Artificial Evolution of Pulsed Neural Networks on the Motion Pattern Classification System

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Abstract

In natural systems, animals discriminate an object through information coming from various receptors. In particular, object's figure and its motion pattern are known to be very important for quick and accurate discrimination. In this work, to give the similar ability of discrimination to an artificial agent, we examine whether artificial evolution is capable of generating artificial neural networks that perform discrimination tasks using the mixed information of figure and motion pattern. The results demonstrate that evolutionary approach is successful in developing the neural network controller using a affordable computational cost.

1 Introduction

Categorization is one of the most important cognitive processes for animals and humans as well as perception or memory. They have many ways to categorize the world, such as through seeing, hearing, and smelling. One of the most powerful ways is seeing. For animals with vision, information of object figures plays the main role in discriminating an object. However, it is known that those animals discriminate an object not only by its figure but also by its motion pattern [16][6]. The information of objects figures and motion patterns is complementary for the discrimination.

An approach to equipping a robot with such ability is based on *classical artificial intelligence*. Here, the hypothesis is that human designers can map from the sensory inputs or patterns to an internal representation of the categories. This kind of approach can be seen in the connectionist models, such as artificial neural networks and fuzzy systems where the output layer represents the categories.

To autonomous agents, we cannot apply this classical approach because the outputs of an agent have a great influence on his own sensory inputs. That is, an agent generates the sensory patterns through his behavior. If sensory and motor systems are not coordinated, then the system would have difficulties in behaving in the environment, because its categories are not grounded in its experience. This problem is called, "symbol-grounding problem" or "frame-of-reference problem". For categorization in autonomous agents, we have to take a sensor-motor coordination into account, which serves to structure the sensory inputs. This idea is exactly one of principles in the embodied cognitive science [11].

Thus, an agent must acquire the appropriate mapping between sensory inputs and motor outputs through the interaction with the real world. One of such methods that enable an agent to acquire the appropriate sensory-motor coordination is the evolutionary approach. This is also called "evolutionary robotics" [4] [1]. The fitter individuals are selected as the members of the new populations. The individuals in this new population now reproduce with mutations. In the process of evolution, the mechanisms of the sensory-motor coordination are self-organized. Consequently, the agent is capable of discriminating between the objects without representations of the categories through the interaction with the environment [1][12][10][9].

In this paper, we investigate whether an agent controlled by the evolved neural networks can discriminate an object using the mixed information of figure and motion pattern. We applied the standard GA to evolve pulsed neural controllers [8] for the motion pattern classification system in order to investigate the performance of agents in the categorization task, then discussed its evolutionary dynamics and the process of self-organization in the neural controllers. Section 2 describes a model of *Pulsed Neural Networks* called *spike response model*, which is used as a controller in an agent in this work. Section 3 describes evolutionary tasks for the discrimination of the motion patterns, then gives the results of our computer simulations. Section 4 discusses the evolutionary dynamics on these tasks, which is typically found in evolution of neural network controllers in robotics. Conclusions are given in the last section.

2 Evolving Neural Controller

2.1 Spike Response Model

The agent's behavior is controlled by the *spike response model* [8], which is one of *Pulsed Neural Networks* (PNN).

[1] In evolutionary robotics, evolutionary computation is generally applied to evolve a neural network controller for an autonomous agent.

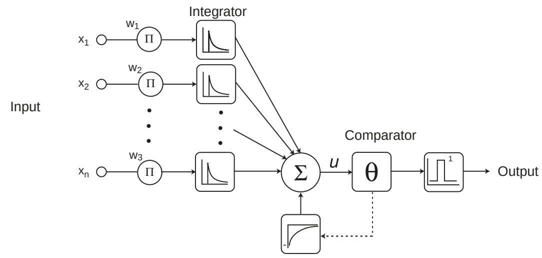


Figure 1: Neuron model.

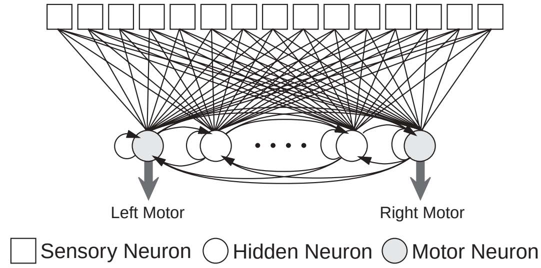


Figure 2: Architecture of the neural network (only a few neurons and connections are shown).

The state of a spiking neuron is described by the voltage difference across its membrane, which is called, "membrane potential" u. Incoming spikes can increase or decrease the membrane potential. The neuron emits a spike when the total amount of excitation induced by incoming excitatory and inhibitory spikes exceeds its firing threshold θ. After firing, the membrane potential of the neuron resets its state to a low negative voltage during which it does not emit a new spike and gradually returns to its resting potential (Fig. 1). This recharging period is called the *refractory period*. The membrane potential of a neuron i at time t is given as follows:

$$u_i(t) = \sum_{t_i^{(f)} \in F_i} \eta_i(t - t_i^{(f)}) + \sum_{j \in \Gamma_i} \sum_{t_j^{(f)} \in F_j} \omega_{ij} \varepsilon_{ij}(t - t_j^{(f)}), \tag{1}$$

where $t_i^{(f)}$ is the firing time of neuron i, F_i is the set of firing times in a neuron i. The neuron i may receive the input from presynaptic neurons $j \in \Gamma_i$. The weight ω_{ij} is a factor which accounts for the strength of the connection.

The function η_i accounts for neuronal refractoriness. The mathematical description of $\eta_i(s)$ is presented in Eq.(2).

$$\eta_i(s) = -\exp(-\frac{s}{\tau_m})H(s), \tag{2}$$

where $s = t - t_i^{(f)}$ is the difference between the time t and the time of firing $t^{(f)}$ of neuron i, τ_m is a membrane time constant and $H(s)$ is the Heaviside step function which vanishes for $s < 0$ and takes a value of 1 for $s > 0$.

The function ε_{ij} describes the response to the postsynaptic spikes. The mathematical description of ε_{ij} is presented in Eq.(3).

$$\varepsilon_{ij}(s) = [\exp(-\frac{s - \Delta^{ax}}{\tau_m})(1 - \exp(-\frac{s - \Delta^{ax}}{\tau_s}))]H(s - \Delta^{ax}), \tag{3}$$

where τ_s is a synaptic time constant, Δ^{ax} is the axonal transmission delay. The amplitude of the response is scaled via the factor ω_{ij} in Eq.(1).

2.2 The Genetic Algorithm

In this work, the agent controller is constructed by the PNN with 15 sensory neurons, 6 fully interconnected hidden neurons and 2 fully interconnected motor neurons (Fig. 2). It has the firing threshold for each neuron. We genetically encode and evolve the connection weights among neurons and the firing threshold for each neuron. The total number of parameters is equal to 192. The parameters are mapped linearly with the following ranges: connection weights $\in$ [-1.0, 1.0], thresholds $\in$ [0.0, 3.9]. The parameters of the neurons and synapses are set as follows: $\tau_m = 4$, $\tau_s = 10$, $\Delta^{ax} = 2$ for all neurons and all synapses in the network according to the recommendation in the reference [3]. The standard GA (SGA) is adopted to evolve PNN parameters. Computer simulations are conducted by setting the population size 50, the length of the genotype 1920 (80 for the firing thresholds, 1840 for the connection weights). Each individual is encoded as binary strings with 10 bits for each parameter. The genetic operation for the SGA is set to be standard bit mutation. The per-bit mutation rate q is set at 0.0005. Crossover is not used with the SGA. Tournament selection is adopted, and elitism [2] is additionally applied. The tournament size is set at 2. A generational GA is used. Each run lasted 10000 generations.

3 Motion Pattern Classification

3.1 Experiment I

Beer [1] has demonstrated that an agent controlled by dynamical neural networks can discriminate an object by its figure. Moreover, an agent must be able to discriminate an object by its motion pattern. In this paper, the evolutionary task is set to be the discrimination of the motion patterns; The objects fall vertically with the horizontal motion with a long period or a short period (Fig. 3). The agent must discriminate between the motions, catching (move close to) the long period while avoiding the short period. An array of proximity sensors allows an agent to perceive an object that falls down from the top of an arena. If an object intersects a proximity sensor, the sensor outputs a value inversely

[2] The individual randomly selected from the individuals whose fitness value indicate maximum at the generation is passed to the next generation as a parental individual.

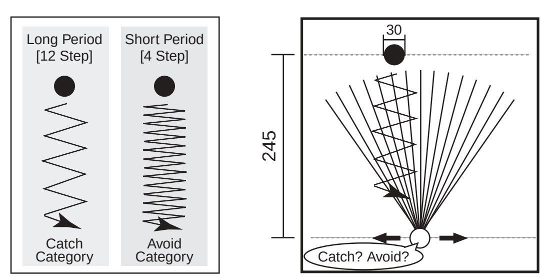


Figure 3: Experimental setup for the discrimination of the motion patterns. Two kinds of period to be classified (left) and the agent with the ray of the proximity sensors in an arena (right).

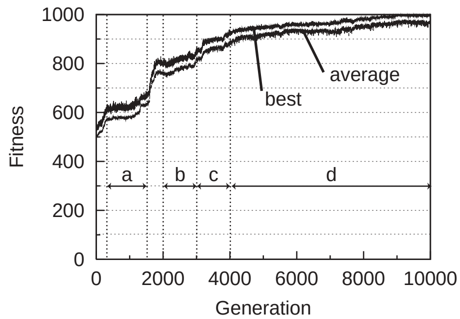


Figure 4: Best and average fitness of the population over generations.

proportional to the separation between the object and the agent. The agent can move horizontally along the bottom. In our experiment, the agent of diameter 30 had 15 proximity sensors of maximum length 220 uniformly allocated over a visual angle of 49 degrees. The horizontal velocity of the agent is proportional to the sum of opposing forces produced by a pair of effectors (with a constant of proportionality of 8). The circular object of diameter 30 drops from the top of an arena with a vertical velocity of 4, a horizontal amplitude of 30 and an initial horizontal offset within ± 50. The horizontal velocity is ± 10 (12 steps in a period) for a long period (LP) and ± 30 (4 steps in a period) for a short period (SP).

The performance measure to be maximized is as follows:

$$Fitness = 1000 \sum_{i=1}^{NumTrials} \frac{P_i}{NumTrials}, \qquad (4)$$

where $NumTrials$ is the number of trials for an individual (8 trials for each period) and

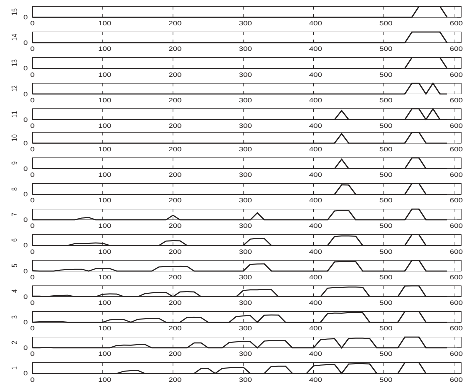
$$P_i = \begin{cases} 1 - d_i, & (LP) \\ d_i, & (SP) \end{cases} \qquad (5)$$

here,

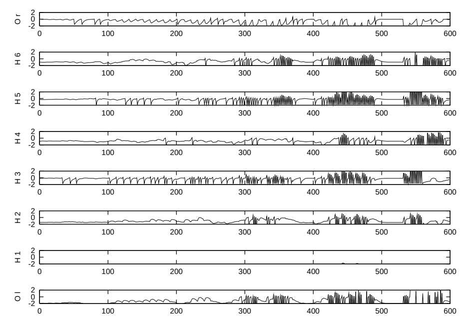
$$d_i = \begin{cases} 1, & hd_i > 60 \\ hd_i/60, & hd_i \leq 60 \end{cases} \qquad (6)$$

hd_i is the final horizontal separation between the center of the agent and the object.

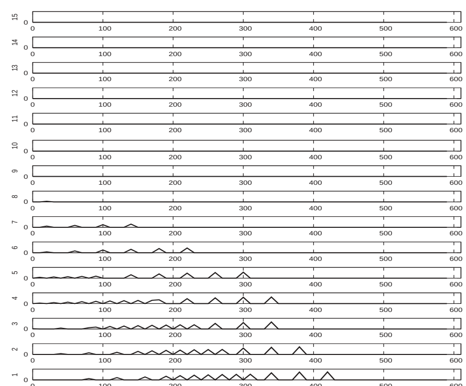
Fig. 4 shows the maximum and average fitness against the generation. The equilibrium periods are found in the period a (between generation 300 and 1,500), b (2000 and 3000), c (3000 and 4000), and d (4000 and 10000). The most of the time is spent in the equilibrium period. The typical behavior of the best agent in generation 10000 is shown in Fig. 10(k) and 10(l). The two figures differ only in the last half steps. Until around 250 steps, the agent is located at the center of the arena. Then the left motor neuron (Ol) repeatedly firing makes the agent move close to the object in the case of LP (Fig. 5(a),5(b)). On the contrary, in the case of SP, the right motor neuron (Or) repeatedly firing makes the agent avoid the object because the left motor neuron almost never fires (Fig. 5(c),5(d)).



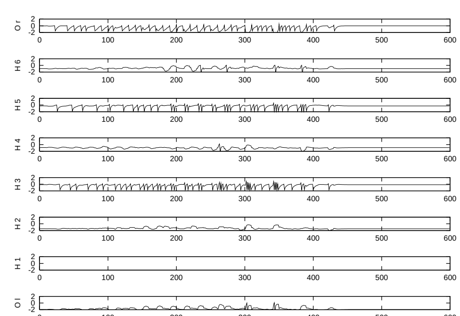
(a) Sensory inputs for LP



(b) Membrane potentials for LP

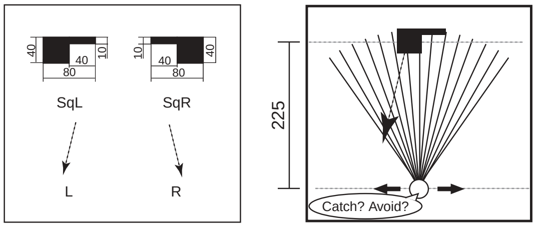


(c) Sensory inputs for SP

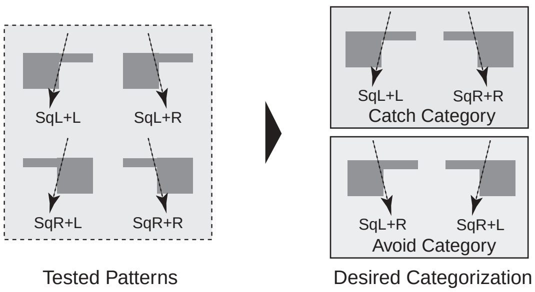


(d) Membrane potentials for SP

Figure 5: The best agent in a typical run in generation 10,000.



(a) The agent moves horizontally.



(b) Objects fall either vertically or diagonally from above.

Figure 6: Experimental setup for the discrimination of the objects by both figures and motion patterns.

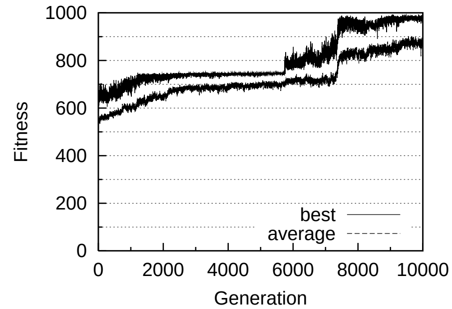
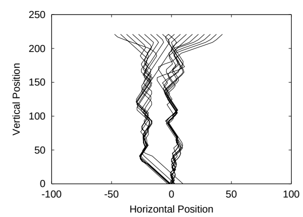
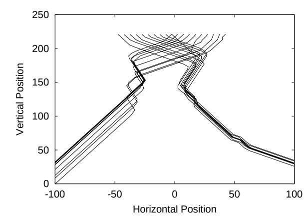


Figure 7: Best and average fitness of the population over generations.



(a) Catch category



(b) Avoid category

Figure 8: Behavior of the best individual in generation 10,000.

3.2 Experiment II

In the previous section, the experiment I demonstrates that an agent controlled by the evolved neural networks is able to discriminate an object by its motion pattern. As for the next step, an agent must be able to discriminate an object by both figures and motion patterns. Thus, another evolutionary task in this paper is the discrimination of an object by both figures and motion patterns; The objects fall either vertically or diagonally from above (Fig. 6(a)). The agent must discriminate between the forehand figures of the object (Fig. 6(b)). The object drops from the top of an arena with a vertical velocity of 4, a horizontal velocity of ± 2.5 and an initial horizontal offset within ± 50.

The performance measure to be maximized is as follows:

$$Fitness = 1000 \sum_{i=1}^{NumTrials} \frac{P_i}{NumTrials}, \tag{7}$$

where $NumTrials$ is the number of trials for an individual (16 trials for each pattern) and

$$P_i = \begin{cases} 1 - d_i, & (SqL+L, SqR+R) \\ d_i, & (SqL+R, SqR+L) \end{cases} \tag{8}$$

here,

$$d_i = \begin{cases} 1, & hd_i > 120 \\ hd_i/120, & hd_i \leq 120 \end{cases} \tag{9}$$

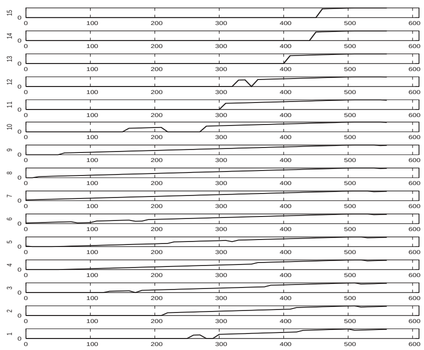
Fig. 7 shows the maximum and average fitness against the generation. The equilibrium period is found in the period between generation 3500 and 5800. The most of the time is spent in the equilibrium period as well as in the experiment I.

The typical behavior of the best agent is shown in Fig. 8. Two figures exhibit a qualitative similarity in the first half steps. Until around 300 steps, the agent is located at the center of the arena repeatedly scanning the object. Then the left and right motor neuron repeatedly firing makes the agent remains close to the object in the case of a "catch" category (Fig. 9(a),9(b)). On the contrary, in the case of a "avoid" category, the right motor stops firing then the left motor neuron fires for the agent to avoid the object for last 250 steps. (Fig. 9(c),9(d)).

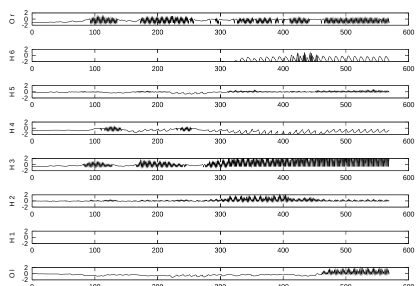
4 Evolutionary dynamics

In the experiment I and II, the equilibrium periods are found where a number of mutations do not have an effect on the fitness of individuals. This kind of fitness landscape including neutrality is called, "neutral networks" [15][5][13][2] which is typically found in evolution of neural network controllers in robotics as well as in the other real-world applications of artificial evolution, such as on-chip electronic circuit evolution [14] and so forth.

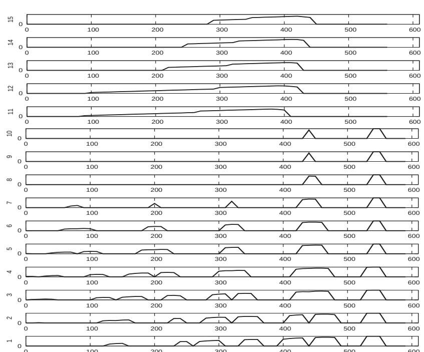
Table 1 shows the Hamming distance between the maximum individual at the beginning of the period and the one at the end (Fig. 4) in Experiment I. A number of bits are flipped during the equilibrium period even though the maximum individual is not identical to the previous one. Additionally, there are more changes in the genotype space than in the fitness space. This indicates that the fitness landscape forms typical neutral networks. Compared to the genes for the firing thresholds, more bits are flipped in the genes for the connection weights in the equilibrium period. Fig. 10 shows the motion trajectories relative to the best agent of objects falling vertically with a horizontal velocity from several different initial horizontal offsets. At generation 300, some trials are found where the best agent can discriminate between both LP and SP. By generation 3000, the agent has become to discriminate between both LP



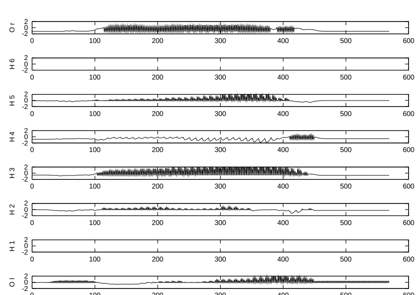
(a) Sensory inputs for a catch category



(b) Membrane potentials for a catch category

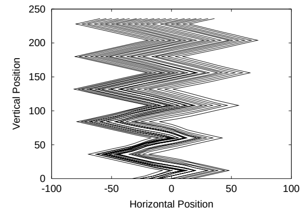


(c) Sensory inputs for a avoid category

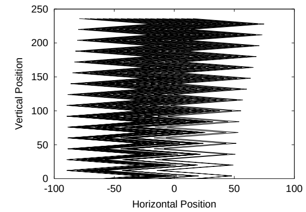


(d) Membrane potentials for a avoid category

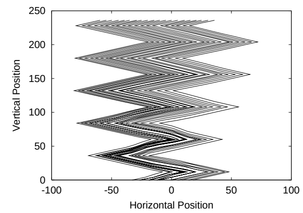
Figure 9: The best agent in a typical run in generation 10,000.



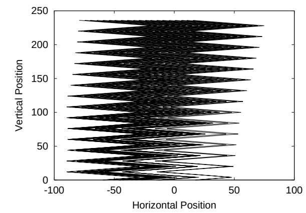
(a) In generation 300 for LP



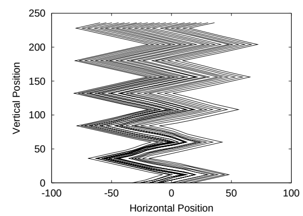
(b) In generation 300 for SP



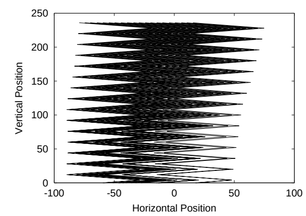
(c) In generation 1500 for LP



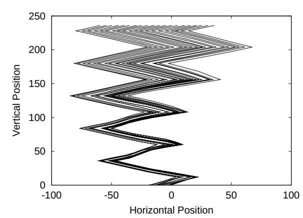
(d) In generation 1500 for SP



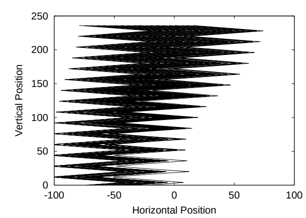
(e) In generation 2000 for LP



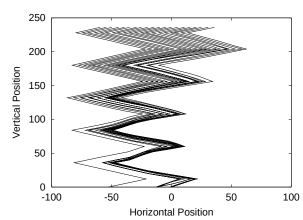
(f) In generation 2000 for SP



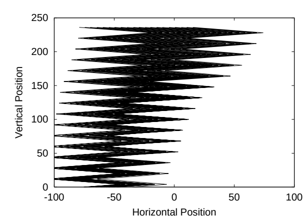
(g) In generation 3000 for LP



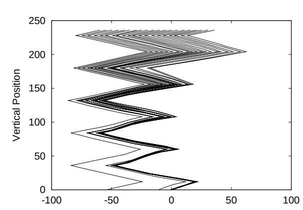
(h) In generation 3000 for SP



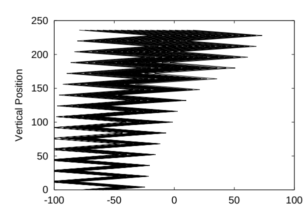
(i) In generation 4000 for LP



(j) In generation 4000 for SP



(k) In generation 10000 for LP



(l) In generation 10000 for SP

Figure 10: Behavior of the best individual for LP and SP in the process of evolution.

and SP on the most of the trials except peripheral trials. The ability of the generalization for initial horizontal offsets is improved with the increase of the fitness. This is the result of the modulation in the connection weights as shown in Table 1. From these results, we can say that the pulsed neural controller is self-organized to enhance the generalization for initial horizontal offsets in the process of evolution.

As for the next step, we are planning to propose an useful genetic algorithm to solve the real-world problems whose fitness landscape includes neutral networks. These experiments will be reported in detail [7].

Table 1: Hamming distance between the best individuals at the first generation and last generation in the periods.

	period a	period b	period c	period d
θ	25	12	15	17
ω	651	517	473	802

5 Conclusions

In this work, we applied the standard GA to evolve pulsed neural controllers for the motion pattern classification system in order to investigate whether an agent controlled by the evolved neural networks can discriminate an object using the mixed information of figure and motion pattern and discussed its process of evolution in the neural controllers.

The obtained results can be summarized as follows:

- The agent controlled by the evolved neural networks can discriminate between the objects with the different motion patterns. Moreover, it can discriminate between the objects by both figures and motion patterns.
- In the process of evolution, the fitness is improved mainly by the modulation in the weights among neurons.
- The equilibrium periods are found where a number of mutation does not have an effect on the fitness of individuals. This means that the fitness landscape forms typical neutral networks.

As we have demonstrated that the evolved agent is able to discriminate an object using the mixed information of figure and motion pattern, the most interesting challenge we front is to investigate in what form the categories are stored in the neural controllers.

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