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Simulating autonomous coupling in discrimination of light frequencies

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Abstract. To study the interfacial complexity between an agent and its environment such as the adaptive selection aspects of sensory inputs, we propose a new coupling mechanism, called autonomous coupling, where an agent can spontaneously switch on or off its interaction with the environment. An oscillatory neural system with autonomous coupling sums the sensory inputs and initiates action selection via a sensorimotor coupling. An example task we designed to show dynamical categorization is the classification of light frequencies. An evolved agent selects specified light frequencies by approaching them and avoiding light of other frequencies. Dynamical categorization and active coupling are the key concepts for the understanding of situated and embodied cognitive functions.

Keywords: dynamical categorization, autonomous coupling, embodiment, evolution.

1. Introduction

Discrimination appears to require a principle, for example, geometrical shapes such as triangles and squares can be distinguished by the number of edges and vertexes. However, we know that the principle of these categories becomes useless when they are found in the real world. When children draw figures of triangles, they seldom satisfy the strict principle of triangles, although they thought they were drawing triangles. We think that everyday categorization requires some sort of perception structure with embodiment. Concerning an embodied aspect of cognition, Lakoff (1987) argued that language and its grammatical structure form a ‘radial’ category; a category has only a prototypical example. That means that everyday categories have no strict boundary between elements that belong to them and those that do not (e.g. is a tomato a vegetable?). We first show that a such radial category indeed occurs in the agent simulations.

When artificial agents categorize objects through ongoing interactions between their bodily movements and the environments, we call this ‘dynamical categorization’. We consider two classes of dynamical categorization. One class puts more stress on the sensorimotor co-ordination and the other puts more stress on the sensorimotor co-ordination and the internal dynamics. The first class is exemplified by Scheier and Pfeifer’s (1995) experiments. They studied a small vehicle that evolved to discriminate between small and large pegs distributed on an arena. Using a learning algorithm, the vehicle came to spend less time interacting with the larger pegs and more time with smaller pegs. The vehicle understands that a small peg is an object that it can grasp. On the other

hand, a large peg is perceived as an object that it cannot grasp. Such a mapping from the small/large concept to grasping/not grasping is a basic principle of *dynamic categorization* (Ikegami 2005). Some other studies of this class can be seen in Nolfi (2002) and Nolfi and Marocco (2002).

The second class is exemplified by Tani and Nolfi (1998). Their agents can discriminate two different rooms through their bodily movements. Two rooms are distinguished by the different arrangements of corners and walls. A door that connects two rooms opens and shuts randomly. When the door opens, the agent moves on to the other room by chance. After going back and forth between two rooms, an agent comes to know which room it belongs to. Namely, the agent comes to possess two mutually exclusive neural modules, one for room A and one for room B. Therefore, we interpret that the agent knows that he is in room A when module A is activated. Again, this example shows that a physical body motion naturally organizes a categorization. The other studies of this class may be found in Marocco and Floreano (2002), Beer (2003) and Nolfi and Marocco (2001).

In all these tasks, the motor sequence provides discrimination of the input sequences from the environment. An adequate sensorimotor coupling realizes the effective radial category that is different from that given by an external principle.

Here we present an extension of second class models in which the internal dynamics can switch on or off the impact of sensory information. By doing that, we realize a mechanism of selective attention that controls the coupling between the internal and external dynamics of the evolved agents. A similar approach can be found in Ziemke and Thieme (2002).

The philosophical motivation of our modelling is the autonomous aspect of biological cognition. Varela (1979, 1992) argued biological cognition with autonomy in terms of an autopoietic system. The surplus of signification, i.e. the difference between the world the autopoietic system sees and the externally defined environment, provides an origin for cognition. To construct this world requires an identity, which amounts to self-produced coherence as a unity. In an example of a cellular autopoietic system, self-produced coherence is generated from interactions between a catalyst and other particles. An emergent boundary, which separates inside and outside, regulates the complex internal interactions as a single unit. The boundary is maintained dynamically by the internal network. This circulation provides 'autonomy' with self-produced coherence as a unit (McMullin and Varela 1997, Ono and Ikegami 2000, Madina *et al.* 2003, Suzuki and Ikegami 2004).

Our proposed autonomous coupling shares the same concept of self-boundary with autopoiesis. In conventional models of embodiment, an agent is forcibly placed in the environment. This means that inputs from the surrounding environment continuously affect the agent's dynamics and therefore strongly restrict the agents' behaviour. The agent's tight coupling with the environment suppresses the self-produced coherence in the agent's dynamics because the internal dynamics depend strongly on the environmental dynamics. Therefore, in the sense of autopoiesis, no cognition appears, as no surplus signification exists.

In this paper, we introduce a non-principle-based task experiment. Agents have to classify a set of light frequencies into two without being given any external principle. Instead of having an external principle, the agents must generate different attractors that differentiate their action patterns. In the present case, the action patterns should be approaching and avoiding.

Evolving such agents using a genetic algorithm, we consider: (1) several aspects of dynamical categorization for this example; and (2) the role of autonomous coupling.

Practically, an agent has a special neuron to control reception of information from outside. The on–off switching of this neuron characterizes the role of autonomous coupling in this paper.

In section 2, we describe the design of the agents, and in section 3, the evolution criterion. In section 4, a discrimination pattern is discussed together with its associated navigation pattern. By changing the simulation conditions, we analyse the role of autonomous coupling. Section 5 is a summary and overall discussion.

2. Model

2.1. Discrimination task

Agents are required to discriminate light sources with different blinking periods. This new task is hinted at by Gibson’s (1962) active perception. A typical example is somatic sensation: when we rub something, we experience different sensations, e.g. sticky, slippery, stiff, etc. through our own rubbing action. Active perception is defined as a sense-feeling carried by a self-motion pattern. In the present task, agents have to generate their navigation pattern to discriminate between different blinking patterns.

The light sources are placed on a two-dimensional arena and we say that agents have discriminated the light patterns when they differ in their motion pattern towards the lights. Using a genetic algorithm (GA), we train the agents’ internal dynamics to have at least two classes: approaching and not-approaching the lights.

For each test phase, a single light source is placed on a plane. Starting from an initial point, an agent organizes its navigation pattern. We use 10 different sinusoidal blinking lights of different frequencies to train the agents.

2.2. Navigation dynamics

The agent has a circular body of radius R , with two diametrically opposed motors and five light sensors (figure 1). The following equations describe the agent’s navigation

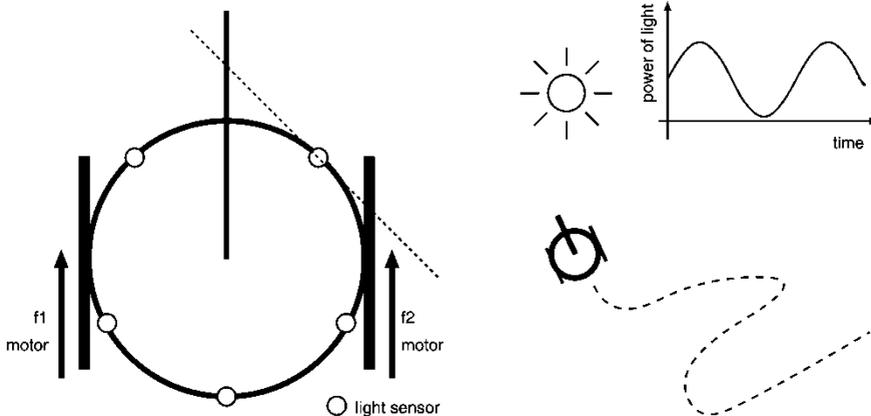


Figure 1. Two wheels (motors) and five light sensors. The mobile robot computes the forward force vector and the torque strength from the force vector (f_1, f_2) for each motor. It can sense the power of light that decays in response to the distance from the source. The light source varies with a predetermined period (see eq. (3)).

pattern in terms of the heading angle (θ) and the navigation speed (v).

$$M\dot{v} + D_1v + f_1 + f_2 = 0, \quad (1)$$

$$I\ddot{\theta} + D_2\dot{\theta} + \tau(f_1, f_2) = 0, \quad (2)$$

where f_1 and f_2 are the forward driving forces, and τ the torque amplitude. D_1 and D_2 are the resistance coefficients, and the agents have mass (M) and inertia (I). We compute the equations using the Runge–Kutta method. At each time, the driving forces are computed from the internal neural activities of the agent. The light intensity $L(T, t)$ oscillates and decays as follows. Each blinking pattern is realized as a sinusoidal with period T . The intensity decays exponentially with distance r .

$$L(T, t) = \frac{1}{2} \left(1 + \sin \left(2\pi \frac{t}{T} + \beta \right) \right) \frac{1}{1 + Ae^{\beta r}}. \quad (3)$$

2.3. Network structure

A neural network consists of input, internal and output neurons. Oscillatory neural dynamics, the so-called chaotic neural dynamics, are used here. The chaotic neural network was proposed by Aihara *et al.* (1990) to consider the unstable oscillatory nature of biological neurons (Nagumo and Sato 1972). Typically, chaotic neural dynamics coupled with M chaotic neurons is described as:

$$y_i(t + 1) = k_i y_i(t) + \sum_{j=1}^M w_{ij} g(y_j(t)) - \alpha g(y_i(t)) + \alpha_i, \quad (4)$$

$$g(x) = 1 / (1 + \exp(-x/\epsilon)), \quad (5)$$

where $y_i(t)$ indicates the internal states of neuron i at time t . k_i , α and w_{ij} represent the decay constant, refractory constant and the strength of synaptic connection from neuron j to i , respectively.

Here, we use a fully connected neural network, shown in figure 2. We use this chaotic neural dynamics because the task studied is suitable for oscillatory networks but it is not necessary to have chaotic behaviour. A requirement is to have spontaneous oscillatory behaviour. We have produced similar behaviour to that described in this paper by using normal neural dynamics. A second reason for adopting oscillatory dynamics was that we thought that the task required rich dynamics to categorize the light frequencies.

2.3.1. On–off switching dynamics. A characteristic of our neural network model is a ‘gate’ neuron. A neuron y_M tunes the strength of couplings between the input neuron z_j and other internal neurons y_j . Actually, we assume that the coupling is set to all or none, filtered by the Heaviside step function $v(t) = H(y_M)$. Each input neuron z_j has a connection to one internal neuron y_j , which is specified in the second term of equation (6). When the state of the gate neuron is less than 0.5, the internal network receives a signal from the input neurons, otherwise the network behaves autonomously.

2.3.2. Output neurons. Two internal neurons, y_{N+1} and y_{N+2} , are used to generate outputs, o_1 and o_2 , and these outputs are recruited to compute the driving force.

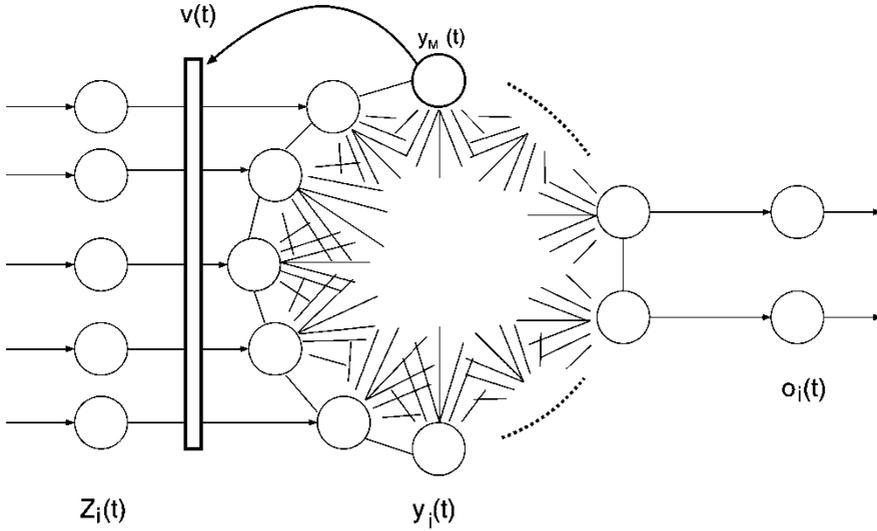


Figure 2. Structure of neural network with the capability of controlling coupling with its environment.

The complete system dynamics, including gating, are expressed by the following equations at each time step t .

$$y_i(t + 1) = k_i y_i(t) + v(t) z_i(t) + \sum_{j=1}^M w_{ij} g(y_j(t)) - \alpha g(y_i(t)) + a_i, \quad (6)$$

$$v(t + 1) = H(y_M(t)), \quad (7)$$

$$o_i(t) = g(y_{N+i}(t)), \quad (8)$$

$$g(x) = 1 / (1 + \exp(-x/\varepsilon)), \quad (9)$$

where M and N are the number of internal and input neurons, respectively. There are four types of internal neurons, each of which plays a specific role, i.e. receiving information from outside (N), controlling on-off switching (1), controlling the motors (2) and others (N_2). In our simulation setting, N_2 is greater than 1, which means that $M > N + N_2 + 1 + 2$ is always satisfied. In this paper M , N , ε and α are set to 14, 5, 0.04 and 0.68, respectively.

2.4. Time-scale and on/off switching

Basically, there are three different time-scales (ΔT_1 , ΔT_2 and ΔT_3), one for vehicle navigation (ΔT_1), one for neural computation (ΔT_2) and one for the light frequency (ΔT_3). Neural computation and the light blinking use a common time-scale, but vehicle navigation is 10 times faster. Using the fourth-order Runge-Kutta method, we set ΔT_1 to 0.1, where ΔT_2 is one. A network structure, evolved by GA, implicitly reflects the time-scale differences.

3. Genetic algorithm (GA)

By using the GAs, we improve an agent's performance for this task. We focus on the emergence of switching dynamics of the input neurons. The weight values and parameter sets, w_{ij} , k_i and a_i , of the network are represented by a real-valued vector in GA. These

values are updated through a mutation operator that adds a small random vector to the genotype at each generation.

First, we prepared Q different blink periods, $\{L(5 \times i, t) | i = 1, 2, \dots, Q\}$. The goal of the agents is to divide these Q periods into two groups. When faced with light flashes belonging to one group, the agents have to head for it, whereas for the other group, the agents must not head for the light; which period belongs to which group is not predetermined.

The fitness value of an agent i is measured by how evenly it can divide the flash frequencies into two groups. Therefore, the number of light frequencies to reach ($\#GET$) over P trials is multiplied by that of non-reachable light frequencies ($P - \#GET$). Here, we define reaching a light as the agent moving to a small region around the light within a specified number of time increments G . The numbers $\#GET$ and $P - \#GET$ are filtered by the piecewise linear map, r . It is better for an agent to reach the light for all P trials or leave it for all P trials. The fitness is further multiplied by the number of inputs ignored (V_i). We adopted this function so that it would make the agent's switching dynamics more effective in solving the task. The fitness function is given as follows.

$$F_i = \sum_{q=1}^Q (r(\#GET(q))) \times \sum_{q=1}^Q (r(P - \#GET(q))) \times V_i, \quad (10)$$

$$V_i = \sum_{q=1}^Q \sum_{t=1}^P \left(1 - \frac{\sum^G v_i(t)}{G} \right), \quad (11)$$

$$r(x) = \begin{cases} 0 & : 0 < x < P/2 \\ x - P/2 & : P/2 \leq x < P. \end{cases} \quad (12)$$

We set both P and Q to 10 and G to 500.

4. Simulation results

Twenty agents were evolved using GA. At each GA step, each agent was tested with the 10 different light source periods. The performance was averaged over 100 trials for 10 basic periods from the random initial spatial locations.

The best agent's performance was improved in a stepwise fashion, as shown in figure 3. The ideal performance was calculated to be 625, with arbitrary units. The ideal agent always shuts off the inputs, but is able to discriminate completely.

The best agent after approximately 5000 GA generations can distinguish two blinking patterns using the switching dynamics. For one class, an agent approaches the light belonging to the class but the agent keeps away from lights belonging to the second class. These behaviours were established by the on-off switching dynamics introduced in the modelling section.

This scheme differs from the conventional plan-action schema in that discrimination and the approaching/avoiding action have to be executed simultaneously. That is, the discrimination pattern is not stored as a static representation but as an action pattern itself. Two opposing action patterns, approaching and avoiding, are somehow prepared within the same network. Hereafter, we analyse the dynamical categorization in detail.

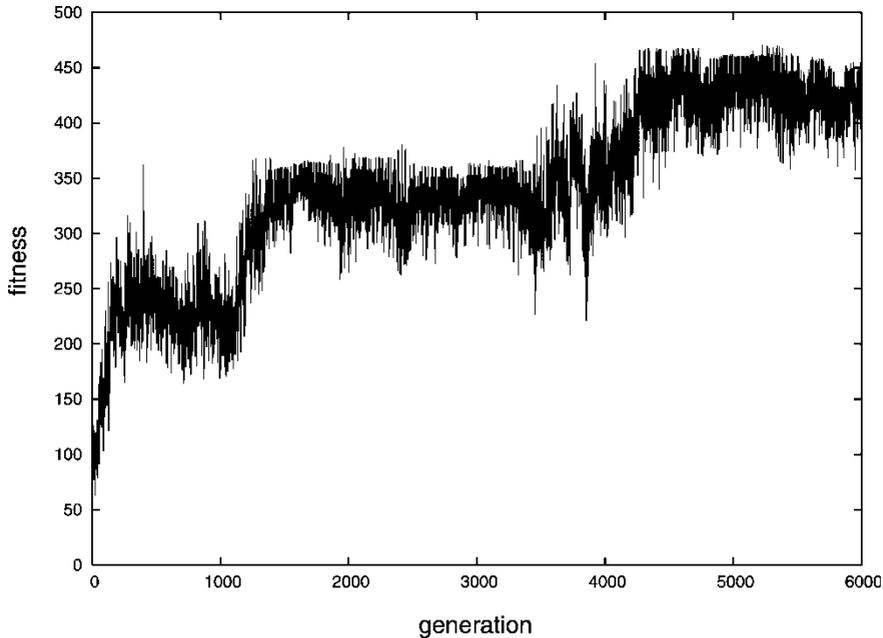


Figure 3. Fitness values of the best agent at each GA generation for a single run.

4.1. Discrimination pattern

Discrimination capability is measured by the probability of reaching the light source over 100 trials for each blinking frequency. Figure 4 shows the performance of an agent from the 5500 GA generations.

An agent was trained by 10 different periods (5, 10, 15, ..., 50) in the GA. In this example, the agent reached four periods (35, 40, 45 and 50) and escaped from the remaining six periods (5, 10, 15, 20, 25, 30). Then its generalization capability was tested against untested light periods, as shown in figure 4.

In this example, the agent tended to approach light sources with the longer periods and to avoid the shorter periods. However, as can be seen, there exists no definite boundary between the approaching and avoiding behaviours. The wandering motions constitute a boundary between approaching and avoiding motions. Although the light frequencies are one-dimensionally parameterized, we have a complex motion boundary; no strict criterion for the categorization was found. This is actually the definition of dynamical categorization.

The reaching probability has some other undecidable features. That means the reaching probability of 20% is difficult to interpret (figure 4). However, it should be remembered that the reaching behaviour is also bounded in time. In our simulation, the light sources have to be reached before 500 navigation steps; otherwise, it is counted as an unreachable case. Therefore, we allowed the agent to move beyond the bounded navigation time, and the result is shown in figure 5. We extended the time limit from 500 to 1000 and some undecidable regions increased their reaching probability. This becomes clearer by computing the distribution of the reaching time at the light sources. Figure 6 shows that when an agent shows reaching behaviour, the time distributes sharply around 250. On the other hand, an agent never reaches some light periods even with the longer time bound. In addition, some distributed regions appear. In this region, the reaching probability changes by extending the time boundary. From

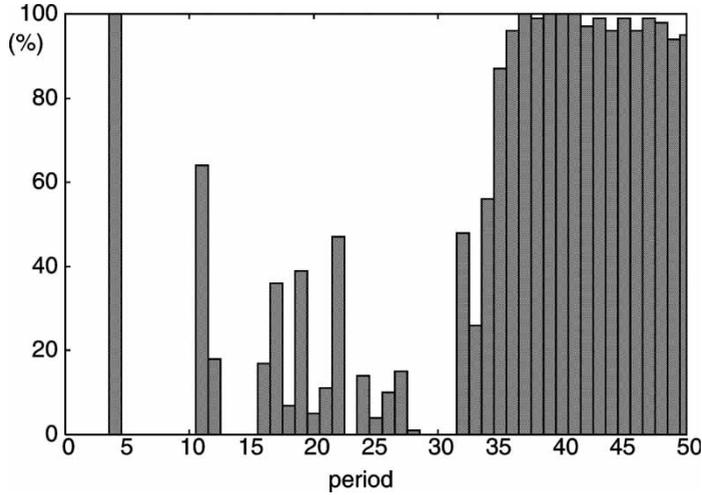


Figure 4. The reaching probability of the best agent at generation 5500 in its interaction with the lights whose periodicity ranges from 1 to 50. Only 10 periods, 5, 10, 15, 20, 25, 30, 35, 40, 45 and 50, were used for the evaluations in the evolutionary process. The reaching probabilities of those periods are 0, 0, 0, 5, 4, 0, 87, 100, 99 and 95, respectively.

these considerations, we classify at least three different navigation structures: reaching, avoiding and wandering. The wandering behaviour corresponds to the undecidable regions. They are studied explicitly in the next section.

Before analysing the spatial navigation pattern, it should be noted that agents can evolve with the different categories. Figure 7 shows the other categorical pattern from a different GA series. Again, we have three different regions, corresponding to avoiding, reaching and wandering behaviour.

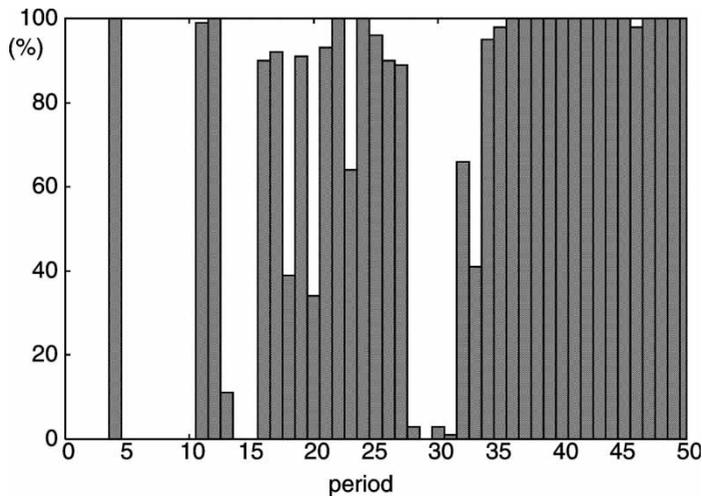


Figure 5. The reaching probability by extending the bounded time, G , of figure 4 to 1000. The reaching probabilities towards the basic periods are 0, 0, 0, 34, 96, 3, 98, 100, 100 and 100, respectively.

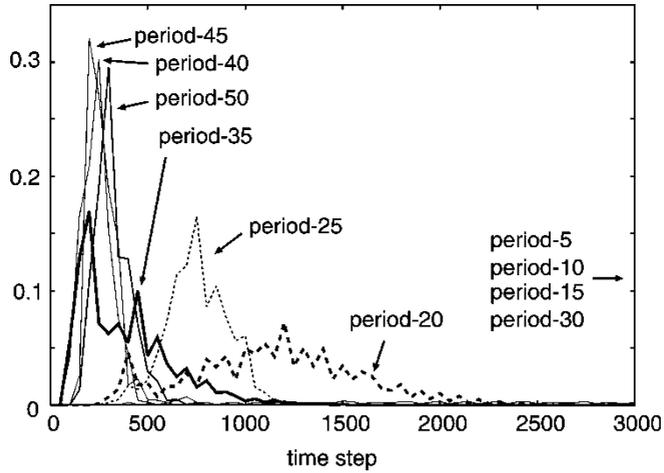


Figure 6. The reaching time distributions of the best agent at generation 5500. We studied whether the light periods were reachable or not from the different initial locations by extending the bounded time. Three different patterns (approaching, wandering and avoiding) are visible here. The avoiding cases of 500 time steps remain unreachable at navigation time step 20000. On the other hand, the wandering cases (periods 20 and 25) have wide time distribution.

4.2. Navigation pattern

A basic navigation structure is composed of two parts, circulation and forwarding motions. Although they are the easiest pattern for an agent to create, combining these two motion patterns, agents generate various navigation patterns. It may be argued

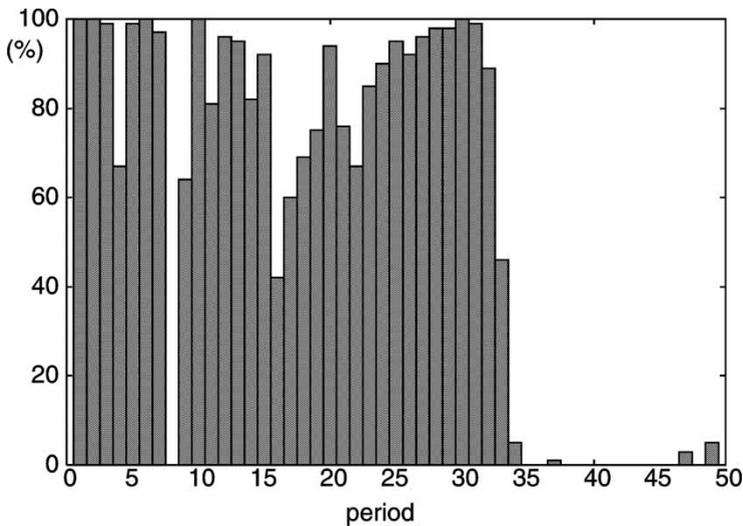


Figure 7. Another example of the reaching probability of an evolved agent from a different evolutionary run. Differing from figure 4, the agent prefers the shorter periods. The reaching probabilities towards the 10 periods are 99, 100, 92, 94, 95, 100, 0, 0, 0 and 0, respectively.

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that the forward motion has to be adopted to approach the light sources. However, we argue that the circulation pattern may be useful for the frequency discrimination.

Figure 8 shows the spatial trails of the best agent from the 5500 GA generation against basic periods. The agent basically generates anticlockwise circular patterns. Comparing the reachable periods (four lower right columns) with the others, we note that the number of circulation patterns is far lower than the unreachable cases.

In the unreachable cases, the agent goes back and forth, so that the trails are retraced several times. The unreachable patterns are further classified into two classes, avoiding and wandering from the navigation pattern. The avoiding pattern is typically observed for periods of 5, 10, 15 and 30. A forward motion towards the light sources is rarely observed in the avoiding pattern. On the other hand, the wandering pattern can approach the light source, but only accidentally. It is difficult to attribute any intention to their behaviours. Therefore, those three motion behaviours are observationally very different from each other. These observations explain the reaching time distribution (figure 6).

We consider whether these motion types are generated effectively by using the autonomous coupling. First, we do not claim that this discrimination task is impossible without this autonomous coupling, rather, we insist that the autonomous view of action can be made explicit by introducing the coupling dynamics. To see the effectiveness of the coupling, we artificially suppress the coupling dynamics to see how the behaviour changes, then we analyse the underlying neural dynamics.

We replaced the coupling dynamics with random on–off dynamics and the network structure was retained. We studied the effectiveness of the coupling dynamics. The resulting reaching probability is shown in figure 9. The behaviour is strictly dependent on the updating random on–off probability, but within the bounded time of 500 intervals, almost no agents reached the light sources. However, when we increased the time limit to 2000, there appeared clear discrimination of the light frequencies for an updating probability greater than 0.3. When the updating probability was set at 0.6, the threshold for discrimination emerged around period 35. No isolated reachable period appeared. It is interesting to note that the isolated reachable regions appear when the on–off probability equals one.

The entire distribution becomes similar to the case of autonomous coupling with the updating probability approaching one. However, this result does not mean that the autonomous coupling is useless, because the navigation pattern with the updating probability of one and that of the autonomous coupling are very different. Figure 10 shows the navigation pattern at different periods. It becomes difficult to distinguish between approaching and other navigation patterns. It seems that the agent without autonomous coupling can only reach the source accidentally. Our claim here is that the autonomous coupling synthesizes the motion repertoire, e.g. approaching pattern.

4.3. Neural dynamics

In this section, we analyse the difference between of the neural dynamics of the reaching and avoiding behaviours. The time evolution of the neural dynamics of a gating neuron $v(t)$ is shown in figure 11.

Different navigation patterns possess different neural activities, as shown in figures 11 and 12. From figure 11, a clumped spiking of the gating neuron is a characteristic of the approaching pattern. During the clumped spiking phase, the agent makes a circular motion towards a light source. In other words, the agent has to turn on the coupling more frequently to reach the light source. Turning off the coupling causes a circular motion. However, as above, such circulation is necessary to discriminate between different blinking periods.

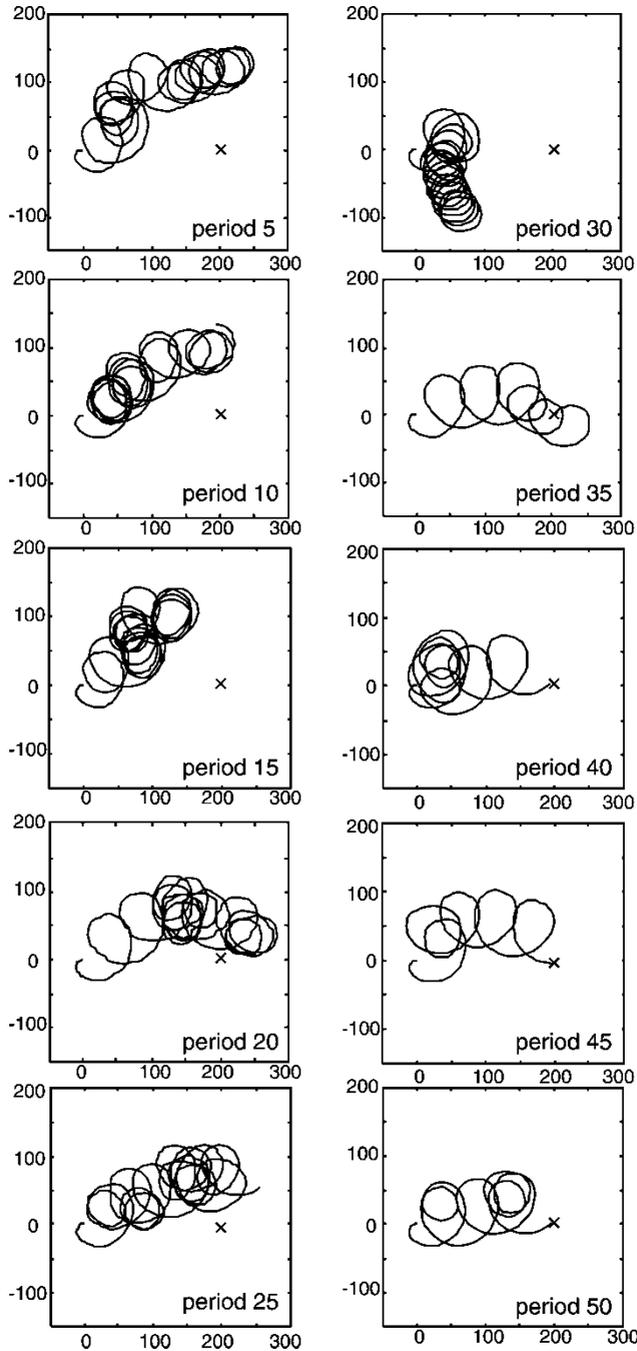


Figure 8. Spatial trails of the best agent at generation 5500. The agent does not touch the lights of periods 5, 10, 15, 20, 25 and 30. The other periods, i.e. 35, 40 45 and 50, are reached. In all cases, the agent started from the initial position (0, 0) and the light source was on (200, 0), which is indicated by \times in the figure.

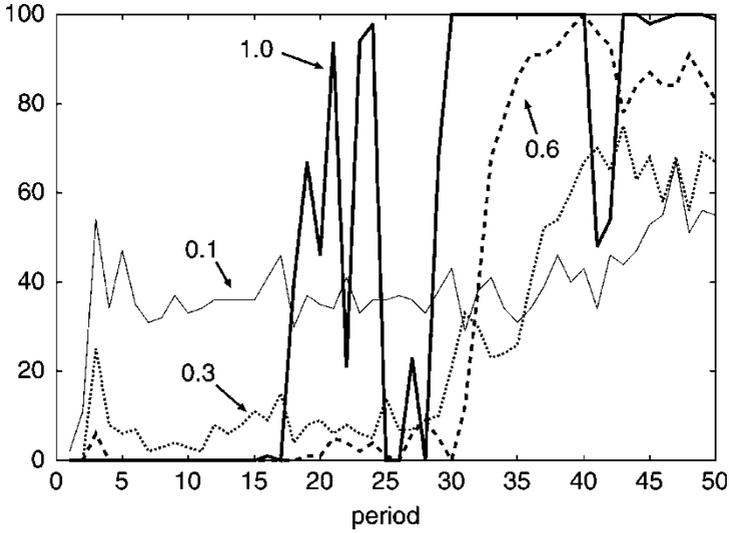


Figure 9. The reaching probability by the best agent with a probabilistic external on–off switching. The numerals on the lines represent the on–off probability. We used G of 2000.

The above argument is more clearly observed in figure 12. The first row corresponds to the avoiding motion (period 15) and the second to the approaching motion (period 45). In the third row, as for comparison, the forced-gate open dynamics is shown. From the figure, we note that different neural activity is associated with using autonomous coupling. It can be seen that the neural activities are greater for the approaching cases

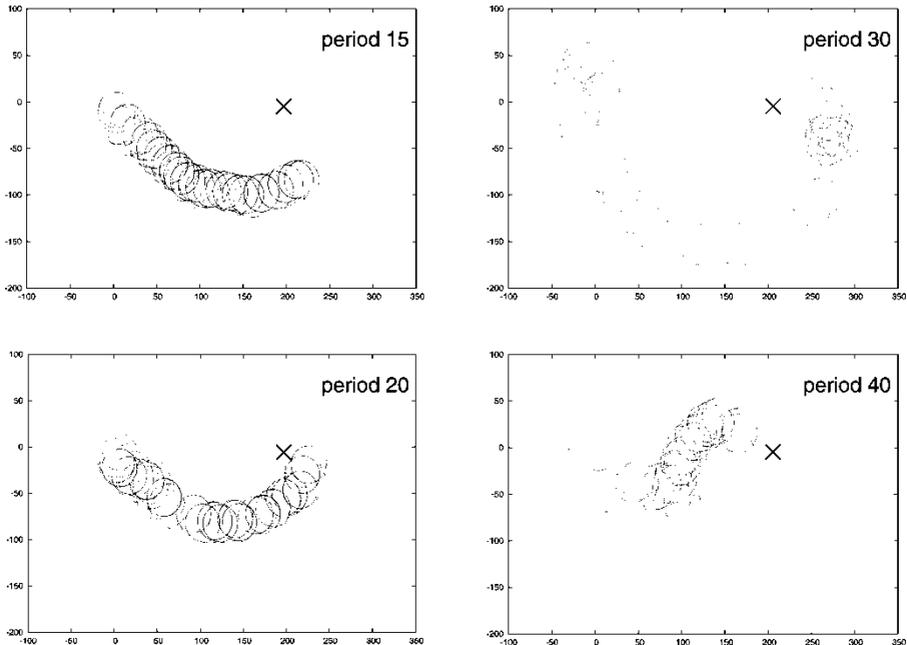


Figure 10. Spatial trails when $v(t)$ is always set to unity, independent from the control neurons. The input sequences continually affect the internal neural network.

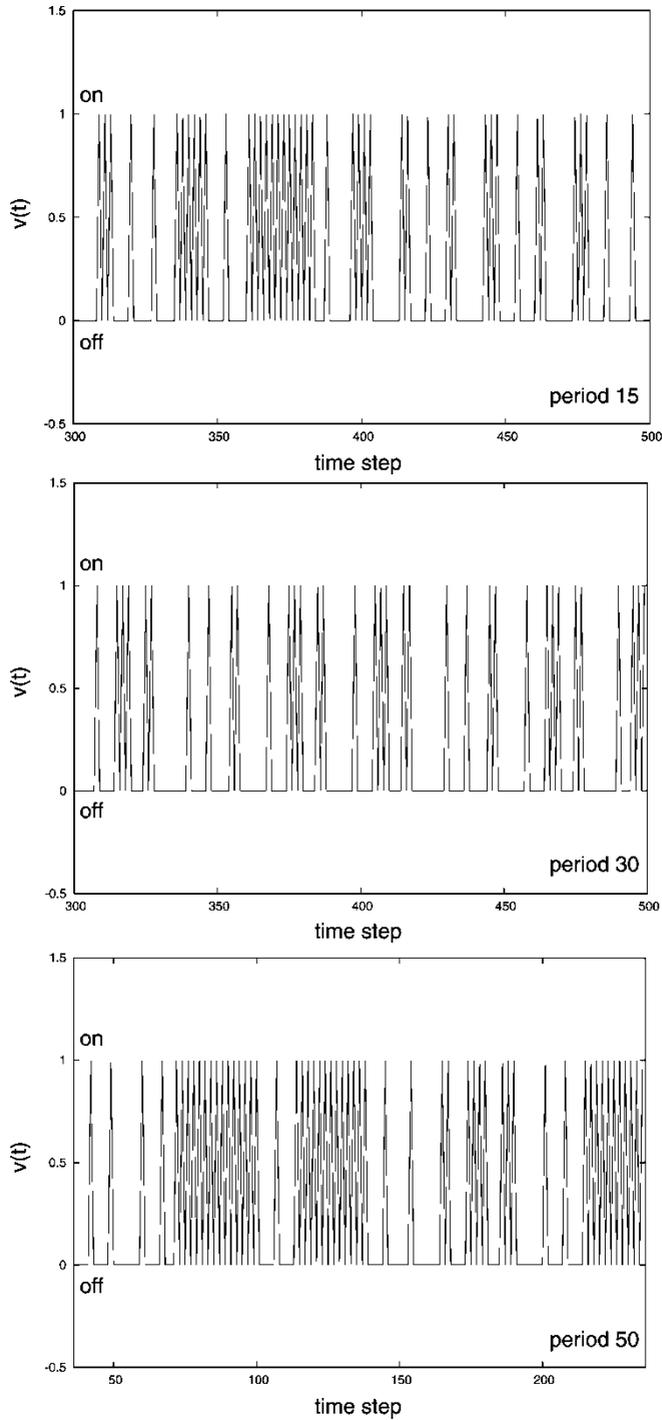


Figure 11. On–off switching dynamics, $v(t)$, of the best agent at GA generation 5500 when interacting with the light periods 15, 30 and 50. The values of $v(t)$ in the last 200 steps are plotted. In the case of light period 50, the agent reaches it at 236 time steps. The graphs for periods of 15 and 30 show examples of unreachable cases.

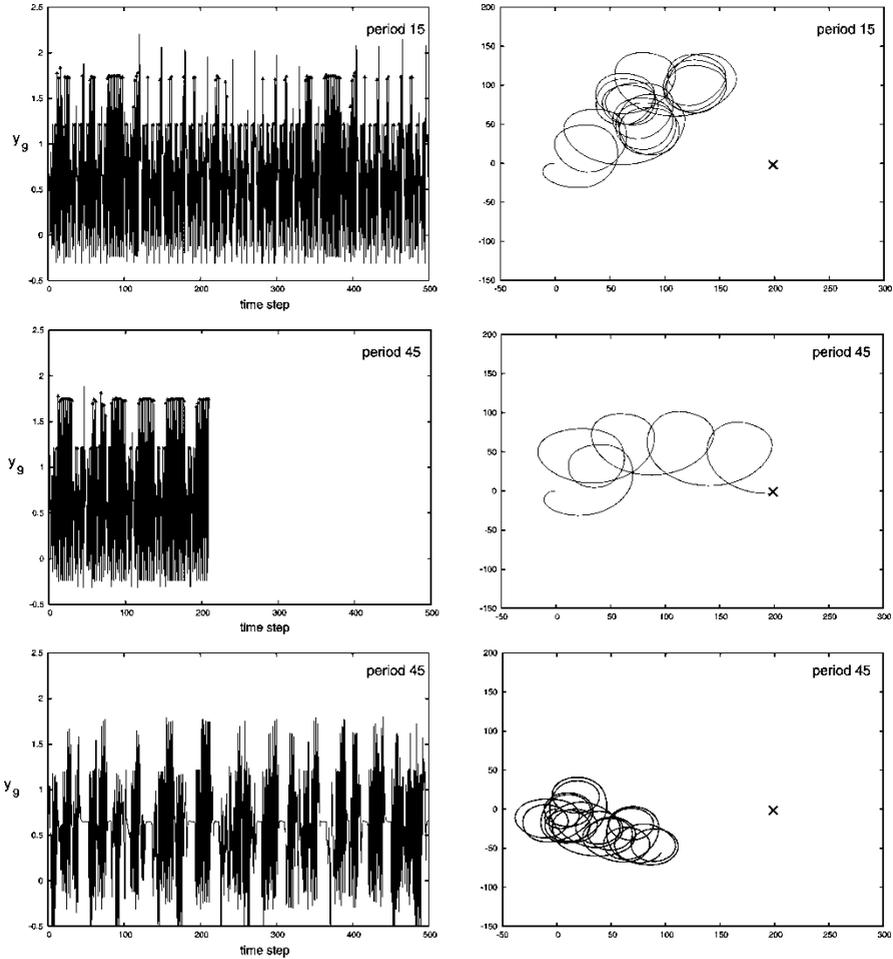


Figure 12. The internal dynamics (left) of a single internal neuron and spatial trails (right), when interacting with light periods of 15 and 45. The closed triangle indicates the internal states at switch on, $v(t) = 1$. The first row is an example of an unreachable case. The second row is for a reachable case. The last row represents the internal dynamics and the spatial trail when $v(t)$ is permanently set to unity independent of the control neuron, as in figure 10.

when the coupling is on. On the other hand, the avoiding pattern cannot sustain the higher activity. In figure 13, it can be seen that the open coupling frequency generally increases as a function of the light period. However, the input signal intensity decreases as a function of the light period. Therefore, the navigation behaviour is very different from that caused by random updating.

In the last row of figure 12, we see that the spiking becomes more chaotic compared with the other cases. The agent can not only generate effective approaching behaviour, but also fail to regulate the behaviour. The regulatory pattern is maintained by the autonomous coupling to reach or avoid the light source. Therefore, it should be noted that the regulatory pattern is not produced by a simple entrainment by the light period.

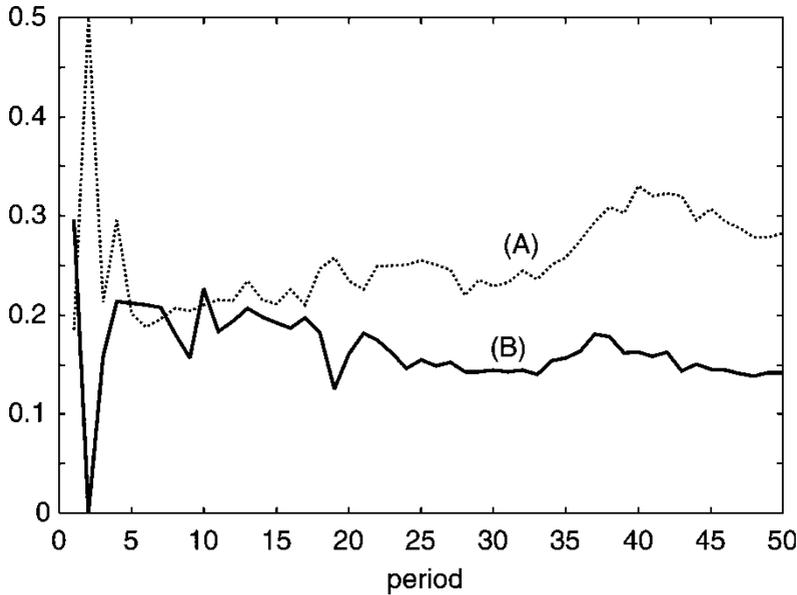


Figure 13. (A) On/off frequency and (B) the averaged intensity of the input signal during the on phase in its interaction with the lights whose periodicity ranges from 1 to 50. The light intensity seen by the agent decreases, while the on/off frequency increases. This tendency roughly holds for the reachable lights of the longer periods.

5. Discussion

Simple sensorimotor co-ordination provides sufficient complex behaviour under certain conditions without having sophisticated internal structures. Theoretically, the view comes from Braitenberg and Walter's vehicles, whose behaviours in a certain environment superficially show some forms of emotions, while they were merely designed by simple hard-wired electrical connections from sensory inputs to motor outputs (Walter 1950, 1951, Braitenberg 1984). However, to generate similar behaviour does not mean we can ignore the internal structure of an agent. The autonomous coupling we have introduced here stresses the importance of active perception in categorization. According to Gibson (1962) and recent papers (O'Regan and Noë 2001), active perception insists that self-action enables us to perceive objects. Even with visual perception, the motion pattern is not optional but becomes a main source of visual information. This dynamic view of perception was recently considered by Morimoto and Ikegami (2004), Nolfi and Marocco (2002) and Marocco and Floreano (2002). In this paper, we have pursued another aspect of active perception. The introduced autonomous coupling shows that interfacial complexity, i.e. editing and selection aspects of sensory inputs, can control categorization behaviour of agents. Categorization without autonomous coupling cannot change its interfacial complexity. As we show, the possibility of control experiments on interfacial complexity gives us an opportunity to consider its functionality.

In our results, irrespective of the agent's approaching or avoiding behaviour, its internal neural dynamics maintain a coherent pattern. It autonomously adjusts the coupling dynamics independent of the light period. However, it should be noted that the coupling dynamics auto-regulate the internal dynamics. This circular relationship organizes self-produced coherence. We believe that our proposed architecture, which

maintains circular self-produced coherence, provides a prerequisite mechanism for active perception. The autonomous coupling and decoupling nature of the interaction is a realization of autopoiesis (Varela 1992).

Instead of a normal neural architecture, we used chaotic neural dynamics, which simulates the collective motion of spiking neurons. Di Paolo (2000) shows another way to realize the self-produced coherence discussed here. He described a plastic neural controller with a homeostatic adaptation, which does not directly depend on input sequences. The controller acquired adaptive behaviour that is not mere sensorimotor co-ordination but relationships between internal stability and adaptation at a higher level. This homeostatic mechanism can be considered a self-produced coherence in the plastic network.

We believe that when an agent is situated in an environment, the interfacial complexity gives rise to an agent's self-produced regularity, i.e. a notion of self. Indeed, we feel that the notion interfacial complexity characterizes the active and adaptive nature of perception. In this paper, we restricted our attention to agents that perceive passive environments. Different kinds of interfacial complexity arise when two adaptive agents interact with each other by e.g. turn-taking (Iizuka and Ikegami 2004). We are currently investigating turn-taking from the aspect of interfacial complexity.

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