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# Neuromodulated Control of Bipedal Locomotion Using a Polymorphic CPG Circuit

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To date, various methods using the concept of neural circuit or so-called central pattern generators (CPGs) have been proposed to create agile locomotion for legged robots. In contrast to these approaches, in this article we propose a polymorphic neural circuit that allows the dynamic change of its properties according to the current situation in real time to be employed instead. To this end, the concept of neuromodulation is introduced. To verify the feasibility of this approach, this concept is applied to the control of a three-dimensional biped robot that is intrinsically unstable. The importance of an adaptive controller is illustrated with the simulations of biped walking on uneven terrain, and the results show that the biped robot successfully copes with environmental perturbation by dynamically changing the torque outputs applied to the joints. Furthermore, the proposed approach outperforms a monolithic CPG model with sensory feedback.

**Keywords** neuromodulation · central pattern generator (CPG) · biped robot · locomotion · real-time adaptation

## 1 Introduction

Legged robots show significant advantages over wheeled robots in uneven and unstructured environments. Yet to build a controller for a legged robot is generally extremely difficult due to the complicated interaction dynamics between the robots and their environment. This challenging task was solved by natural agents showing agile and adaptive locomotion even in unstructured environments. Neurophysiological investigations suggest that locomotion (e.g. walking, swimming, flying) is generated by specific neural circuits, or so-called *central pattern generators* (CPGs). Based on these findings various approaches have been proposed

for legged robots with artificial CPG controllers consisting of a set of *neural oscillators* (Taga, Yamaguchi, & Shimizu, 1991; Cruse et al., 1995; Wadden & Ekeberg, 1998).

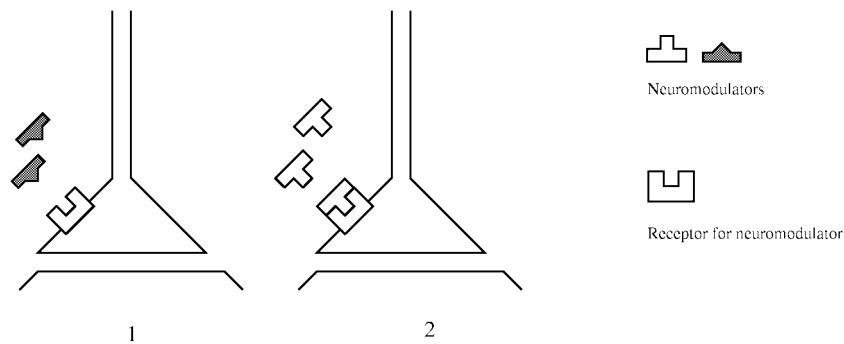
In contrast to these approaches in which *monolithic* CPG neural networks are used to control locomotion, this study employs a *polymorphic* neural circuit that allows dynamic changes of its properties according to the current situation in real time. We are not only intrigued with simply generating stable locomotion patterns, but also with investigating how sensory information modulates locomotion patterns according to the current situation. To realize this aim, the concept of *neuromodulation* with a diffusion–reaction

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**Figure 1** Illustration of the proposed neuromodulatory concept. The interactions between the neuromodulator and its receptor depend on their steric properties, represented here as different shapes. In case 1 the diffused neuromodulator cannot alter the synaptic weight. In case 2 the interaction is specific enough to modulate the synapse.

mechanism of chemical substances called *neuromodulators* is introduced.

Typically artificial neural networks are defined as massively distributed processors made up of single units (the structure of the network) and a learning algorithm allowing modification of the synapses, which is usually a slow process. Biological investigations of small neural networks in lobsters clarified the importance of nonsynaptic communication via diffusible neuromodulators among the neurons, in contrast to localized synaptic transmission. It was shown that the stomatogastric nervous system is able to dynamically rearrange its functional structure by diffusing special substances, so-called neuromodulators (Hooper & Moulins, 1989; Meyrand, Simmers, & Moulins, 1991). This rearrangement is done by enabling or blocking the functioning of the synapses, which express special receptors for the neuromodulators on their surface (see Figure 1). The specificity of the neuromodulators relies not on the diffusion processes, but on the interactions of the neuromodulators and the expressed receptors on the synapses. A change in a synapse due to a particular neuromodulator takes place only if a synapse expresses the corresponding receptor and if the neuromodulator concentration at the synapse is high enough. The specificity of the interaction between a neuromodulator and its corresponding receptor depends on their steric properties. By introducing such a neuromodulator concept synaptic changes on a different time scale can be investigated, because the interactions between neuromodulators and receptors allow an immediate change of the synaptic information transfer.

As there is no current existing theory about how such neural networks can be created, the evolutionary approach is the method of choice in exploring the

interactions among neuromodulators, receptors, synapses, and neurons. Although the neuromodulators diffuse freely to the other neurons in a net, they can specifically influence synapses by using specific interactions with the receptors on the synapses. Only those synapses that have an appropriate receptor will be influenced by a neuromodulator. Possible interactions can then be explored by an evolutionary algorithm by changing the expression of different receptors on the synapses and the production of neuromodulators.

Another reason for the interest of neuromodulators is their potential to overcome the reality gap (Miglino, Lund, & Nolfi, 1995; Jakobi, Husbands, & Hervey, 1995; Jakobi, 1998; Nolfi, 1997). An example of a peg-pushing agent controlled by neuromodulators was first evolved in a simulator and then successfully transferred to the real world (Eggenberger, Ishiguro, Tokura, Kondo, & Uchikawa, 2000). The basic idea is to evolve adaptive controllers that are able to sense their current situation and to test the same controller for slightly different situations, which leads to robust and adaptive behavior of the simulated agent as well as the robot.

Here, as the initial step of the investigation, we attempt to create neural controllers with a neuromodulation mechanism for a three-dimensional biped robot in the sagittal plane. Simulations were carried out in a physical simulator to verify the feasibility of our proposed method.

## 2 Related Work

Concerning the evolutionary creation of controllers for legged robots, various methods have been proposed. Beer and colleagues evolved dynamically recurrent

neural networks for a hexapod robot (Beer, Chiel, & Sterling, 1991). Jakobi introduced the concept of *minimal simulation* not only to speed up the evolutionary process but also to bridge the gap between simulated and real environments. He applied this concept to evolve a controller for an octopod robot (Jakobi, 1998). Gruau and Quatramaran (1997) proposed the *cellular encoding scheme* based on genetic programming and implemented it to evolve a hexapod controller. Kodjabachian proposed a *geometry-oriented encoding scheme* called SGOCE and evolved a neurocontroller for a legged robot (Kodjabachian & Meyer, 1998a, b). Ijspeert evolved a controller to mimic a salamander's locomotion and the resultant controller could smoothly switch between swimming and walking (Ijspeert, Hallam, & Willshaw, 1998; Ijspeert, 2000).

There are mainly two points to be noted from the above-mentioned works. First, most of these methods are based on *monolithic* neural networks, that is, the properties of the controllers such as synaptic weights are fixed once acceptable controllers for the given task are evolved. Second, as mentioned above, so far various methods have been proposed for quadruped, hexapod, and octopod robots; however, still very few biped robots have been evolved in spite of their remarkable mobility. This is presumably due to their high instability.

Concerning the evolutionary creation of plastic neural controllers, Floreano and Mondada (1996) evolved neural controllers by assigning a learning rule to every synapse. In contrast, our approach allows us to evolve learning rules, which can correlate not only the activity of neighboring neurons and their synapses, but also the activities from distant neurons depending on which neuromodulators are diffused in a given situation. Fur-

thermore, by introducing a blocking function, the neuromodulators can also dynamically rearrange the structure of the neural network.

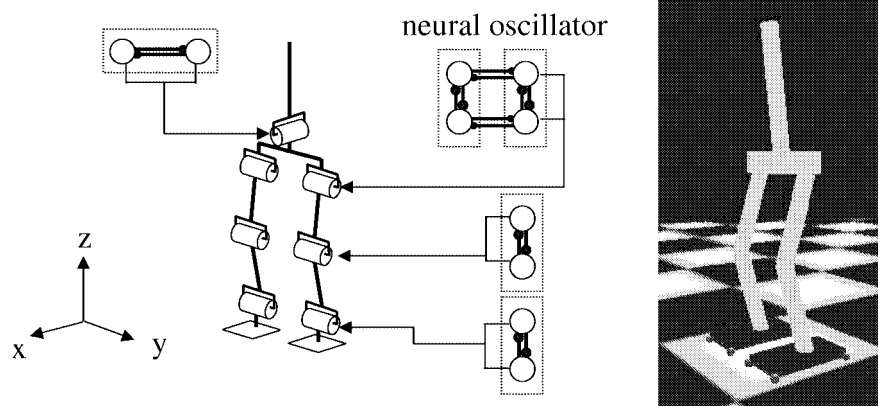
Husbands et al. (1998) introduced a gas model (nitric oxide), which allows the modulation of synapses. The main difference to our approach is that we use specific receptors to locate an effect on a neuron or a synapse. Using the receptor concept a cell can diffuse a neuromodulator to all cells, but only those that have the corresponding receptor will be changed by the neuromodulator; all the others remain unchanged.

### 3 Locomotion Control Using Neuromodulation

#### 3.1 Biped Robot Model

The three-dimensional biped robot model used in this study is illustrated in Figure 2. This robot is composed of eight rigid parts (i.e., torso, waist, thighs, shanks, and feet) and seven joints. These joints are all independently driven by pairs of antagonistic actuators, *flexor* and *extensor*, to take not only the static torque but also the stiffness of the joints (for energy efficiency) into account. The robot has an angle sensor at the hip joints, informing how the concerned joint rotates. In addition, an incline sensor exists, detecting how the robot inclines in the sagittal plane. This incline sensor returns a positive value when the robot leans forward, and a negative value otherwise.

The following simulations were conducted with the use of a physics-based, three-dimensional simulation environment.<sup>1</sup> This environment simulates both the inter-



**Figure 2** Three-dimensional biped robot model used in the simulation. This robot has in total 7 degrees of freedom. For simplicity, the torso is allowed to move only in the lateral plane.

**Table 1** Body parameters of the biped robot.

| Body part | Size (m)           | Mass (kg) |
|-----------|--------------------|-----------|
| Torso     | 0.56               | 2.0       |
| Body      | 0.1 × 0.36 (d × w) | 1.0       |
| Thigh     | 0.44               | 1.0       |
| Shank     | 0.47               | 1.0       |
| Foot      | 0.1 × 0.36 (d × w) | 1.0       |

nal and external forces acting on the agent and objects in its environment, as well as various other physical properties such as contacts between the agent and the ground, and torque applied by the motors to the joints within an acceptable time limit. The body parameters used in the following simulations are listed in Table 1.

### 3.2 Structure of the Neural Circuit

The whole structure of the CPG circuit employed to generate biped locomotion is illustrated in Figure 3a. This CPG circuit consists of seven sets of neural oscillators, one for each joint in the robot. In this study, *Matsuoka's oscillator model* was employed to create rhythmic locomotion patterns, where two neurons mutually inhibit each other (see Figure 3b; Matsuoka, 1987).

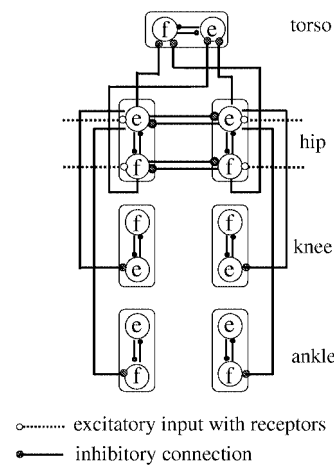
The dynamics of each neuron in the oscillator obeys the following first-order differential equations:

$$\tau_r \frac{du_i}{dt} = -u_i - \sum_{j=1}^n w_{ij}y_j + \text{feed}_i - bf_i + s_i \quad (1)$$

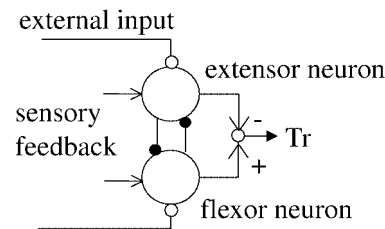
$$\tau_a \frac{df_i}{dt} = -f_i + y_i \quad (2)$$

$$y_i(u) = \max\{0, u\} \quad (3)$$

where  $u_i$  is the membrane potential of neuron  $i$ ,  $f$  is the variable representing the degree of self-inhibitory effect of the neuron concerned,  $b$  is the parameter determining the strength of self-inhibitory effect,  $w_{ij}$  is the synaptic weight from neuron  $j$  to neuron  $i$ ,  $y$  is the output of the neuron,  $s$  is the external input coming from a neuron, the output of which is set to be constant, and  $\text{feed}_i$  is the sensory feedback applied to neuron  $i$ .  $\tau_r$  and  $\tau_a$  are the time constants. Note that one of the neurons in the oscillator is responsible for the generation of the extension torque, whereas the other is



(a) CPG circuit



(b) Neural oscillator

**Figure 3** Controller for the biped robot. Each joint is controlled by a neural oscillator, composed of two mutually inhibiting neurons. For stable entrainment between the central pattern generator (CPG) circuit and the musculo-skeletal system, each hip neuron receives sensory feedback from its corresponding angle sensor equipped at the hip joint.

responsible for the flexion torque of the joint. As a result the torque  $T_f$  that will actually be applied to this joint is proportional to the difference of the activities of these two neurons.

To establish stable entrainment between the neural system and the musculo-skeletal system, a sensory

feedback is implemented at the hip joints. The information from the angle sensor is positively fed back to the extensor neuron of the hip joint, whereas negatively to the flexor neuron as:

$$\text{feed} = +k \cdot \theta_{\text{hip}} \quad (4)$$

for the extensor neuron at the hip joint

$$\text{feed} = -k \cdot \theta_{\text{hip}} \quad (5)$$

for the flexor neuron at the hip joints

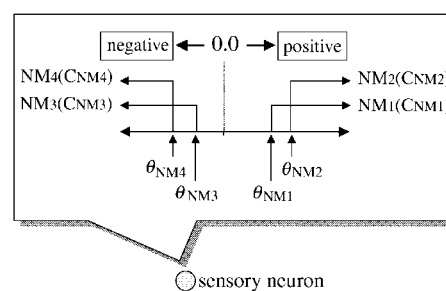
where  $k$  is the feedback gain, and  $\theta_{\text{hip}}$  is the sensor reading from the angle sensor.

### 3.3 Neuromodulation Mechanism

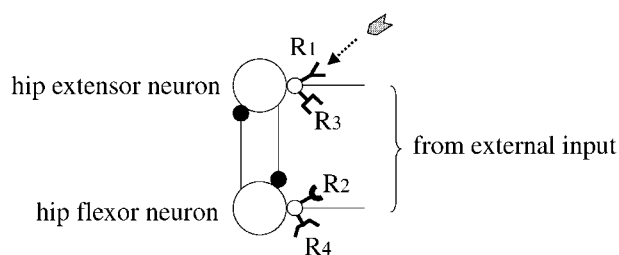
The neuromodulation mechanism employed to regulate the behavior of the aforementioned CPG circuit was designed in the following way:

**Diffusion Process.** In the present work, for simplicity, only the incline sensory neuron is allowed to diffuse specific (i.e., genetically determined) types of neuromodulators (NMs) as long as its neuronal activity  $y$  is within the corresponding diffusible area, which is also to be genetically determined. A schematic diagram indicating how the NMs are diffused is depicted in Figure 4a. The incline sensory neuron diffuses two types of neuromodulators depending on the sign of its activity. The neuromodulators  $\text{NM}_1$  and  $\text{NM}_2$  ( $\text{NM}_3$  and  $\text{NM}_4$ ) are diffused if the sign of the activity is positive (negative) and greater (less) than a threshold  $\theta_{\text{NM}_1}$  and  $\theta_{\text{NM}_2}$  ( $\theta_{\text{NM}_3}$  and  $\theta_{\text{NM}_4}$ ), respectively. Each type has a specific value assigned to it, the so-called concentration  $c_{\text{NM}_k} \in [-1.5, 4.0]$  ( $k \in 1,2,3,4$ ), which will be used to modify dynamically the synaptic weights of the CPG circuit. Note that the value of the concentration and the diffusion threshold (represented by  $c_{\text{NM}_1}$ ,  $c_{\text{NM}_2}$ ,  $c_{\text{NM}_3}$ ,  $c_{\text{NM}_4}$ ,  $\theta_{\text{NM}_1}$ ,  $\theta_{\text{NM}_2}$ ,  $\theta_{\text{NM}_3}$ , and  $\theta_{\text{NM}_4}$  in Figure 4a) are genetically determined for each type of NM.

**Reaction Process.** The diffused NMs are specifically interacted with receptors positioned on the synapses of the CPG. This allows us to modify the synaptic weights selectively and dynamically according to the diffusion patterns of the NMs. Since four types of NMs are used, there exist four types of receptors in the CPG circuit, as represented by  $R_1$ ,  $R_2$ ,  $R_3$ , and  $R_4$  in Figure 4b. Note that the receptor can specifically recognize the diffused NM with the same



(a) Diffusion mechanism



(b) Reaction mechanism

**Figure 4** A schematic diagram of the neuromodulation mechanism. There are in total four types of neuromodulators, two of which are assumed to influence the synaptic property at the hip extensor neuron, and the others the hip flexor neuron. Details are explained in the text (Section 3.3).

number (e.g.,  $\text{NM}_1$  for  $R_1$ ). In the present work, these receptors are assumed to be merely on the synapses concerning the external inputs at the hip joints:  $R_1$  and  $R_3$  for the extensor neuron of the joint,  $R_2$  and  $R_4$  for the flexor neuron (see Figure 4b). Once the NMs are diffused, each synapse with the corresponding receptors will be modified as

$$w(t+1) = w_d + \sum_{k=1}^4 c_{\text{NM}_k}(t) \quad (6)$$

where  $w_d$  is the default synaptic weight, which will be used to create basic oscillatory behavior (see below) and  $c_{\text{NM}_k}$  is the concentration of the NM of type  $k$ . The meaning of this equation is that the synaptic weights are modified according to the genetically determined concentration of the diffused NM.

### 3.4 Evolutionary Creation of the Diffusion-Reaction Rules

To create an appropriate neuromodulation mechanism, the following parameters were evolved:

1. The default synaptic weights of the CPG circuit  $w_d$ , and the parameters of the neural oscillator  $\tau_r \in [0.01, 0.075]$ ,  $\tau_a \in [0.04, 0.75]$ ,  $b \in [1.25, 2.0]$ , and  $s \in [0.0, 5.0]$ .
2. The diffusion threshold value and concentration of each type of NM:  $\theta_{NM_1} \in [0.0, 1.0]$ ,  $\theta_{NM_2} \in [0.0, 1.0]$ ,  $\theta_{NM_3} \in [-1.0, 0.0]$ , and  $\theta_{NM_4} \in [-1.0, 0.0]$ ,  $c_{NM_1} \in [-1.5, 4.0]$ ,  $c_{NM_2} \in [-1.5, 4.0]$ ,  $c_{NM_3} \in [-1.5, 4.0]$ , and  $c_{NM_4} \in [-1.5, 4.0]$ .

Note that these parameters should be determined by taking the body dynamics and the interaction dynamics with the environment into account. Thus, in this study a genetic algorithm was employed to meet this requirement. As mentioned before, the objective of this study is to develop an adaptive CPG circuit that can cope with gradient changes of the terrain. To efficiently create such a neural circuit, an incremental two-staged evolutionary scheme is adopted. In the following section it is shown how each stage of the evolution was conducted.

**3.4.1 The First Stage of the Evolution (Acquisition of the Default CPG Circuit)** The aim of this stage is to create the basic structure of the CPG circuit, which can generate rhythmic and stable locomotion patterns on flat terrain. More specifically, the default synaptic weights of the CPG circuit and the parameters of the neural oscillator were evolved. These parameters were encoded as a binary-bit string, which will be used as a chromosome for the evolutionary process. Each individual was tested on flat terrain, allowed to move for 30 s, and the following fitness function was employed for this purpose:

$$f_1 = D_{\text{flat}} \quad (7)$$

where  $D_{\text{flat}}$  is the resultant walking distance traveled during the evaluation period (i.e., 30 s).  $D_{\text{flat}}$  only contributed to the fitness if the height of the waist was beyond the pre-specified threshold (70% height of the upright posture). This scheme was adopted to encourage the generation of stable and successful walking by alternatively stepping forward. One hundred individuals were evolved through 200 generations with a crossover rate of 0.2 and mutation rate of 0.1.

**3.4.2 The Second Stage of the Evolution (Acquisition of the Neuromodulation Mechanism)** The targets to be evolved in this stage were the neuromodulation mechanisms that can appropriately modify the synaptic weights of the CPG circuit obtained in the previous stage of the evolution according to the current situation. The population obtained at the last generation in the first stage was used as the initial population of this stage and was evolved through 200 generations. Here, each individual was tested under two different environments, namely 5° uphill and 5° downhill, and the following fitness function was used as the evaluation criterion:

$$f_2 = D_{\text{uphill}} \times D_{\text{downhill}} \quad (8)$$

where  $D_{\text{uphill}}$  and  $D_{\text{downhill}}$  are the resultant distance traveled on the uphill and the downhill slopes, respectively. The encoding scheme (i.e., binary-bit chromosome) and the parameters of genetic operators (i.e., crossover and mutation rates) were exactly the same as in the first stage of the evolutionary process.

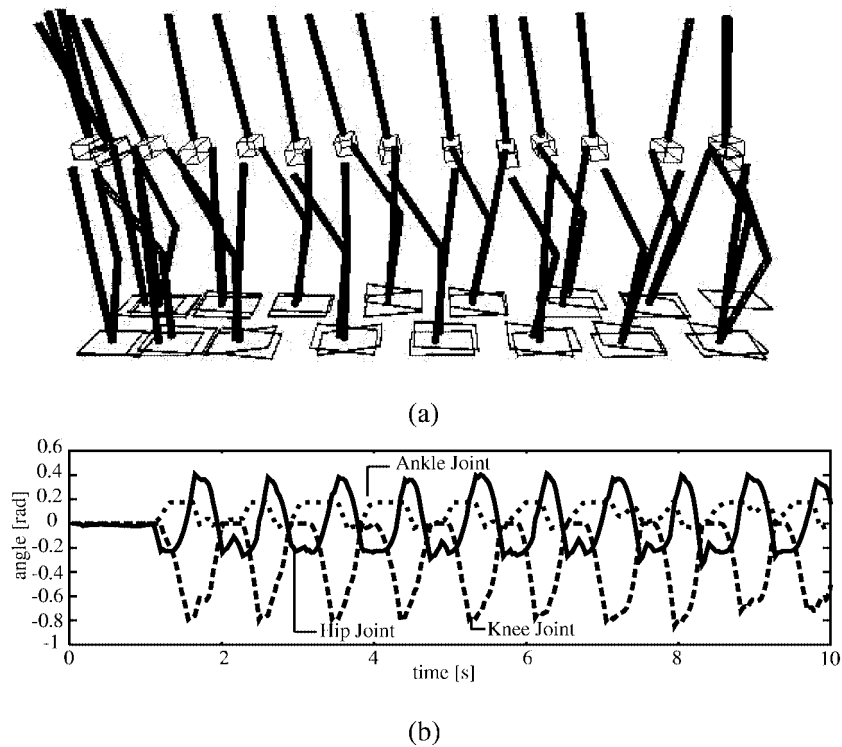
## 4 Simulation Results

### 4.1 Acquisition of Locomotion on Flat Terrain

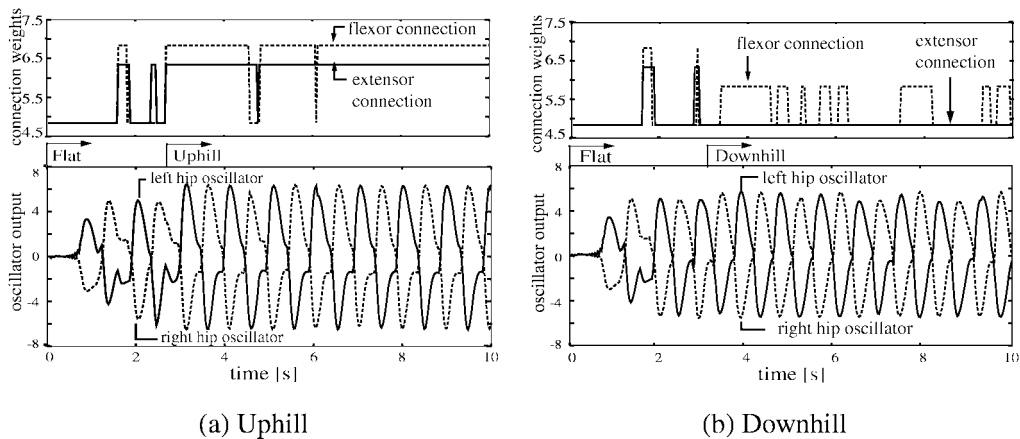
Figure 5a shows the locomotion of the best-evolved agent obtained in the first stage. In this figure the robot moves from left to right. Figure 5b indicates the transition of the hip-joint angle, knee-joint angle, and ankle-joint angle of the right leg. As the figures show, the robot can successfully walk on the flat terrain by periodically and alternately stepping forward. However, it is observed that this evolved controller is unable to adapt to gradient changes. Note that at this stage only the angle sensors were employed for the sensory feedback.

### 4.2 Acquisition of Locomotion on Inclined Terrain

Figure 6a and b show the transition of the oscillator outputs from the hip flexor and extensor neurons and the synaptic weights of the best-evolved agent obtained in the second stage, respectively. As the figures represent, the robot can continue walking without falling down by modulating the applied torques.



**Figure 5** (a) The obtained locomotion through the first stage of evolution. This snapshot indicates the locomotion recorded between 0 and 8 s. (b) The transition of the hip-joint angle, knee-joint angle, and ankle-joint angle of the right leg. This indicates that the robot can successfully walk.



**Figure 6** Transition of the oscillator outputs from the hip flexor neurons and the connection weights during (a) uphill and (b) downhill walking. The different connection weights of the hip's extensor and flexor neurons reflect the adaptation of the controller to these two different tasks. The controller is therefore changing dynamically (reflected by the dynamic change of the synaptic weights), which is by definition an adaptive and not a robust control.

### 4.3 Validation of Adaptability

**4.3.1 Compound Environment** To investigate the adaptability of the evolved neuromodulation mechanism, the best-evolved robot obtained in the second stage was placed on the slope schematically illustrated

in Figure 7. Remember the environments experienced in the second stage were purely uphill and downhill slopes. Thus, the robot has never experienced gradient changes (e.g.,  $0^\circ \rightarrow 5^\circ$ ,  $-5^\circ \rightarrow 0^\circ$ , etc.) during the evolutionary process.





**Figure 7** Test terrain with downhill, flat, and uphill components. This terrain was used to test the adaptability of the evolved neural controllers for the biped. Note that the robot has never experienced this environmental configuration during its evolutionary processes.

Shown in Figure 8 is the resultant locomotion under this test environment. Interestingly, as the figure indicates, the robot changes its locomotion pattern to cope with this environment. To visualize this adaptation process, the transition of the synaptic weights (i.e., flexor and extensor neurons) and the oscillator outputs applied to the hip joints (i.e., right and left oscillator outputs) during this walking are shown in Figure 9. These figures show that depending on the gradient of the terrain, the diffusion patterns of the synaptic weights are changed dynamically, which leads to the real-time regulation of the torques applied to the hip joints.

**4.3.2 Impulsive Force** Shown in Figure 10 are the data obtained after disturbing the biped. In this experiment a constant force was applied at the hip toward the frontal direction between 4.05 and 4.8 s. From the figure, the robot resumed its stable locomotion at approximately 11 s. It is also observed that the robot can continue walking under the existence of impulsive force applied oppositely (i.e., toward the backward direction). It is of great interest that such a simple neuromodulation mechanism can adapt to these environmental changes.

**4.3.3 “Knock-out” Test** To verify the feasibility of the created neuromodulatory mechanism, a “knock-

out” test was conducted. Figure 11 shows a simulation result in which one of the neuromodulators was artificially eliminated from the best-evolved agent. As in the figure, the adaptability of the robot was significantly reduced. This strongly suggests that the created nonsynaptic communication via neuromodulators plays an essential role as the feedback control against environmental disturbances.

#### 4.4 Comparison with a Monolithic CPG Circuit

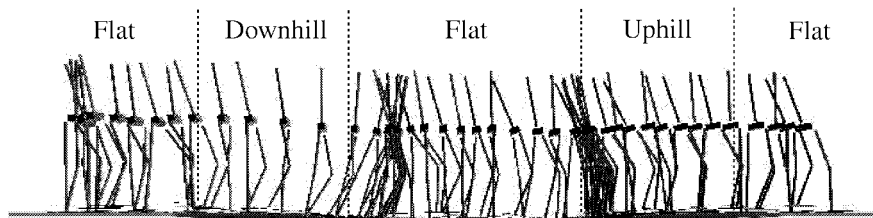
In this section we compare the neuromodulated circuit with an evolved monolithic CPG circuit having a fixed sensory feedback from the incline sensor. For the sake of fair comparison, the incremental evolution scheme mentioned above was also employed here: The population obtained at the last generation in the first stage described in the previous section was employed as the initial population of the second stage, and the connectivity and its strength between the evolved CPG circuit and the incline sensory neuron were evolved through 200 generations.

The feedback signals from the incline sensor are expressed as

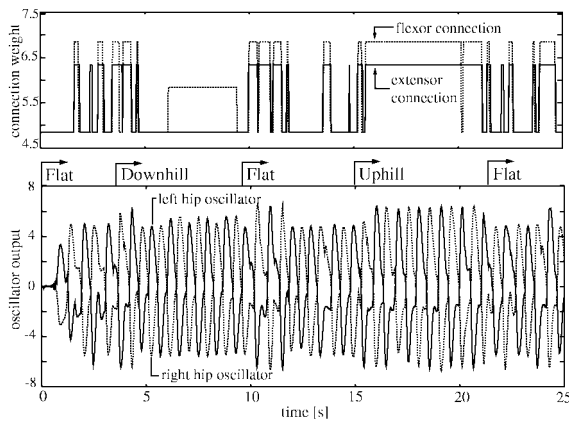
$$\text{feed}I_e = + \text{signal} \cdot w_e \cdot \text{Incline} \quad (9)$$

$$\text{feed}I_f = - \text{signal} \cdot w_f \cdot \text{Incline}, \quad (10)$$

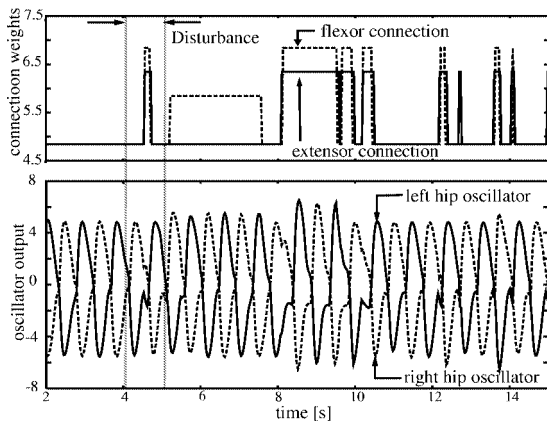
where  $\text{feed}I_e$  and  $\text{feed}I_f$  are the feedback signals to the extensor and flexor neuron of the hip oscillator, respectively (see Figure 12);  $\text{signal}$  ( $= -1, 0, 1$ ) is a parameter that determines the properties of the synaptic connection between the hip oscillator neuron and the incline sensor (e.g., if  $\text{signal}$  is 1,  $\text{feed}I_e$  will act as the positive feedback); and  $w_e$  and  $w_f$  are the strength of  $\text{feed}I_e$  and  $\text{feed}I_f$ , respectively. In this stage, the targets



**Figure 8** Obtained trajectory. This snapshot was recorded under the test environment. Interestingly, the robot seems to be *struggling* at the place where its gradient changes significantly. It is also observed that the robot changes its locomotion speed and step width according to the gradient.



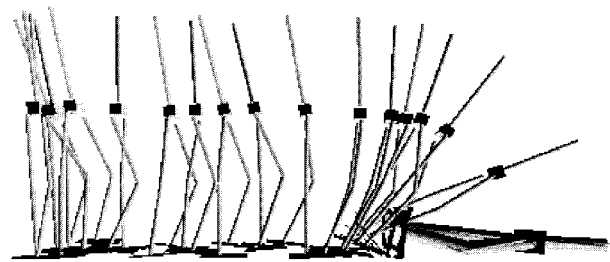
**Figure 9** Transition of the oscillator outputs from the hip flexor and extensor neurons and the connection weights under the test environment. As this figure indicates, the neuromodulation mechanism changes the synaptic weights dynamically according to the gradient of the terrain. This leads to the real-time regulation of the torques applied to the hip joints (e.g., bigger torques at the uphill compared to the flat terrain).



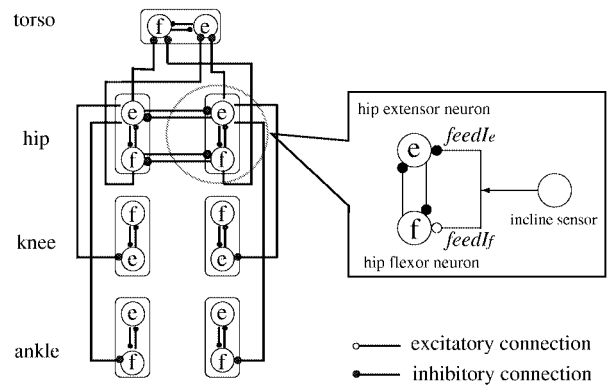
**Figure 10** Transition of the oscillator outputs applied to the hip joints and connection weights due to an applied disturbance. A constant force was applied at the hip toward the frontal direction between 4.05 and 4.8 s, indicated by shaded lines. The robot returned back to its stable locomotion pattern at approximately 11 s.

to be evolved are signal,  $w_e$  and  $w_f$ . The environment and the fitness function employed in this evolutionary process are exactly the same as in the second stage.

Shown in Figure 13 is the comparison of the fitness transition between the aforementioned CPG circuit with the neuromodulation and the monolithic CPG circuit with the sensory feedback. These curves were obtained by averaging over six trials. The results indicate that the proposed neuromodulation mechanism



**Figure 11** A representative result of the knock-out test with disturbance. In this test, one of the neuromodulators was artificially eliminated from the evolved neuromodulation mechanism with the result that the robot could no longer walk. This strongly suggests that the created diffusion–reaction mechanism of neuromodulators acts as an adaptive sensory feedback to the CPG circuit.

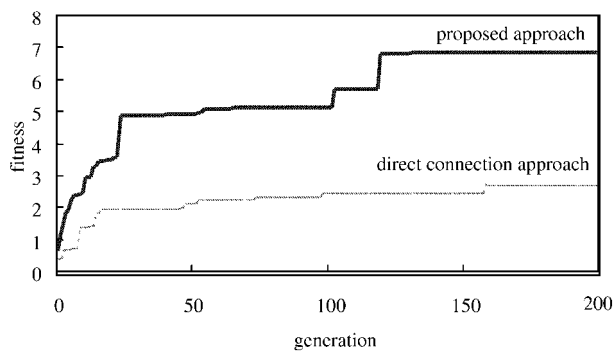


**Figure 12** Structure of the monolithic CPG circuit with the fixed sensory feedback. The signal coming from the incline sensor is fed back to the extensor and flexor neurons of the hip oscillators. The connectivity (i.e., excitatory/inhibitory) and the strength of each connection are genetically determined.

outperforms the fixed sensory feedback approach not only in terms of adaptability but also evolvability.

## 5 Discussion and Conclusion

In this article a neuromodulator-based method to evolve an adaptive CPG circuit for a biped robot has been investigated. To this end the concept of neuromodulation, widely observed in biological nervous systems, has been introduced to the control of a three-dimensional biped robot, which is intrinsically unstable. Simulation results have shown that the proposed method can create an appropriate locomotion pattern according to the environmental perturbation. As the present work has mainly focused on the feasibility of



**Figure 13** Comparison of the fitness transition between the proposed CPC circuit with neuromodulation and the CPG circuit with direct sensory feedback (i.e., monolithic CPG circuit). As the figure indicates, the neuromodulation approach outperforms the CPG circuit with direct sensory feedback. This implies that evolutionary creation of appropriate sensory feedback would greatly depend on the sensory modality.

the neuromodulation concept in terms of adaptability, the number of sensory modalities has been intentionally minimized (i.e., angle sensor and incline sensor). To increase the ability to cope with a wide range of environmental changes, various types of sensory modalities will be necessary (e.g., vision, reaction force from the ground, etc.). In addition, the number of degrees of freedom of the body structure has to be increased to ameliorate maneuverability. Nevertheless, the neuromodulation concept discussed here will allow us to increase the adaptability of the evolved controller effectively compared to the conventional monolithic neural networks.

## Note

1 MathEngine SDK; [www.cm-labs.com](http://www.cm-labs.com)

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## References

- Beer, R., Chiel, J., and Sterling, L. (1991). An artificial insect. *American Scientist*, 79, 444–452.
- Cruse, H., Bartling, C., Dean, J., Dreifert, M., Kindermann, T., & Schmitz, J. (1995). Walking: A complex behavior controlled by simple networks. *Adaptive Behavior*, 3, 385–418.
- Eggenberger, P., Ishiguro, A., Tokura, S., Kondo, T., & Uchikawa, Y. (2000). Toward seamless transfer from simulated to real worlds: A dynamically-rearranging neural network approach. In J. Wyatt & J. Demiris (Eds.), *Proceedings of the Eighth European Workshop on Learning Robots (EWLR-8)* (Lecture Notes in Artificial Intelligence 1812, pp. 44–60). Springer.
- Floreano, D., & Mondada, F. (1996). Evolution of plastic neurocontrollers for situated agents. In P. Maes, J. Mataric, J.-A. Meyer, J. Pollack, & S. W. Wilson (Eds.), *From animals to animats 4: Proceedings of the 4th International Conference on Simulation of Adaptive Behavior* (pp. 401–411). Cambridge, MA: MIT Press.
- Gruau, F., & Quatramaran, K. (1997). Cellular encoding for interactive evolutionary robotics. In P. Husbands & I. Harvey (Eds.), *Proceedings of the Fourth European Conference on Artificial Life, ECAL97* (pp. 368–377). Cambridge, MA: MIT Press.
- Hooper, S., & Moulins, M. (1989). Switching of a neuron from one network to another by sensory-induced changes in membrane properties. *Science*, 244, 1587–1589.
- Husbands, P., Smith, T., O’Shea, M., Jakobi, N., Anderson, J., & Philippides, A. (1998). Brains, gases and robots. In L. Niklasson, M. Boden, & T. Ziemke (Eds.), *Proceedings of the 8th International Conference on Artificial Neural Networks ICANN98* (pp. 51–63). Springer.
- Ijspeert, A. J. (2000). A neuromechanical investigation of salamander locomotion. In H. Kimura, H. Witte, & G. Taga (Eds.), *Proceedings of the International Symposium on Adaptive Motion of Animals and Machines, AMAM2000*. (ID no. TuP-II-1). CD-ROM. <http://www.kimura.is.uec.ac.jp/amam/index.html>
- Ijspeert, A. J., Hallam, J., & Willshaw, D. (1998). From lampreys to salamanders: Evolving neural controllers for swimming and walking. In R. Pfeifer, B. Blumberg, J.-A. Meyer, & S. W. Wilson (Eds.), *From animals to animats 5: Proceedings of the Fifth International Conference on Simulation of Adaptive Behavior* (pp. 390–399). Cambridge, MA: MIT Press.
- Jakobi, N. (1998). Running across the reality gap: Octopod locomotion evolved in a minimal simulation. In P. Husbands & J. Meyer (Eds.), *Proceeding of the First European Workshop on Evolutionary Robotics* (pp. 39–58). Springer.

- Jakobi, N., Husbands, P., & Hervey, I. (1995). Noise and the reality gap: The use of simulation in evolutionary robotics. In F. Moran, A. Moreno, J. Merelo, & P. Chacon (Eds.), *Third European Conference on Artificial Life (ECAL95), Advances in Artificial Life* (pp. 704–720). Springer.
- Kodjabachian, J., & Meyer, J.-A. (1998a). Evolution and development of modular control architectures for 1-d locomotion in six-legged animats. *Connection Science*, *10*, 211–237.
- Kodjabachian, J., & Meyer, J.-A. (1998b). Evolution and development of neural networks controlling locomotion, gradient-following, and obstacle-avoidance in artificial insects. *IEEE Transactions on Neural Networks*, *9*, 796–812.
- Matsuoka, K. (1987). Mechanisms of frequency and pattern control in the neural rhythm generators. *Biological Cybernetics*, *56*, 345–353.
- Meyrand, P., Simmers, J., and Moulins, M. (1991). Construction of a pattern-generating circuit with neurons of different networks. *Nature*, *351*, 60–63.
- Miglino, O., Lund, H., & Nolfi, S. (1995). Evolving mobile robots in simulated and real environments. *Artificial Life*, *2*, 417–434.
- Nolfi, S. (1997). Evolving non-trivial behaviors on real robots: A garbage collecting robot. *Robotics and Autonomous Systems*, *22*, 187–198.
- Taga, G., Yamaguchi, Y., & Shimizu, H. (1991). Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment. *Biological Cybernetics*, *65*, 147–159.
- Wadden, T., & Ekeberg, O. (1998). A neuro-mechanical model of legged locomotion: Single leg control. *Biological Cybernetics*, *79*, 161–173.

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