A Simple *Aplysia*-Like Spiking Neural Network to Generate Adaptive Behavior in Autonomous Robots

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In this article, we describe an adaptive controller for an autonomous mobile robot with a simple structure. Sensorimotor connections were made using a three-layered spiking neural network (SNN) with only one hidden-layer neuron and synapses with spike timing-dependent plasticity (STDP). In the SNN controller, synapses from the hidden-layer neuron to the motor neurons received presynaptic modulation signals from sensory neurons, a mechanism similar to that of the withdrawal reflex circuit of the sea slug, *Aplysia*. The synaptic weights were modified dependent on the firing rates of the presynaptic modulation signal and that of the hidden-layer neuron by STDP. In experiments using a real robot, which uses a similar simple SNN controller, the robot adapted quickly to the given environment in a single trial by organizing the weights, acquired navigation and obstacle-avoidance behavior. In addition, it followed dynamical changes in the environment. This associative learning scheme can be a new strategy for constructing adaptive agents with minimal structures, and may be utilized as an essential mechanism of an SNN ensemble that binds multiple sensory inputs and generates multiple motor outputs.

Keywords *Aplysia* · associative learning · autonomous mobile robot · presynaptic modulation · spike timing-dependent plasticity · spiking neural network

1 Introduction

The spiking neural network (SNN) is the latest generation of artificial neural networks (ANNs). It follows the first generation, which used binary threshold-gate neuron models, and the second generation, which used continuous sigmoidal-gate neuron models (Maass, 1997). In the older generations of ANNs, the rate of action-potential firing in natural neurons was represented in principle by the activation of artificial neurons. These ANNs lacked synaptic plasticity, and

therefore, in applications where dynamical adaptation to environment was essential, dynamics in plasticity were realized by changing synaptic weights in response to different patterns of activity in a history-dependent manner (Tuci, Quinn, & Harvey, 2003).

SNNs, whose properties are currently being investigated, have been applied in tasks that were not performed well by the first and second generations of ANNs (Floreano & Mattiussi, 2001; French & Damper, 2002). The attractive features of SNNs include the ability to handle structured codes based on the timing

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of action potentials (Gerstner, Kreiter, Markram, & Herz, 1997) and a greater computational power than similar networks with sigmoidal-gate neurons (Maass, 1997). SNNs have been shown to perform novel types of computations, such as the recognition of temporal patterns using transient synchrony (Hopfield & Brody, 2001), and to support synaptic plasticity (Worgotter & Porr, 2005).

Recently, there have been many attempts, with various levels of success, to develop an adaptive controller with SNNs for autonomous mobile robots (Floreano, Zufferey, & Nicoud, 2005; Kubota & Sasaki, 2005; Natschläger, Ruf, & Schmitt, 2001). In these studies, neurons in SNNs are mutually interconnected using the conventional synapse model. That is, postsynaptic neurons fire when the weighted sum of synaptic inputs exceeds a threshold. Most of those works use the evolutionary approach, where the connectivity among spiking neurons, as well as the functionality of neurons, is expressed by the chromosome and the desired behavior is expressed by the fitness function (Floreano et al., 2005). After generations of evolutionary processes such as selection, mutation, and crossover, the best-fitted individual is obtained. However, as each individual in all generations must be evaluated in the environment, the applications are limited by disadvantages including the necessity of a trial-and-error process, the necessity of a long time period to isolate a good individual, and no capability to automatically adapt to new environments. Some researchers have tried to overcome these disadvantages by using a robot simulator during the initial period of evolution instead of a real mobile robot (e.g., Kubota & Sasaki, 2005).

The Hebbian rule has also been used, for the adaptation of an autonomous robot with SNN (Natschläger et al., 2001). Synaptic strength is adjusted depending upon the activities of presynaptic and postsynaptic neurons. Although a robot with this mechanism incrementally adapts to a given environment in a time span much less than that with genetic evolution, problems arise because there is no known method to determine the number of neurons in the hidden layer required for ideal robot movements. Therefore, the size of the hidden layer can only be experimentally or arbitrarily defined. The use of an excessive amount of neurons would result in slow adaptation and unnecessary calculations. Hebbian learning may also lead to runaway processes of potentiation and cannot account for the stability of neural function.

It is well known that one of the simplest forms of learning and memory is associative facilitation in the withdrawal reflex circuit of the sea slug, *Aplysia* (Kandel, 2006; Squire et al., 2003). In this neuronal circuit, presynaptic modulation plays a crucial role. Specifically, a synapse on a presynaptic element (synapse on synapse) regulates the synaptic efficacy and the plasticity. In addition, spike timing-dependent plasticity (STDP) has been found in natural synapses, and is considered an essential mechanism for learning and memory (Abbott & Blum, 1996; Bi & Poo, 2001). The synaptic strength is adjusted depending on the timing of presynaptic and postsynaptic firings of action potentials. Robotic applications of STDP have been exploited, although they remain limited (Di Paolo, 2003).

In this article, we explore whether such a simple SNN as the associative facilitation circuit of *Aplysia* may work as an adaptive controller of a mobile robot that organizes itself in a single trial in the environment. In the SNN, we have introduced the mechanism of presynaptic modulation, as well as STDP. We have tested this model on a real mobile robot, in both a static environment and a dynamically changing environment. We have quantitatively compared the performance with that of a robot controller produced by the conventional evolutionary approach.

This article is organized as follows. In Section 2, we describe the framework of the proposed SNN. In Section 3, we describe the implementation of the proposed SNN in a real miniature mobile robot, Khepera (Mondada, Franzi, & Lenne, 1993), and the experimental setup used in this study. We also explain the evolutionary method that was used for comparison. In Section 4, we present experimental results for the adaptation process and we compare these with the conventional evolutionary process. In Section 5, we discuss the results and draw some conclusions. In addition, we mention some ideas for the future, such as multiple sensor fusion and motor control.

2   Framework

In this section, we describe the details of the *Aplysia*-like SNN, the STDP, and the spike response model (SRM), the neuron model used in this study. In addition, we explain the quantitative measure of behavior.

(a)

(b)
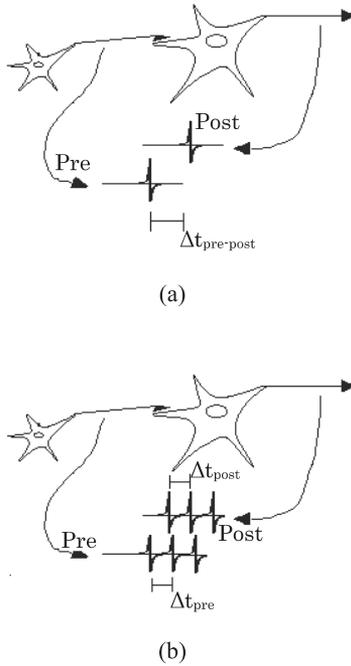
Figure 2 Two types of STDP. (a) One type of STDP based on the spike time interval between presynaptic and postsynaptic sites. Presynaptic and postsynaptic spike pairs are induced with a time interval $\Delta t_{\text{pre-post}}$ and the synaptic efficacy is modified as a function of $\Delta t_{\text{pre-post}}$. (b) Another type of STDP based on the difference in the firing rates in presynaptic and postsynaptic sites. Synaptic efficacy is modified as a function of the difference between the presynaptic spike interval Δt_{pre} and the postsynaptic spike interval Δt_{post}.

the postsynaptic neuron, as shown in Figure 2a. That is, when the presynaptic site and postsynaptic neuron are excited at t_{pre} and t_{post}, respectively, the synaptic weight is modified in proportion to the difference $\Delta t_{\text{pre-post}}$, where

$$\Delta t_{\text{pre-post}} = t_{\text{pre}} - t_{\text{post}} \tag{1}$$

the second type of the STDP model, which we used in this series of studies, is based on the firing rate as shown in Figure 2b. If the presynaptic site and postsynaptic neuron are generating action potentials with average time intervals of Δt_{pre} and Δt_{post}, respectively, the synaptic weight is modified in accordance with the difference $\Delta t_{\text{pre-post}}$, where

$$\Delta t_{\text{pre-post}} = \Delta t_{\text{pre}} - \Delta t_{\text{post}} \tag{2}$$

we used this second model and assumed that a sensory input generates a barrage of presynaptic action potentials and that the firing lasts longer than that required for the generation of postsynaptic spiking. After the synaptic modification, the postsynaptic neuron would tend to respond more quickly to the presynaptic spiking.

2.3 Spiking Response Model

Artificial SNNs are classified into two types: pulse-coded neural networks and rate-coded neural networks (Maass, 1999). There are several models of spiking neurons that show various degrees of detail (Gerstner & Kistler, 2002). In this study, we focus on the SRM, which is the easiest to understand and implement, especially with STDP.

We used the SRM developed by Floreano and Mattiussi (2001). This SRM uses a single variable υ_i, the membrane potential to describe the state of a neuron. As shown in Figure 3, in the absence of a spike, υ_i is at its resting value (here we assume it is zero). Each incoming spike generates a postsynaptic potential that takes time before returning to zero. If the summation of such effects by several incoming spikes reaches a threshold θ, an output spike is triggered. Once a spike is generated, the neuron goes into a refractory period, during which spikes are hardly evoked.

As shown in Equation 3, υ_i is the weighted sum of postsynaptic potentials from several inputs. An incoming spike that occurred at time s generates the postsynaptic potential following the function $\varepsilon(s)$. The weight of the synapse from jth input to the neuron is ω_j^t. The function $\eta(s)$ expresses the refractory effect after spike generation by the neuron:

$$\upsilon_i(t) = \sum_j \omega_j^t \sum_f \varepsilon_f(s_f) + \sum_i \eta_i(s_i) \tag{3}$$

$$\varepsilon(s) = \exp\left[-(s-\Delta)/\tau_{\text{m}}\right] \times \left\{1 - \exp\left[-(s-\Delta)/\tau_{\text{s}}\right]\right\} \tag{4}$$

$$\eta(s) = -\exp(-s/\tau_{\text{m}}) \tag{5}$$

in Equation 4, the function $\varepsilon(s)$, the time course of the postsynaptic response generated by one incoming

(a)

(b)
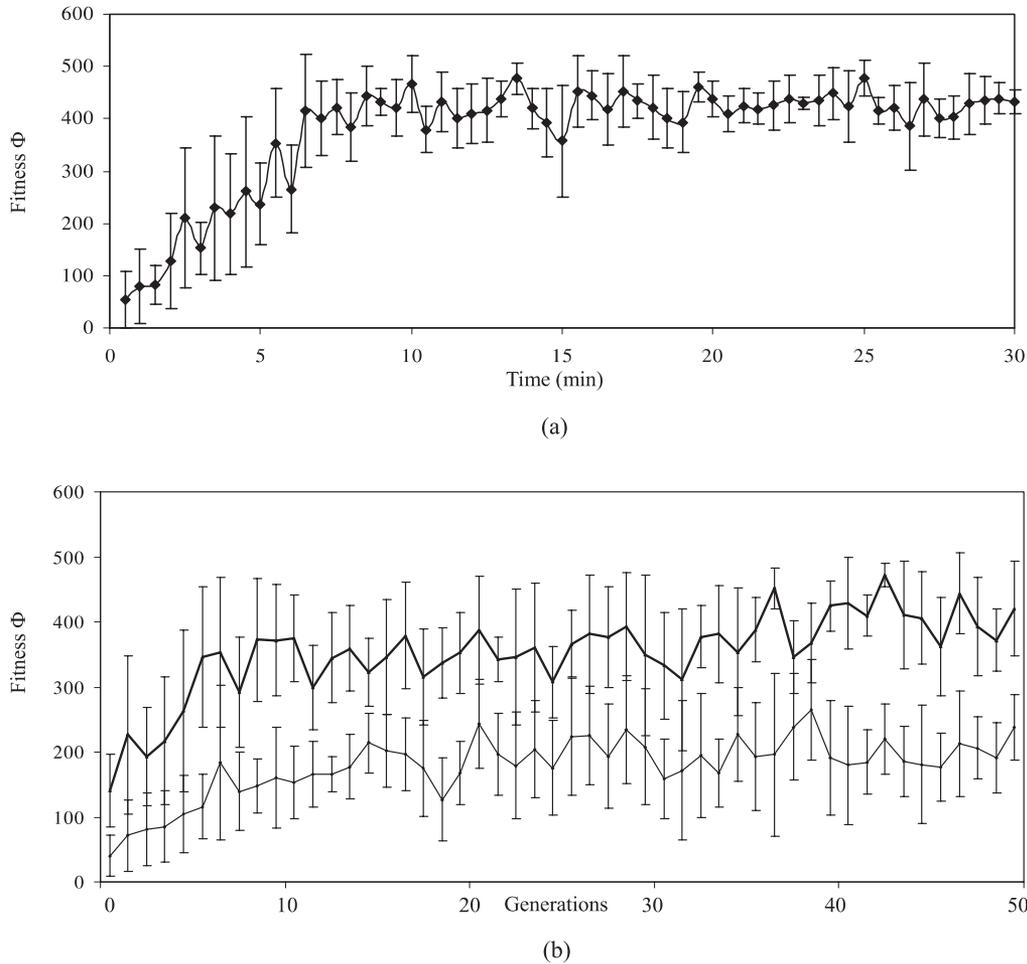
Figure 8   The fitness values by adaptation (a) and evolution (b). (a) The fitness value obtained with the proposed *Aplysia-like* SNN adaptive controller is illustrated. The fitness values are shown every 30 s for a single trial of the adaptation process for 30 min. The graph illustrates the average and standard errors of five different runs with different initial values. (b) The evolutionary process with the conventional genetic algorithm is illustrated. Average and standard errors of the best (thick trace) and average (thin trace) fitness over five different runs are shown.

a result of the robot's movement. Because of their STDP nature, *LMW* and *RMW* changed, as seen in Figure 7c, while no change occurred in *LSW* and *RSW* as they were fixed throughout. Notice in Figure 7d where the firing intervals of the left and right output-layer neurons, *LMF* and *RMF*, were forced to be closer to that of the hidden-layer neuron, *HNF*, after changes in the synaptic weights by STDP.

In Figure 7e, where the left and right motor values, *LM* and *RM*, are shown, the left (right) motor incrementally learned to be positive whenever the left (right) sensor was activated. Shortly, the robot learned to avoid the nearby left obstacles by turning right and kept moving in the environment, likewise for the right obstacles.

Arrows X and Y in the figures illustrate examples of the changes that took place in the synaptic weights, neuron firing interval, and motor values when the right and left sensors were activated, respectively.

We measured the quality of behavior during the adaptation process by the fitness function, Φ, defined by Equation 6. This value is a function of the speeds of the two motors and the values of two proximity sensors. We calculated Φ at every 6 s for 30 min of the adaptation process. We repeated the process five times, and the average and standard errors at each time point were calculated. The result is shown in Figure 8a; notice that the values of Φ are shown every 30 s. From the figure, the behavior is observed to reach a stable state in less

than 10 min, when the robot began to perform the navigation and obstacle avoidance tasks successfully in the environment.

4.3 Adaptation to Environmental Changes During Navigation

In order to see how dynamically the robot adapts to changes in the environment, we modified the environmental conditions twice during the course of navigation. The robot was first allowed to move freely and to adapt to the environment where obstacles were placed as shown in Figure 9a. After the robot adapted to the environment and became capable of navigating and avoiding obstacles, a fluorescent light was turned on to illuminate the entire arena. We called this new situation, environment A. Because the robot's IR sensors are sensitive to the environmental brightness, the exposure to the stronger light must lead to changes in weight values in order to properly avoid obstacles. After the robot adapted to environment A, we turned off the light and relocated the obstacles as shown in Figure 9b. We called this situation, environment B.

Figure 9c and d show changes in the synaptic weights and motor values, respectively, when the environment was changed to environment A at 30 min after adapting in the initial environment, and then to environment B at 35 min. As seen in Figure 9c, the synaptic weights on output-layer neurons, *LMW* and *RMW*, were modified after both changes in environment because of the STDP nature. These changes took place whenever the robot collided with or approached obstacles. In environment A, for example, *LMW* changed twice while *RMW* changed once, as shown by the arrows in Figure 9c. These weight changes allowed the robot to correct the behavior. The *RMW* change (marked X in the figure) allowed the motor output, *RM*, to become positive, and for the robot to avoid the obstacle by turning left (see Figure 9d). Weights on the hidden-layer neurons, *LSW* and *RSW*, were fixed throughout.

The unique feature of the adaptation mechanism proposed in this study is that it corrects the pattern of reflex movement instantaneously whenever (and only when) the robot collides with obstacles. As shown in Figure 7b–e, the robot updates its synaptic weights whenever the robot reaches very close to the obstacles during its navigation. By the weight update based on STDP, the sensitivity of the postsynaptic neuron to the

activity of its corresponding presynaptic neuron becomes higher. For instance, when the robot collided with the obstacles on the left, as shown by Y in Figure 7b, the value of *LMW* was adjusted by the rule of STDP, as seen by Y in Figure 7c. This makes the robot respond faster to left-side obstacles in the future. That is, the firing rate of the left postsynaptic neuron *LMF* becomes closer to that of the presynaptic neuron *HMF* than that of the right postsynaptic neuron *RMF* (Y in Figure 7d). Therefore, the left motor value *LM* becomes larger than the right motor value *RM* avoiding the left-side obstacle (Y in Figure 7e).

4.4 Quality of Behavior Measured by Fitness Function

The quality of behavior after these environmental changes was quantitatively evaluated by using the fitness function Φ in Equation 6. We measured the fitness value at every 6 s for the 40 min period during which the environment was changed to A at 30 min and to B at 35 min. We repeated the experiment five times, and the average and standard errors of the fitness values at each time point were calculated. The averaged fitness values every 30 s are shown in Figure 10a. The fitness value reached a stable state within 10 min in the initial environment. After changing to environment A, the fitness value decreased, but recovered to the original level in less than 5 min. After the second change to environment B, the fitness value recovered within a minute. The inserts a_1, a_2, and a_3 show examples of the robot behavior during 60 s in each of the environments. As apparent from the trajectories, the robot adapted to the new environments after several hits to the wall, and navigated smoothly in the environments afterwards.

4.5 Comparison with Conventional Genetic Evolution

We tested whether the STDP mechanism for weight changes that worked in a single trial would be comparable to the genetic evolution that involves a population of individuals at every generation. The SNN structure of the robot used for the genetic evolution was the same as that with STDP, except that the left and right input-layer neurons make direct synaptic connection to the respective output-layer neurons, as shown in Figure 4b. The fitness function was identical

to that used to evaluate the behavioral quality (Equation 6). Because the lifetime of each individual was 6 s and there were 20 individuals in a generation, the evaluation of all individuals in a generation required 2 min, in principle. As we inserted a random walk for 2 s between individuals, the actual time needed for one generation was 2 min and 40 s. Other details of the genetic parameters are given in Section 3.4.

4.5.1 Adaptation Processes

The evolutionary process is shown in Figure 8b. The averages of the maximum and average fitness values (thick and thin lines, respectively), as well as the standard errors in five runs, are illustrated. As seen in the figure, at least 20 generations are required to evolve a good individual, which is more than 30 min. This is much longer than the time required for the robot with STDP to adapt to the environment, as seen in Figure 8a.

4.5.2 Adaptation to Environmental Changes

We changed the environment during evolution, to environment A at generation 50 and to environment B at generation 100. The evolutionary process is illustrated in Figure 10b and the robot behavior during 60 s in each of the environments is illustrated in the inserts b_1, b_2, and b_3, respectively. Again, Figure 10b shows the average of five runs. As apparent from the figure, whenever the environment was changed, at least 10–15 generations are required to reach a stable state, which is much longer than that needed for the robot with the STDP to adapt (Figure 10a). In environment A, although the fitness values increased with time, they failed to reach the maximum value. This may be caused by the structural difference to the counterpart (direct connection versus synapse-on-synapse). While we have tried to evolve SNNs having a larger number of hidden-layer neurons, it required a much longer time than that with this simple SNN, although the fitness value improved (results not shown).

4.5.3 Behavioral Difference

It is well known that automatic adaptation to a dynamically changing environment is not an easy task for physical robots. Manual adjustment of the control system at every environmental change is not practical at all. The evolutionary approach needs re-evaluation of all individuals and genetic operations whenever the behavior becomes inadequate to the environment; besides, the robot has to know or to be notified when the environment is changed.

Figures 9 and 10a exhibit how a mobile robot with the proposed controller can quickly cope with sudden changes in the environment. As seen in Figure 9, the change to environment A induced changes of weight *RMW* once and that of *LMW* twice only. Further change to environment B induced the weight changes in the same manner. Accordingly, the inter-neuron's firing, as well as the motor speeds *RM* and *LM* were altered (Figure 9), so as to continue the behavior. Figure $10a_1$–a_3 shows the traces of the robot's movement at time points indicated by the arrows in Figure 10a, and the black dots in the figures show the instances when weight changes occurred. After three changes in weights, the robot was able to navigate in the new environment A, and after two changes in environment B.

In the evolutionary approach, in contrast, a number of trials are needed until the best individual to the environment is found. Although the best individual was able to navigate in the initial environment as shown in Figure $10b_1$, the change in environment to environment A produced a drop of fitness (Figure 10b) and the evolutionary process was started. Even after five generations, the good individuals were yet to appear, as seen in Figure $10b_2$, where switching of individuals is indicated by black dots. Similar trial and error took place when the environment was changed further to environment B (Figure $10b_3$).

These results clearly indicate that the robot with the proposed controller has two significant advantages over the conventional genetic approach. First, the adaptation is achieved in a single individual. Second, the number of trials and errors is minimal. The correction of weights takes place only when the robot senses changes in the environment by itself. The quality of behavior is identical to that of genetic evolution, as seen from the fitness values in Figures 8 and 10, and the time needed for adaptation is much less.

5 Discussion

In this study, we have investigated the validity of a simple SNN as an adaptive controller for a mobile robot. The simple SNN was inspired by the network structure of *Aplysia* and the synaptic rule of STDP. A

real mobile robot with the *Aplysia*-like SNN controller quickly acquired adaptive behavior, navigation, and obstacle avoidance behavior in an open environment in a single trial, and followed the changes in environment quickly. The quality of behavior was comparable to a robot evolved by the conventional genetic approach.

5.1 Sensorimotor Reflexes in Behavior-Based Robotics

Behavior-based robotics relies on the direct coupling between sensing and action, in contrast to classical artificial intelligence, where sensory events need to be analyzed and described logically until an action to be taken is selected (Brooks, 1991). Behavior-based robotics claims that activations of a variety of such sensorimotor reflexes in response to a dynamically changing situation compose intelligent behavior without logical reasoning. This reflects the well-known mechanism of subsumption architecture (SA; Brooks, 1986), which is now widely used in robots that have to work in an open environment, although it is often mixed with the classical artificial intelligence approach to various degrees. In SA, a set of sensorimotor reflexes, as well as the hierarchy among them, needs to be defined explicitly with the designer's knowledge a priori.

ANNs are also used to generate motor signals from sensory inputs. In ANNs, synaptic weights, as well as the network structure, must be determined to generate the desired reflexes in various situations. The genetic algorithm (GA) is considered a powerful tool to determine the weights (Nolfi, Floreano, Miglino, & Mondada, 1994). However, in evolutionary robotics (Nolfi & Floreano, 2000), a long period of time is required before a good individual is found, because all individuals in every generation are tested and evaluated in the environment. In addition, the trial-and-error process is often unrealistic because it is dangerous and/or hazardous. There is no general guideline in the network structure, and therefore it is determined arbitrarily in most cases. In addition, the design of the fitness function is essential, but difficult, especially for complex tasks.

Therefore, an understandable and reasonable new scheme is desired with which the necessary sensorimotor reflexes are generated in a single trial.

5.2 Neuronal Correlates of Sensorimotor Reflexes

In humans, sensorimotor reflexes occur at many levels, and many parts of the central nervous system contribute. The lowest level is the spinal reflex, such as the tendon–skeletal muscle reflex and the withdrawal reflex of the arm to heat stimuli. In addition to such somatosensory reflexes, intestinal reflexes also take place mostly at the spinal level. Involuntary reflexes, such as the salivary conditioning of Pavlov's dogs, receive contributions from the striatum and other regions of the brain. The cerebellum generates a series of motor control signals in response to visual and other sensory inputs. Examples include those needed for playing tennis and dancing. These higher-order complex sensorimotor reflexes are acquired after training. The robotic applications that simulate these higher-order complex sensorimotor reflexes have been achieved by using learning algorithms of ANNs (e.g., Atkeson et al., 2000).

Underlying mechanisms of associative learning, including Pavlovian conditioning (classical conditioning), are the target of intensive research in neuroscience. Kandel and his colleagues found that associative learning takes place in the siphon–gill and tail–siphon withdrawal reflexes of *Aplysia*, and they investigated the cellular and molecular mechanisms responsible for this associative learning. As mentioned in Section 2.1, sensorimotor synaptic connections are enforced by conditioning stimulation through presynaptic modulation by synapse-on-synapse contact.

Presynaptic modulation by neuromodulators, including serotonin, dopamine, nitric oxide, and carbon monoxide, has been shown to play a key role in the induction of neuronal plasticity in higher vertebrates as well (e.g., Ikeda & Murase, 2004). The activity of these substances and their consequences occur on different timescales, producing a variety of short-term and long-term responses (Squire et al., 2003). In addition, the vertebrate central nervous system contains many more glial cells than neurons, 10 times or greater, and recent studies have revealed that they may mediate and/or modulate neuronal signaling and plasticity (e.g., Ikeda, Tsuda, Inoue, & Murase, 2007).

Modeling the processes of associative learning is certainly beneficial to realize behavior-based robots. In addition, it is essential in understanding natural systems.

successfully realized this, at least in part (Alnajjar & Murase, in press). Also, it is essential to incorporate short-term and long-term plasticity in the networks in order to balance the stability and plasticity of the artificial systems. One possibility is to use an SNN ensemble that is incrementally assembled. A constructive algorithm for SNN ensembles, similar to that for conventional neural network ensembles (e.g., Islam, Yao, & Murase, 2003), is now under investigation.

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