, 1, 2, 3) \tag{9}$$

where ρ_i denotes the belt speed of the treadmill. In the swing phase, on the other hand, the limbs can move freely without any constraints. Therefore, the oscillator dynamics is defined as the gradient dynamics in Eqs. (2)–(6). The relative phase adjustments are feasible only in this phase.

In these dynamics, the natural frequencies ω_i and relative phase represent locomotion patterns, and ρ_i represents environmental conditions.

ADAPTATION DYNAMICS

The minimum point of the potential function becomes the steady state in the gradient system. There, the gradient leads the state to the minimum point and it ensures the stability of the reference pattern. In the dynamics equations

(2)–(6), the oscillator interactions f_i correspond to the gradient in the relative phase dynamics. Because the gradient disappears at the minimum point, these interactions become zero at the steady state.

Stability allows the disturbed relative phases to return to their reference state by the effect of the oscillator interactions. In the decerebrate cat experiment, however, the locomotion pattern is disturbed whenever the left forelimb is placed on the faster treadmill belt; that is, disturbance is applied before the pattern completely returns to the reference state. As a result, the oscillator interactions and disturbance are balanced on the timescale of the locomotion cycle. In this situation, even though the oscillator interactions, which will produce the reference pattern, are always acting, this reference pattern cannot be achieved. This is because the reference pattern itself is inappropriate under the varied environment. This is why the reference pattern is adjusted in the adaptation process.

Since the inappropriate reference pattern causes oscillator interactions, the adaptation dynamics should be defined as making the oscillator interactions to become small. The parameters to adjust are the reference of the CPG; that is, the natural frequencies and relative phases. They are adjusted in each step following these adaptation dynamics:

$$\omega_i^{(n+1)} = \omega_i^{(n)} + \tau_\omega \int_T f_i dt \quad (i = 0, 1, 2, 3) \tag{10}$$

$$D_0^{(n+1)} = D_0^{(n)} + \tau_D \int_T (f_0 - f_1) dt \tag{11}$$

$$D_1^{(n+1)} = D_1^{(n)} + \tau_D \int_T (f_0 - f_3) dt \tag{12}$$

$$D_2^{(n+1)} = D_2^{(n)} + \tau_D \int_T (f_1 - f_2) dt \tag{13}$$

Here, n is the number of the locomotion step, and τ_ω and τ_D are parameters that change the speed of the above adaptation dynamics. They are equivalent to modifying the potential function in the gradient dynamics.

SIMULATION

The computer simulation was performed according to our previous paper (Ito et al. 1998). The parameters are as follows: $\beta = 2/3$, $\omega_i = 6.8$, $\rho_i = 6.8$, $D_0 = \pi$, $D_1 = 3\pi/2$, $D_2 = -\pi/2$, $\tau_\theta = 2.0$, $\tau_\omega = 0.25$, and $\tau_D = 0.02$. In the disturbed condition, ρ_0 is set 1.7 times the above value. Figure 4 shows the gait patterns obtained from these simulations, which are similar to the gait pattern shown in Figure 1.

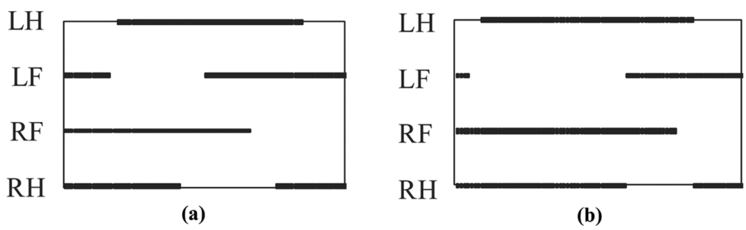

FIGURE 4 Gaits obtained by a mathematical model: (a) normal gait and (b) adapted gait.

Motion Pattern Memory

Learning and selection process

Although the CPG in the previous section can adjust the reference pattern as the adaptation, there are no functions for storing the adapted results. From this point of view, a motion pattern memory is introduced at the upper level of the CPG.

The motion pattern memory works as the higher center of the nervous system in a biological system: it memorizes the motion patterns, among which an appropriate one is designated as a reference to the CPG at the lower (spinal cord) level. This reference command makes the CPG actually generate the rhythmic pattern. This decoding process from the reference command to the actual rhythm is depicted in Figure 5(a) and is called *recollection*.

Now, assume that the environmental conditions have varied. This variation may render the reference pattern inappropriate. In such a case, the CPG not only adaptively produces an appropriate pattern but adjusts the reference in a self-organizing manner. This adjustment process, as depicted in Figure 5(b), is called *adaptation*.

If the new environmental condition is kept for a long time or is repeatedly presented, the motion pattern newly produced by the CPG is stored in to the motion pattern memory as one of the references to the CPG. This memorization is called *learning*, as shown in Figure 5(c).

Now, two motion patterns are stored in memory, as shown in Figure 5(d). When the environmental condition is presented, the motion pattern memory selectively designates the most appropriate one from memory. This process is called *selection*.

Formulations

In this section we define the learning and selection process.

The selection process is described as a dynamical process. Here, the memorized pattern should be represented as an attractor in the parameter space of motion pattern. The attractor is represented as a minimum point

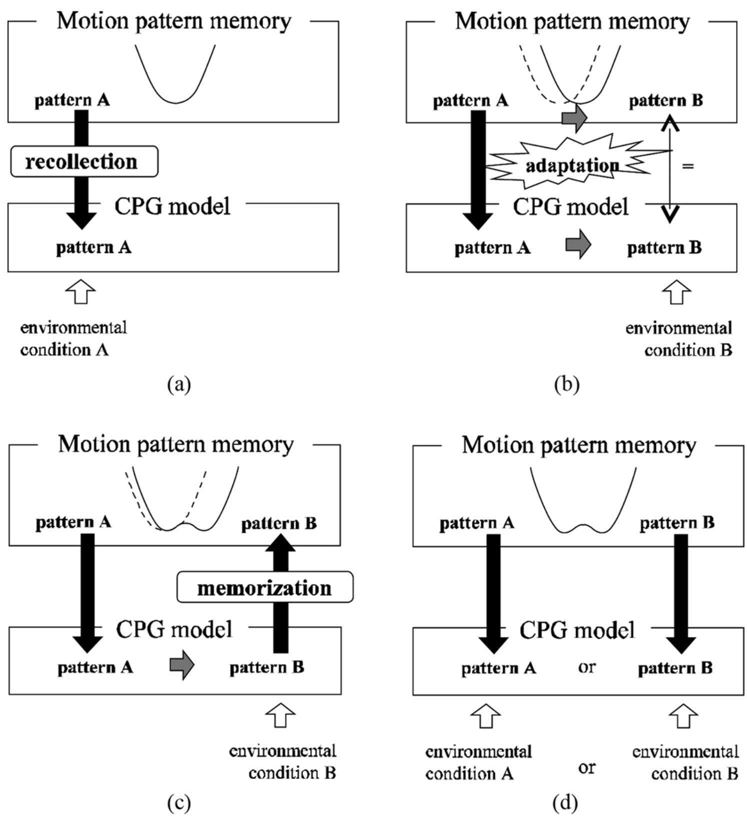

FIGURE 5 Our concept on an adaptation and learning process: (a) sole pattern generation, (b) adaptive generation, (c) learning process, and (d) selective generation.

of the potential function if the gradient dynamics is utilized for the description of the selection process. The main object of this article—that is, to additionally store a new motion pattern—is then represented as the deformation process of the potential function: this potential function originally has one minimum point. By the learning, a new minimum point bifurcates from the sole minimun point. As a result, the potential function with multiple minimum points is generated.

The scenario 1 in the section on motion pattern learning allows us to assume that the standard locomotion pattern "walk" gait is originally and permanently stored in memory. Restricting the number of memorized patterns to two, the potential function is defined as the fourth-order polynomial that can possess two minimum points:

$$V_P = \sum \left(p^{(j)} - p_1^{(j)}\right)^2 \left(p^{(j)} - p_2^{(j)}\right)^2 \tag{14}$$

Here, $p_1^{(j)}(j = 1, \ldots, m)$ and $p_2^{(j)}$ denote the memorized patterns and the minimum points of potential function, and m is the number of the parameter representing the motion pattern; that is, natural frequencies and reference relative phases in the CPG. First only the points gait ($p_1^{(j)}$) is in memory. This situation is expressed as a function with a single minimum point where two minimum points are duplicated ($p_2^{(j)} = p_1^{(j)}$). With respect to the environmental variation, a new motion pattern is adaptively generated in the CPG. At the same time, the reference is adjusted to generate this adapted pattern immediately. This adjusted reference $p_{now}^{(j)}$ is sent to and stored in the motion pattern memory, by producing a potential function with two minimum ($p_2^{(j)} \neq p_1^{(j)}$):

$$\dot{p}_2^{(j)} = \tau_\beta (p_{now}^{(j)} - p_2^{(j)}) \tag{15}$$

This dynamics describes the learning process.

Thanks to this potential function, the selection process is described as the gradient system of V_P:

$$\dot{p}^{(j)} = -\tau \frac{\partial V_P}{\partial p^{(j)}} \tag{16}$$

This produces a reference either $p_1^{(j)}$ or $p_2^{(j)}$, which is sent to the CPG as the reference command.

SIMULATIONS

Conditions

Taking the decerebrate cat experiment as an example, the simulation was performed under the following conditions:

1. All of the treadmill belts were driven at the same speed (normal condition).
2. The left forelimb was driven 1.7 times faster than the other limbs (disturbed condition).
3. The normal condition and the disturbed condition were presented repeatedly.

The parameters in these simulations are the same as the previous paper (Ito et al. 1998). These parameters make the oscillator interaction zero at the steady state of the normal condition. The remaining parameters were set to $\tau_\beta = 0.5$, $\tau = 8.0$.

The selection dynamics was triggered by a threshold: the oscillator interaction of the left forelimb—that is, $|f_0|$—exceeds it. The initial values of this dynamics are set followed by

$$p^{(j)}(0) = \frac{p_2^{(j)} - p_1^{(j)}}{\rho_{disturbed} - \rho_{normal}} (\rho_{now} - \rho_{normal}) + p_1^{(j)} \tag{17}$$

This equation linearly interpolates the relation between the locomotion parameters in memory and the environmental conditions given by the treadmill speed. The parameter values $p^{(j)}$ that were obtained in the locomotion period after the selection dynamics started were selected as the reference commands to the CPG.

Results

The simulation results for case 2 are shown in Figure 6. This graph illustrates the time course of the following variables: (a) natural frequencies, (b) desired

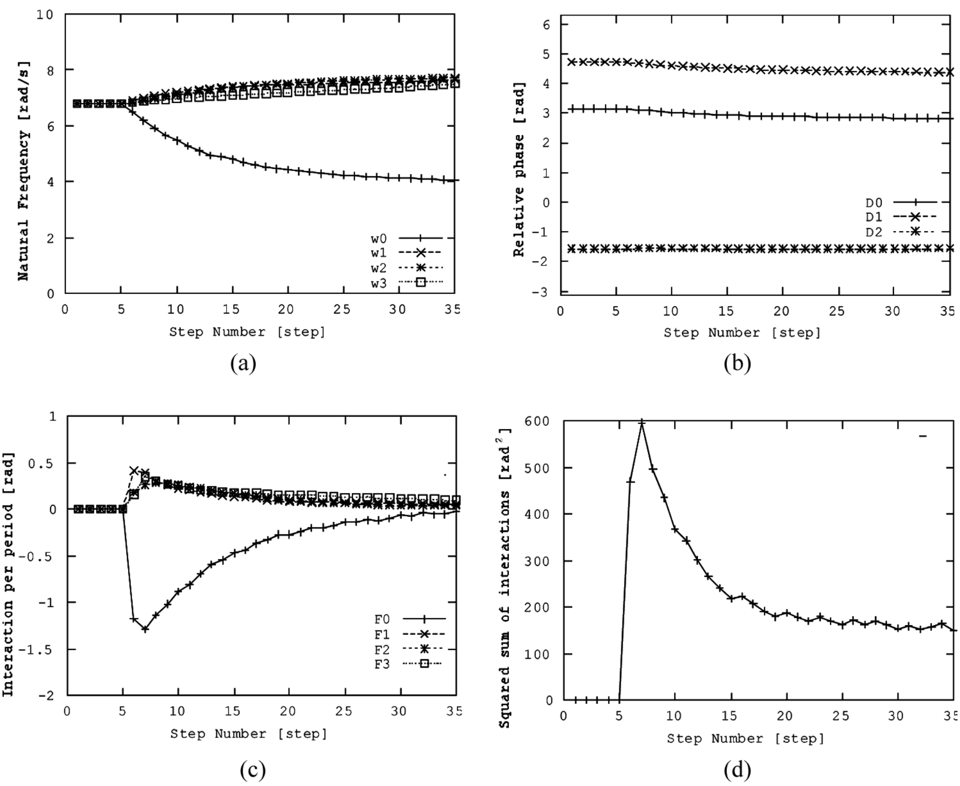

FIGURE 6 Simulation results in the disturbed condition: (a) natural frequencies, (b) relative phases, (c) interaction integrated during one step period, and (d) squared sum of integrated interactions.

relative phase, (c) oscillator interactions integrated during one locomotion cycle, and (d) squared sum of interactions integrated during one cycle. The horizontal axis in all four parts represents the step number of the locomotion. The natural frequencies and relative phases were adjusted, which decreased the oscillator interactions. The gait pattern obtained from this simulation is shown in Figure 4(b). This pattern was sent to the locomotion pattern memory and memorized there as a new pattern. The transection of the potential function along the ω_0, ω_1, D_0, and D_1 axes are shown in Figure 7. A deformation process was observed where the single minimum point bifurcated and the double minimum points was produced.

Finally, the simulation results for case 3 are shown in Figure 8. In this simulation, the environmental condition was switched from the normal to disturbed condition at the 10th steps. Then the condition was alternatingly switched in each 35 steps between the normal and the disturbed condition. The locomotion pattern immediately changed at the moment when the normal condition is provided. When the disturbed condition was presented, the locomotion pattern under learning was selected as the reference and the learning restarted from this pattern.

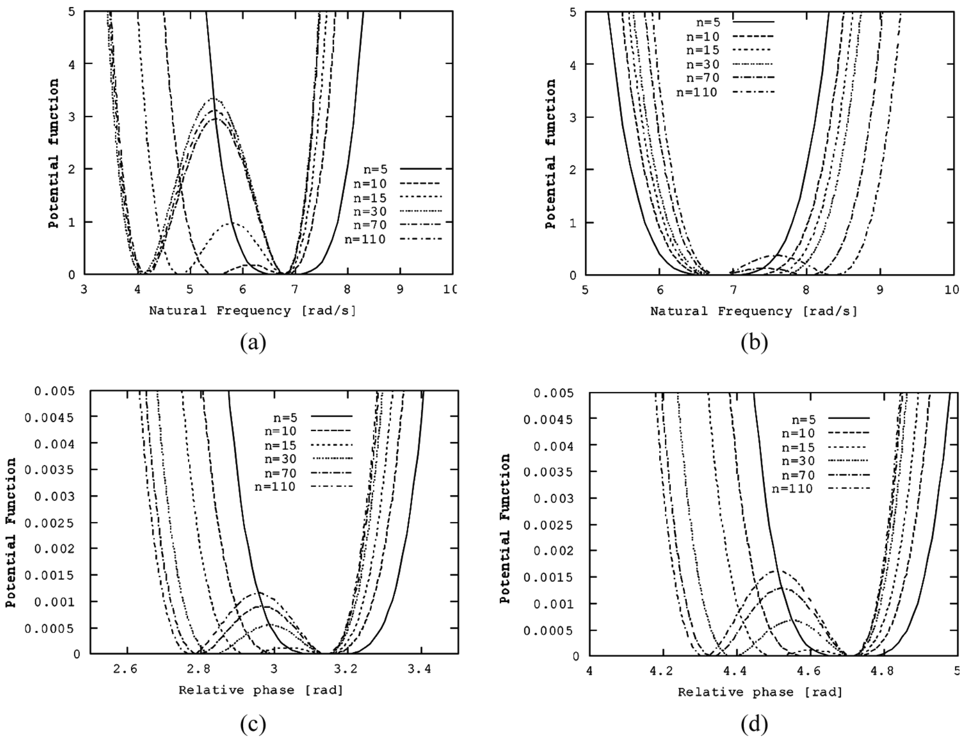

FIGURE 7 Deformation of potential function by learning: (a) potential function with respect to ω_0, (b) potential function with respect to ω_1, (c) potential function with respect to D_0, and (d) potential function with respect to D_1.

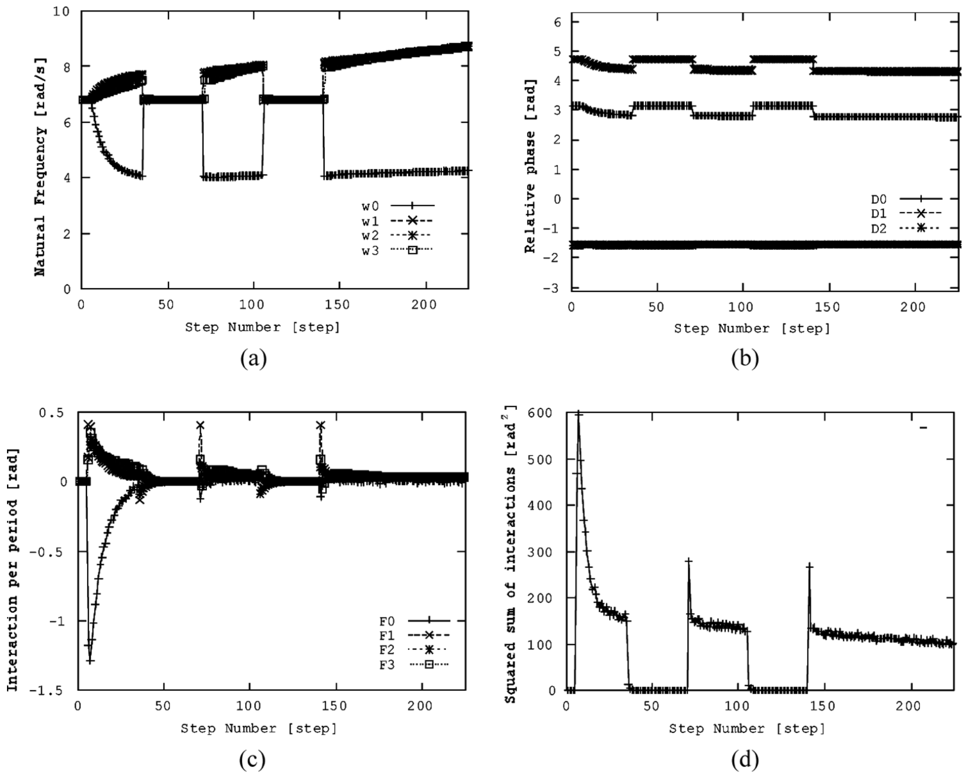

FIGURE 8 Simulation results where the environmental conditions are altered: (a) natural frequencies, (b) relative phases, (c) interaction integrated during one step period, and (d) squared sum of integrated interactions.

DISCUSSION AND CONCLUDING REMARKS

Restricting the object of study to the decerebrate cat's locomotion, adaptation and learning process have been considered based on the hypothesis that a multiple motion patterns can be memorized if multiple environmental conditions are repeatedly presented. The mathematical description of the following three processes is crucial: pattern generation, adaptation, and learning. We distinguish the adaptation and learning process as follows: the pattern generator receives the reference command from memory. The adaptation process in the pattern generator adjusts the reference according to the currently generated pattern. However, the results of this reference adjustment is not sent back to memory and thus is not stocked: the adjusted reference is usable only in the current environment. In the learning process, on the other hand, these results are accumulated in memory for reuse, which increases the repertoire of the motion pattern through the actual motion.

As for the pattern generation, the environment is parameterized by the treadmill speed in the decerebrate cat example, whereas the pattern is represented by the natural frequencies of and relative phases among oscillators in the CPG. These parameters are decoded by the oscillator dynamics based on the gradient system: the reference pattern becomes the minimum point of its potential function and the environmental variation acts as the disturbance. To elucidate mechanisms for the simple parameterizations of the motion pattern as well as recollection from them is the first step in understanding the variety of motion pattern generation in biological systems as well as its mathematical explanation.

The adaptation process is defined as follows: it adjusts the reference to the CPG to decrease the interactions among oscillator components. These interactions works as the error system: the difference between the reference and the actual patterns triggers their action. The situation where the interactions are permanently working implies that this reference is unachievable and thus should be adjusted. The above definition of the adaptation process comes from this idea. The magnitude of the oscillator interactions is utilized as the evaluation of the motion patterns, which also determines whether or not to switch the pattern. Generalization of such an adaptation rule is an important problem for future works.

The learning process is a key topic of this article. In order to memorize new reference patterns obtained by the adaptation process, the motion pattern memory is introduced under the restriction that the memory can store only two patterns. The main problems are how to define the expression of the memory itself and how to describe the increment of the number of memorized motion patterns. Here, the potential function is utilized: the minimum points correspond to the memorized pattern and its bifurcation expresses the increment of the number of the memorized patterns. Usually, the environmental conditions have infinite possibilities, whereas the number of the memorized pattern is finite, implying that mapping from the environmental condition to the memorized motion pattern has to be defined. This process corresponds to the selection process. In the decerebrate cat example, the gradient dynamics of the memory potential fulfills the role of selection. Then, the initial value of the selection process is set using a linear mapping from environments to patterns, where environmental conditions appropriate to each memorized motion pattern are needed to have been stored simultaneously.

Computer simulation realizes new pattern learning, the simultaneous memorization of two different patterns, and the immediate pattern switch between them. The immediate pattern switch is significant if the motion performance such as efficiency, stability, speed, and so on are improved as a result of this pattern transition.

Some problems remain for generalization of this learning scheme: how the environmental variations are detected, how the control system judges whether the pattern should be switched or not, whether the current pattern should be memorized or not, and how many patterns should be memorized. Although it is difficult to derive general solutions, we must address such problems in addition to the model extension, including physical locomotion dynamics such as limb swing and postural stability.

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