ELSEVIER

Bio Systems

From a homeostatic to a homeodynamic self

Takashi Ikegami *, Keisuke Suzuki

*Department of General Systems Sciences, The Graduate School of Arts and Sciences,
The University of Tokyo, 3-8-1 Komaba, Tokyo 153-8902, Japan*

Abstract

Life as an autonomous homeostatic system is discussed. A mechanism that drives a homeostatic state to an autonomous self-moving state is examined with two computational cell models. The mechanism is met with Ashby's ultrastability, where random parameter searching is activated when a system breaks a viability constraint. Such a random search process is replaced by the membrane shape in the first model and by chaotic population dynamics in the second model. Emergence of sensors, motors and the recursive coupling between them is shown to be a natural outcome of an autonomous homeostatic system.
© 2007 Elsevier Ireland Ltd. All rights reserved.

1. Background

The mission of artificial life study is to construct life-like forms in computer simulations and to create a theory for a possible evolutionary scenario from proto cells to higher order cognitive agents. The definition of a life form is provided only vaguely, and we try to refine the definition step by step by synthesizing new life forms.

But there are basic properties we reserve for understanding life forms, which we tend to synthesize in artificial life systems. A most well known property that we think essential for a life form is "self-reproduction". First, we briefly describe how this idea has developed since its definition by John von Neumann (1966). Then we discuss the fundamental problems with this idea and propose a second idea, i.e., life as a "homeostatic system". The advantage of this second line is that we

can make a connection between cognitive functions and basic life processes. This paper is to pursue this idea of the homeostatic nature of life with new perspectives.

The idea of life as self-reproduction was formulated for the first time by John von Neumann with 29 states of two-dimensional cellular automata (CA). He designed a CA rule set to make a special spatial configuration capable of reproducing itself. A message from the study is that self-reproduction needs a self-description "tape" to do exact copying. A universal constructor was defined as a universal cell configuration that can build any machine structure coded on the description tape, where this tape was also given by a spatial configuration.

Since this pioneering work, a new design principle for self-reproducing machines has been studied using two-dimensional CA. In particular, Langton (1984), Tempesti (1995), Reggia et al. (1993), and more recently Sayama and Salzberg (Sayama, 1998, 1999; Salzberg et al., 2003; Salzberg and Sayama, 2004), and Suzuki and Ikegami (2006)'s works have made certain progress in this line. Those systems show not only beautiful replicating pat-

---

* Corresponding author. Tel.: +81 3 5454 6541.
E-mail address: ikeg@sacral.c.u-tokyo.ac.jp (T. Ikegami).

terns, but also evolutions of new replicating patterns by way of mutual interactions among replicators.

A major drawback is that reproduction in CA cannot be stable against noise. A self-reproducing state turns out to be very rare because a single bit flipping is fatal to self-reproduction. This cannot be a problem if the system is essentially noisy. Alan Turing (1952)'s approach was to use a reaction diffusion system to understand life forms, which is much more robust than CA. Turing's approach is now represented by the Gray and Scott (1983) model and the reproducing machine in CA is replaced by a reproducing chemical spot. Turing did not take into account the self-description tape. Instead, he assumed mutual reacting activator and inhibitor chemicals. Under the condition that the inhibitor chemical diffuses much faster than the activators, the system generates a variety of spatio-temporal patterns, called Turing patterns. One such pattern produces self-reproducing spots. A particle-based simulation with a minimal chemical network also demonstrates robust self-reproduction, particularly with a rigid cell boundary (Ono and Ikegami, 2000, 2003, Madina and Ikegami, 2004).

But most of the Turing pattern models lack "universal reproductivity", i.e., you cannot reproduce any kind of pattern. More seriously, self-replicating spots have no internal structures, so it is difficult for them to have memory or heritability. Too much robust self-reproduction thus loses essential properties of life systems. On the other hand, a robust self-replicator in one-dimensional CA is proposed by Gacs (2001). He elaborated a system design that can repair any given pattern under any noise level. Gacs' CA can self-emulate the "right" self-image pattern to repair the perturbed pattern, which requires many complex instructions. This complex rule is for self-repair, not self-reproduction. We have to get back to rudimentary levels of simulating life forms. In the following, we examine the necessary conditions for life as self-preservation. We study Turing pattern dynamics and a set of chemical networks used for self-reproduction as a basic platform for self-preservation.

2. Ashby's Ultrastability

Different from the approaches of John von Neumann and Turing, Ashby (1960) raised an interesting design principle for brain (and life forms) outside self-reproduction. Ashby was mainly concerned with homeostasis. He thought life's adaptive behavior is only an outcome of homeostatic property. We can further generalize this idea by saying that "self" is an outcome of homeostasis. We know that the living condition involves far non-equilibrium states, and this sustains a type of
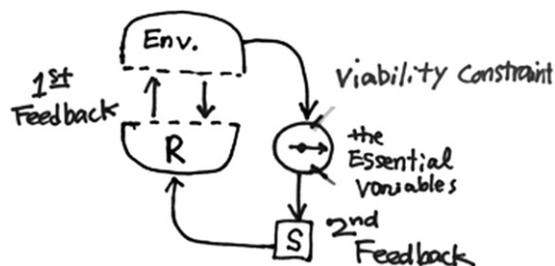

Fig. 1. An illustration of Ashby's ultrastability (modified from Ashby (figure 7/5/1 1960)).

identical states as a kind of "self" in the form of attractors. Assume that we have a set of chemicals. Those chemicals can constitute a dynamic state comparable to a self-preserving attractor, which we like to label as a primitive sign of self. But these self-preserving attractors can exist only when we hold an adequate parameter set that controls their stability. Thus, we call the parameter range a viability constraint because out of the range, no self-preserving property appears.

This idea of viability constraint can be found in Ashby's ultrastable system, where he illustrated double feedback interactions between a system (reacting part) and an environment (Fig. 1). A primary feedback loop is a mutual interaction between complex sensory and motor channels and the environment. Another feedback goes from viability constraints to a reacting part through essential variables that control the reacting part. Usually, the second feedback loop is executed intermittently because it changes the meta-parameters of the system. When the parameter values are out of the viability constraints, the second feedback adjusts the essential parameters to let the system move towards the attractors.

The difference between variables and parameters is made explicit when writing down equations. Variables temporally evolve, and parameter values are fixed in time. In real systems, the difference is not that simple. Variables change much faster than parameters. For example, in modeling evolutionary ecosystems, the population of each species changes in time, but the mutation rate is usually fixed during the simulation. A mutation rate is a parameter of such a system. However, in real evolutionary ecosystems, the mutation rate itself must change over a long time span. We have studied a system in which both population and mutation rate evolve in time. There we discussed a weak chaos with large degrees of freedom, called "homeochaos", which serves as a mechanism for dynamic homeostasis (= homeodynamics) (Kaneko and Ikegami, 1992; Ikegami and Kaneko, 1992). In this paper, we will also argue for a dynamic mechanism of homeostasis.

Ashby's viability constraint and the second feedback mechanism deliver an important message to artificial life studies because most artificial life creatures never die. Any adaptive behavior should be grounded in the viability constraint, if the behavior is truly adaptive. For example, assume that artificial agents are attracted by light targets like the one discussed in Braitenberg (1984)'s vehicle. The tendency to move toward the light has nothing to do with the survivability of the agent. The light seeking tendency has been decoupled from the basic requirement of viability. An important lesson from Ashby's ultrastability is that the second feedback loop through the essential variables of the system is independent of how a system copes with the environment. This is why the second feedback can provide adaptive behavior. But a link from homeostasis to adaptive behavior and to further cognitive functions is not yet well understood (Di Paolo, 2003). Regarding these points, we will study the missing link from homeostatic states to adaptive and cognitive behaviors. In the next section, we clarify our starting point by introducing the notion of sensorimotor couplings, autonomous motion and a theory of autopoiesis.

3. Sensorimotor Couplings

Sensorimotor coupling (See e.g. Scheier and Pfeifer, 1995; Pfeifer and Scheier, 2001; Ikegami and Zlatev, 2007) is a way to understand life forms, particularly when we deal with cognitive functions. A definition of sensorimotor coupling is an agent's mapping from motor sensory input patterns to motor outputs, but the mapping is not necessarily fixed all the time. Evolutionary robotics takes a synthetic approach toward cognitive behaviors by generating adequate sensori-motor couplings. Usually, the sensorimotor coupling is developed using evolutionary techniques, e.g., genetic algorithms (Morimoto and Ikegami, 2004). The outcome of the sensorimotor coupling is to provide a new way of perceiving the world. By exploring the environment using its own action patterns, an agent obtains sensorimotor-based knowledge, which we call a dynamic categorization.

The concept of dynamic categorization originates from Gibson's (1962, 1979)"ecological" theory of perception and in particular his emphasis on perception as a form of activity, which is often referred to as active perception. Gibson's insights have been developed and re-interpreted in multiple ways. Sasaki (2000, 2002) applied a Gibsonian analysis to various situations, such as a blind man's navigation patterns in a town, people's usage of the visual landscape, and the action structure of breaking an egg. According to Costall (2007), the most important characteristics of Gibson's concept is that it is equivalent neither to external sensory input, nor to "representations" generated in one's brain, but constitutes a dynamic, relational category that arises as an active perceiver interacts with an environment. The following three aspects are particularly important in rethinking the concepts of active perception (see Sasaki, 2000, 2002, O'Regan and Noë, 2001):

(i) Perception can emerge via self-movement; (ii) perceiving the environment means to explore it; (iii) any action has inherent multiplicity.

An instance of the first aspect is active touch. Gibson (1962) reports on experiments with blind subjects touching different shapes of cookie cutters. If the cutter was placed on the subjects' palms, they could tell the correct shape with only 50% accuracy. When the cutter was pushed randomly on their palms, the subjects could tell the shape with 72% accuracy. Only by touching the cutter in a self-guided manner could they recognize the object in more than 95% of the cases. This study also illustrates point (ii) that perception is a form of exploration: As we will discuss in this paper, exploration is not just a method to arrive at perception; rather perception is equivalent to an on-going exploratory process.

The third aspect is especially important for simulations of artificial agents. An issue that often comes up in this context is how to select the most appropriate set of actions. However, aspect (iii) implies that no discrete action set (a "plan") needs to be prepared in advance. Our body schema (Gallagher, 2005) has a huge number of degrees of freedom. Even a simple action pattern (e.g., sitting down on a chair) consists of multiple sub-level actions, and the exact sequence will be afforded by the environment as the action proceeds.

The notion of active perception is often evoked within the "embodied cognition" approach in the field of cognitive robotics (Pfeifer and Scheier, 2001). In this context "embodiment" refers to spatial/temporal dynamics and the physical constraints of a robot's body with respect to a given environment. Of course, there is no reason to suppose that such "artificial creatures" have any kind of phenomenal experience. Nevertheless, the agents can illustrate how categorization can result from mastering sensorimotor coordination with certain aspects of the environment, and in the process creating dynamic categories of them without forming concepts.

Recently, many studies of dynamic categorization have involved "artificial creatures". Some of these studies involve actual, physical robots (Scheier and Pfeifer, 1995), whereas others involve computational simulations (Morimoto and Ikegami, 2004). Although some scholars, such as Brooks (1999) and Steels (1994), insist

on the importance of using real physical devices in "embodied AI", there are good reasons to rely on simulations as well.

4. Autopoiesis and the Beyond

One purpose of this paper is to see how homeostatic dynamics generate sensorimotor coupling. A basic idea is taken from autopoiesis, which is a central framework for understanding life systems from an organizational point of view (Varela, 1992, 1979). Autopoiesis treats the essence of a life system as an autonomous organization of boundary structures/conditions. This definition is particularly relevant for chemical life systems. First, metabolic chemicals create membrane chemicals by way of catalytic processes. Those membrane chemicals cooperatively create a closed membrane structure. A catalytic chemical is spatially trapped by a closed membrane chain, and the reproduction of membrane chemicals is carried on. This preserved closed membrane is called a boundary. Indeed, a chemical synthesis of a proto cell has been experimentally studied under such conditions (Toyota et al., 2006). A boundary should be autonomously produced in a proto cell.

The interaction between a cell system and the environment in autopoiesis becomes what F. Varela calls structural coupling. When an autopoietic cell system is acting in an environment, it receives various feedback from the environment. Some effects are fatal to the system. But once the system has survived a severe condition, it is engraved as the survival limit. Under the survival limit, a system undergoes structural changes, and the interaction with the environment that causes a structural change is called a structural coupling. When the structure of a system changes, the system can preserve its organization. But as Di Paolo (2003) argued carefully, autopoiesis and structural coupling are insufficient to generate adaptive behaviors or "sense-making" behaviors in life systems.

So there is a missing link between autopoiesis and cognitive behavior which should be addressed. A hint can be found in what Ashby calls the second feedback loop; autonomous and unintentional controlling of a system's essential variables when the system leaves the viability constraint (see Fig. 1).

There are studies on the relationship between cognition and the viability constraint. (Moreno and Etxeberria, 2005). argue that the adaptive behavior of a single cell (e.g., moving toward a fertile environment by sensing the chemical gradient) is the result of satisfying the viability constraint by means of an internal metabolic network. Di Paolo (2000) simulated homeo-adaptive behavior in

a neural net with a special Hebbian dynamics. There he actually showed that the right and left eyes can be exchangeable even after development – unless the adaptation (this time developing visual sensors) is not evolved functionally – by simply rewiring neural circuits. We have this robust adaptability only when the model is based on homeostatic dynamics that maintain the viability range.

But if we superimpose homeostasis on an already developed sensorimotor system, the system becomes difficult to motivate. We need to follow the synthetic order, and there should exist an intermediate stage between homeostasis and well-developed sensorimotor couplings. Such an intermediate stage is what we mainly discuss in this paper.

In the following sections, we start by introducing two different computational models of abstract chemical agents. In Section 5, we investigate the viability constraint with motile cell modeling. By extending Varela's original model on autopoiesis, we discuss membrane fluctuation as a source for autonomy and adaptability. Membrane dynamics that cause entire cell movement can be varied by local membrane morphology. In Section 6, we introduce another chemical agent using Daisy world homeostasis. An explorative action pattern with homeodynamics is discussed. We will show that this homeostatic mechanism is the outcome of spatio-temporal chaotic dynamics. By preparing an adequate motor computation, we can develop an explorative sensorimotor coupling, which is necessary for activating the second feedback loop in ultrastable systems. Then again, a sophisticated membrane structure has an important role in connecting the homeostatic property and sensorimotor coupling. In the last section, we discuss the viability condition in terms of homeostasis.

5. Autopoietic Cell Model

5.1. Basic Metabolism

In a proto cell system, sensory and motor systems cannot be independent of the self-maintaining process. In primitive cell systems, the metabolism of membrane components is regarded as reconfiguration of the sensory device, in the sense that it changes penetrative properties. Furthermore, the same membrane can work as a primitive form of actuator. There is evidence that such a dichotomy happens in real-life systems. The movement of slime mould is achieved by the continual dissolution and recreation of the membrane with the protoplasm flow. Moreno et al. (2005) argue that

the adaptive behavior of a single cell moving toward a fertile environment by sensing the chemical gradient is the result of evolving metabolic networks. And they also argue that self-preservation and self-motility might occur synchronously in a proto cell system. Emergence of a nervous system can segregate self preservation and autonomous movement.

Below, we show a simple cell model that exhibits chemotactic behavior owing to dynamic changes of the membrane. By considering proto cell systems, we would like to analyze the relationship between homeostasis and sensorimotor coordination in organisms.[1]

5.2. Substrate/Catalyst/Link Model

A simple computational model of autopoiesis has been proposed by Varela et al. (1974). The model has three kinds of chemicals (substrate/catalyst/link). Therefore it is called the SCL model in this paper. S, C and L are mutually reactive chemicals. The reaction between catalyst C and substrate S makes a chemical L, which is mutually connected, and finally generates a circular boundary to enclose catalyst C. We regard this membrane boundary and the area enclosed within the membrane as a cell. When this membrane breaks up, the catalyst will escape, and the membrane will no longer be sustained. By successfully enclosing the catalyst, the inner region surrounded by the membrane maintains the reaction. It repairs the membrane by keeping the catalyst inside it. This circular relationship provides an example of self-preserving cell dynamics. We extend this SCL model to discuss the development of cell motion and of primitive sensors on the membrane.

5.3. Mobile SCL Model

In the original SCL model, chemicals can diffuse on two-dimensional lattice space. S or L chemicals can share the same lattice site, but neither S and C nor L and C can. By this constraint, S chemicals can freely cross bonded L chemicals (which we call the membrane), but a C chemical is trapped by the membrane. Two L chemicals can form a linear bond when they occupy the Moore neighborhood. But each L particle can bond with at most two other L chemicals (See Fig. 2).

The basic reaction is the following. When two S chemicals occupy the Moore neighborhood of the catalytic chemical, they will become a single L chemical.
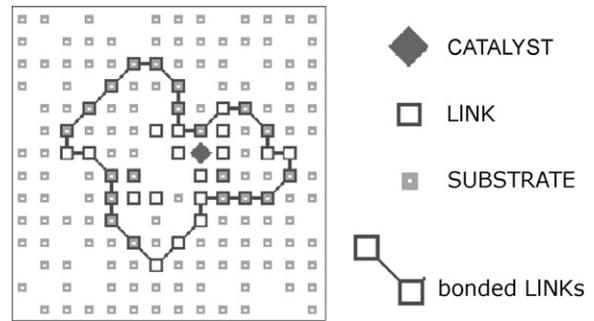
Fig. 2. An example of spatial configuration of the cell region of the SCL model.

$S + S + C \rightarrow L + C$ we inherited these basic settings from the original model. Our main modification is in the metabolic process of L chemicals on the membrane. In the original model, the L chemicals dissolve into two S chemicals at a certain probability, so that the cell should repair a hole on the membrane with the extra L chemicals inside it. Instead of indiscriminate dissolution of L chemicals, we introduce the following new rules:

(i) A produced L chemical is absorbed into the neighboring link boundary with a rate P_i, if the neighboring link is formed from the L chemicals in its Neumann neighborhood.

(ii) The reverse process, releasing L chemical from the link when three L chemicals form a right angle, is concerned/allowed. The released L chemical becomes two S chemicals. This process occurs with the rate P_r (Fig. 3 a). Additionally, we introduce the movement of the bonding membrane.

(iii) Each of the bonded L chemicals can move randomly at the rate P_m without breaking the link. A cell as a whole shows random Brownian motion (Fig. 3b).
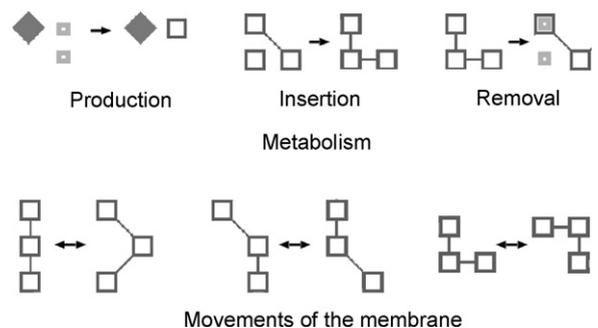
Fig. 3. Reactions and movements of L chemicals are illustrated. (a) Production, insertion and re-moval of L chemicals. (b) Three kinds of random-lined L chemicals.

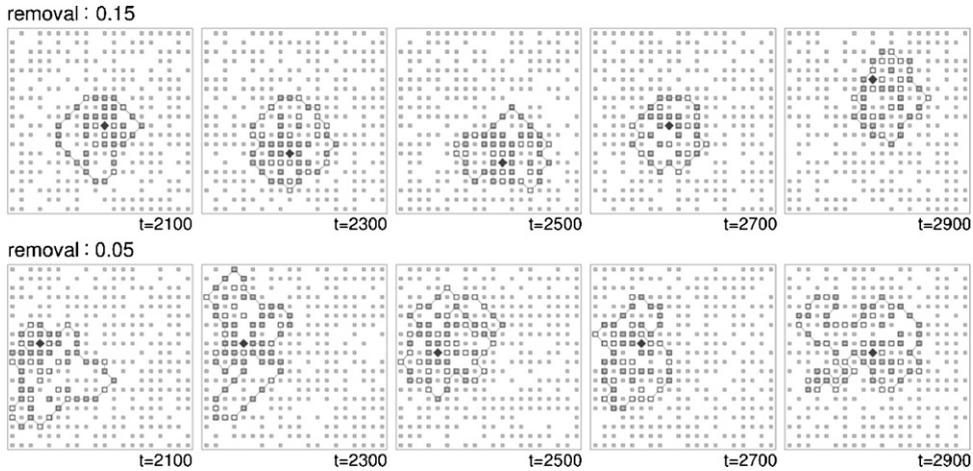[1] The detail discussion of this secsion should be referred to Suzuki and Ikegami (2007).

Fig. 4. Two different cell configurations with different removal rates. A smooth circular form with a removal rate at 0.15 (above) and a spiky rugged form with the rate at 0.05 (below).

5.4. Chemotaxis with Shape Dynamics

It should be noticed that, under the new conditions, a cell can change its size, but it never breaks (the minimal cell size is four particles). But this assumption does not spoil the original model. The size of the membrane is controlled by two parameters, the insertion rate (Pi) and the removal rate (Pr). If the removal parameter is high enough, the size will shrink to the minimal size. If the insertion rate is high enough, the membrane size will increase. There is an adequate parameter range that sustains moderate cell size. We see different cell configurations by changing the removal rate in Fig. 4. With a large removal rate, a membrane has a smooth configuration with a large curvature. But with a small rate, it has a rugged spiky configuration with a small curvature. In other words, by changing the removal rate, the membrane can take different configurations.

We demonstrate that different configurations have different sensitivities to the chemical gradient when putting a source and a sink of S chemicals at different positions, which creates a flow of S chemicals from the source to the sink. In Fig. 5, we compute the distance from the S chemical source as a function of time. The space size is 60×60; the center of source is placed at (48, 0), and the center of the sink is placed at (30, 30). The source/sink size is 3×3. By increasing the removal rate, we noticed that the cell approaches the source more swiftly. That is due to the spontaneous symmetry breaking, which is why circular forms can climb up the gradient. We noticed that spiky forms generate a more complicated tangled surface structure, so that their free movements are highly restricted. Circular forms are more sensitive to the environmental gradient than spiky forms. By draw-

ing a transition diagram among different configurations, we noticed that the spiky forms are easily trapped by the meta-stable configurations.

This tendency can be explained from the microscopic point of view. S chemicals do not distribute equally in the area surrounded by the membrane. Fig. 6(a) demonstrates that they have different concentrations in the fore and rear sides of the cell with respect to the source side. A membrane is more frequently broken and repaired in the sites where the S chemical has a low concentration, which occurs on the rear side of the cell. L chemical has a higher concentration at the same site (Fig. 6(b)). In Fig. 6(b), we computed that on which part of the membrane the motile L chemicals was detected. In the sharp cell, that value is much larger than that in the round cell. It means that the L chemicals are more distributed in the sharp cell than in the round cell. However, the sharp cell has more pinning sites in the membrane, so that the local
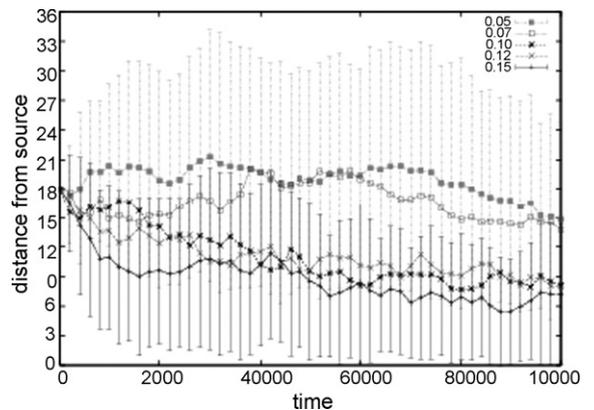

Fig. 5. Distance from an S chemical source as a function of time. Different colors correspond to different removal rates.
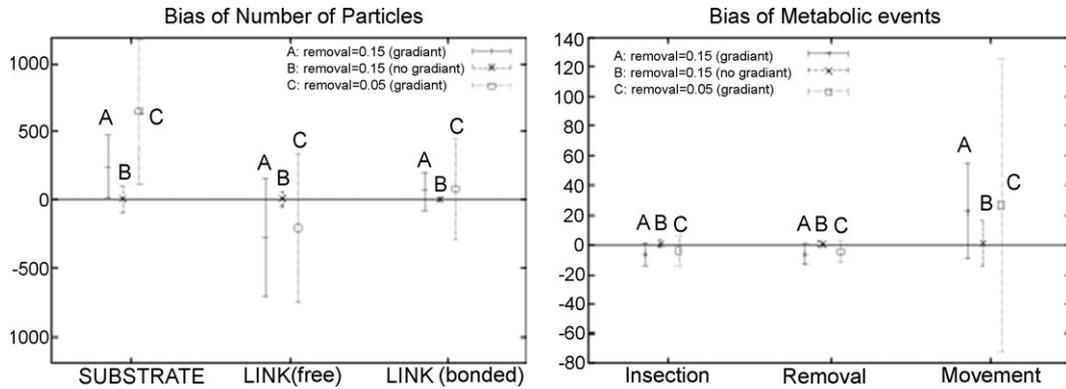
Fig. 6. The spatial fluctuation of the number of S, free L, and bonded L chemicals inside the membrane are computed for two different membrane forms(left). The spatial fluctuation of the number of Insertion, Removal, and Movement events are computed The values are calculated by subtracting the number of particles on the left side of the barycenter of the membrane from the number on the right side.

L chemicals may sometimes move only in the opposite direction to the source site. Thus, the sharp cell as a whole cannot simply follow the outside gradient. We hypothesize that this pinning effect surpresses the chemotaxis in case of the sharp cell.

In other words, the spatial metabolic organization generates self-movement as well. Therefore, chemotaxis appears to be guided naturally by the membrane form.

5.5. Viability and Behavioral Constraints

As mentioned above, the balance of the removal rate and the insertion rate expands the area where L chemicals are generated. Both extremes of the two parameters make the cell fall into a "dead" state with a shrunken area. In this sense, the insertion and removal rates can work as viability constraints to cell activity. When we see the cell as a sensorimotor system, the metabolic process that determines the physiological limit becomes a new factor determining the sensitivity to the substrate gradient in the environment. The gradient-climbing-up tendency of the cell naturally emerges from the continuing flow of the metabolic process of L chemicals and incoming S chemicals through the membrane. This spontaneous chemotactic behavior is caused by the cell metabolism in our model. The cell does not just sustain its existence passively, but actively moves toward the region of high substrate density so that it continues to exist.

On the other hand, we showed that the different membrane shapes, which are controlled by the Pr parameter, lead to different motion patterns of the cell system. Here, the motion patterns are whether the cell climbs up the gradient or walks around rather randomly. The configuration of the membrane can be seen as a kind of

constraint determining cell behaviors. It is worth noticing that this membrane configuration is also constructed by the metabolic self-maintaining process.

When the cell responds toward the environment only in a self-maintaining process, its viability constraint can be described as a pure physiological property, such as the density of the substrate or the extent of the reaction area. However, once a cell performs as a sensorimotor system, and certain constraints are required to maintain consistent sensorimotor activity, cell viability becomes central to this behavioral constraint because the membrane configuration as a behavioral constraint originated with basic metabolism. There is a mutual constraint between the physiological constraint and the behavioral constraint. The cell should sustain itself within the metabolic limitation, and that constrains its behavior. Conversely, the cell should demonstrate consistent sensorimotor behavior, and that constrains the metabolic process. Thus the viability constraint in a motile cell system is effectively changed.

6. Modeling by the Daisyworld Agent

6.1. Daisyworld Model

Global regulation of the atmosphere of a planet with a biosphere is named the Gaia hypothesis (Lovelock, 1972). A complex hierarchical network of living species can behave cooperatively to regulate temperature at the earth's surface, so that the network itself can be preserved. This feedback mechanism is demonstrated using a simplified ecosystem with two competing species of daisies, black and white (Watson and Lovelock, 1983). The simple story is that white and black daisies have different albedo (reflection of the sunlight) and their growth

rate depends on the local temperature. Because black and white daisies have opposite tendencies toward the sunlight, they can self-regulate the temperature by tuning their population size. If there are more black daisies, the temperature goes up as the average albedo gets lower, whereas if there are more white daisies, the temperature goes down due to the higher albedo value. This simple scenario is certainly realized with Watson and Lovelock's modeling and with other variations (e.g., Staley, 2002; Harvey, 2004). Harvey (2004) did further simplifications and demonstrated robust homeo-static control. What is interesting with Inman's work is that he used the homeostatic mechanism to model a sensing system. A circular body agent can rotate around its center with the force from a tentacle with a sensor. Many tentacles on the surface cooperatively work to "correctly" rotate the agent toward a light source, for example. This is an example of a homeostatic sensing mechanism.

Although the original paper on Daisyworld paid little attention to the population dynamics of the daisies, there are several arguments that population dynamics do affect the system (Staley, 2002; Zeng et al., 1990). Apart from the Daisyworld modeling, population dynamics do affect environmental conditions (e.g., Tyrrell, 1999). From theoretical points of view, population dynamics can have rich properties that may be useful for homeostatic control. Actually, we have demonstrated (Kaneko and Ikegami, 1992; Ikegami and Kaneko, 1992) that weak chaos with large degrees of freedom can sustain species diversity. Thus, in the following, we study a homeodynamic regulation mechanism of daisy population dynamics. Then, in the next part, we will use the mechanism to model the navigation behavior of an agent. The purpose is, as we have discussed so far, to see how homeodynamic regulation leads to sensorimotor couplings.

6.2. Simulation Model

The Daisyworld is theoretically equivalent to Turing's reaction diffusion system. A black daisy has a low albedo, so it raises the local surface temperature where it grows. Whereas white daisies have a high albedo, so they lower the temperature where they grow. We assume no direct interaction between black and white daisies; they interact only by way of the surface temperature. We express the population size of black daisies at spatial site i as x_i and that of white daisies by y_i. The local temperature at that site is expressed as T_i. Due to heat conduction at the rate D_T, we have the following equation for the time evolution of the local temperature for each location

i ($i = 1 \ldots N$):

$$\frac{\partial T_i}{\partial t} = \alpha(T_e - T_i) + k(x_i - y_i) + D_T \nabla^2 T_i \qquad (1)$$

where T_e is the external temperature (e.g., the temperature of the sunlight) and the third term is the conduction process given by $D_T \nabla_i^2 T_i = D(T_{i+1} + T_{i-1} - T_i/2)$ where we assume that the Daisyworld is the one-dimensional with a periodic boundary.

The second term is a feedback from the black and white daisies, which corresponds to Ashby's first feedback. Here we simply assume that the feedback effect is proportional to the difference in population size of black and white daisies. Population growth and decay of daisies are governed by the following equation for each location i:

$$\frac{\partial x_i}{\partial t} = R(T_i)x - K(x_i) + D_B \nabla_i^2 x_i \qquad (2)$$

$$\frac{\partial y_i}{\partial t} = R(T_i)y - K(y_i) + D_W \nabla_i^2 y_i \qquad (3)$$

where $R(T_i)$ is a reproduction rate that is a function of the local temperature T_i, and $K(x_i)$ is the death rate. In the Daisyworld models, $R(T)$ is usually given as a parabolic function. In other words, the growth rate takes a positive value between T_1 and T_2, and it vanishes outside that range. We simply assume that $R(T)$ takes a constant value β in between T_1 and T_2 and $K(x)$ is proportional to population size when it is large (i.e., larger than X_c) but it is a given constant $-\gamma$, when population size is small. We use this threshold death process in order to have a long memory effect. The dynamic equation of daisies contains a diffusion (immigration) process with the rates D_b and D_W, where $D \nabla_i^2 x_i = D(x_{i+1} + x_{i-1} - x_i/2)$. Similar to the Turing instability, we use the inequality condition s.a. $D_W \geq D_b$. Additionally to the above settings, we use a one-dimensional periodic boundary condition, and the system size N is 200.

6.3. Simulation Results

Depending on the parameter values, the external temperature, and the initial configuration of the daisy population, different attracting states emerge, such as attractors with no daisies (dead state), with only white or black daisies or with both daisies. When both daisies coexist, the stationary state can be further classified by the population dynamics. Basically, the attractor state consists of traveling clusters of black and white daisies, which we call daisy solitons (See Fig. 7). This daisy soliton is organized by a population of black daisies followed by that of white daisies. There can exist many
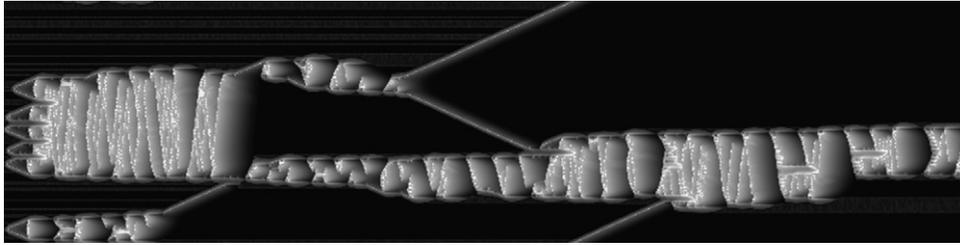
Fig. 7. A spatial (vertical axis)-temporal (horizontal axis) pattern of the Daisyworld. The grey scale represents the mixture pattern of black and white daisies. The transverse waves denote solitons and other gradually spreading regions denote turbulent states.

solitons at the same time, and each of them can run either directions. When solitons meet, they are annihilated in pairs or passed through. But sometimes they create a turbulent state, where unstable waves of daisies are localized in some regions. This turbulent state often expands slowly in both directions and finally dominates the whole space, but it also decays out or shoots new solitons. This rather complicated situation is sometimes observed in specific cellular automata rules and other spatially extended chaotic systems. In terms of temperature, daisy solitons carry heat pulses (singular high temperatures), and the soliton turbulent state creates heat turbulence.

When soliton turbulence over-dominates the whole space, the average temperature is well regulated as long as the external temperature lies between 0.26 and 0.63(see Fig. 8). This region is greater than the given viability range of 0.4 and 0.6 for the growth function R. A known regulation mechanism (e.g., Harvey, 2004) is that a population is temporally fixed, but the ratio of black and white daisy regulates the average temperature. Here, the mechanism is more dynamic as the temporal structure of the daisy population regulates the temperature. Due to this new mechanism, the local temperature is

intensively fluctuating locally. Daisyworld is regulating the average temperature by the chaotic dynamics.

When there is no soliton turbulence, it is difficult to have homeostasis. When the daisies are decaying, the average temperature simply obeys the external temperature. Around the upper regulatory temperature (this time around 0.63), a partially turbulent state or simple soliton-coexistence phase emerges. In such cases, average temperature is not simply determined by the external temperature. This region has a strong hysteresis, so that the final state (and the outcome of the average temperature) is very sensitive to the profile of the system. This is also true in the lower temperature region. When we raise the external temperature to greater than around 1.4, the average temperature obeys the external temperature.

In sum, this dynamic and complicated version of the Daisyworld regulatory dynamics reproduces the basic homeostatic result of the usual version. The observed mechanism is very general and results from the Turing instability, so we can use it for a general regulatory mechanism.

6.4. Simulating Mobile Agents

Using the Daisyworld modeling, we now simulate a mobile agent with a circular body of a radius r whose surface is covered with the daisy population (see Fig. 9). We assume that mobility of the agent is determined by the surface temperature. As a simple example, we assumed that when a local temperature is lower than the average temperature, there is a force vector from that site to the direction of the center of the circular body. Also we computed the population size difference at each site and used it to determine the amplitude of the force:

$$\vec{F}_i = -k_1\theta\left(T_i - \sum_i \frac{T_i}{N}\right)\vec{n}_i\cos(\psi_i) \qquad (4)$$

$$\vec{\tau}_i = -k_2\theta\left(T_i - \sum_i \frac{T_i}{N}\right)\vec{\tau}_i\sin(\psi_i) \qquad (5)$$
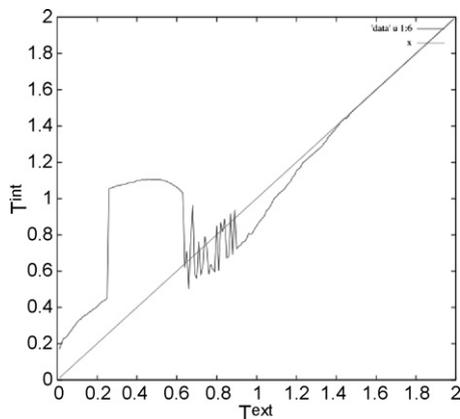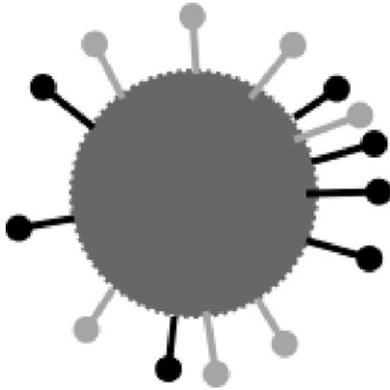

Fig. 8. The surface temperature as the function of the external temperature. The flat temperature region found in (0.26, 0.63) is a homeostatic region associated with chaotic population dynamics.

Fig. 9. An illustration of an agent that has a Daisies (black and white daisies are represented by pins) on its surface.
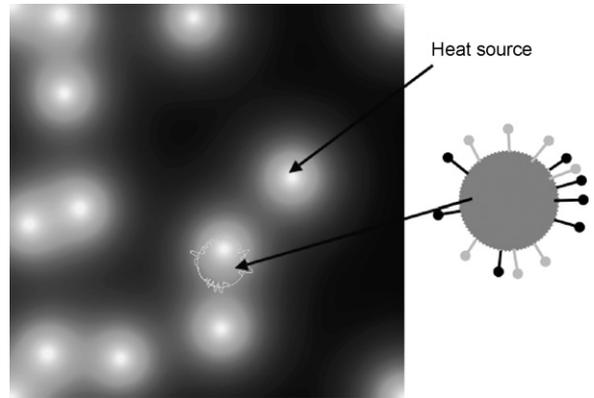

Fig. 10. An example of heat sources distributed in the two-dimensional space, where the daisy at the position r receives the sum of heat flux $\sum_i H_{max} \exp^{-|r-r_i|/r_h}$ from each source. A brighter color represents a higher temperature region. An agent is located in the center of this figure. The boundary pattern of the circular agent represents temperature distribution.

where $\vec{n}_i$ is the normal vector and $\vec{t}_i$ the tangential vector at that site of the body and θ is the step function. The amplitude of the force is given by the $k_1 \cos(\psi_i)$, where $\psi_i = \tan^{-1}(x_i - y_i)$ Also in the tangential direction, there is a torque vector whose amplitude is proportional to the $k_2 \sin(\psi_i)$. This setting provides that the agent walks randomly when the temperature distribution is chaotically varying over space and time. But when the temperature distribution is fixed spatially and temporally, the agent shows a marching movement. If there is an equal amount of white and black daisies, or if the local temperature is higher than the averaged value, no force or torque exists. This set of the equation of motion is found by trial and error, however, the result of the simulation below is not too sensitive to the details of this choice.

We now put the agent in an environment with distributed heat sources, that is, T_e in Eq. (1) becomes the function of space. Due to the finite body size, daisies generally have different T_e depending on the body sites. The business of the Daisy world is to regulate the body temperature, but this time the agent moves autonomously. In this model, no explicit sensors are prepared for the agent. Instead, adequate heat flux from the environment activates the daisies on the agent's surface, which substitutes for the agent's sensory system. It happens that the daisy soliton bifurcates when the heat flux becomes intense. When that happens, the agent becomes double sensitive to the heat flux because it has two solitons on its surface. In other words, a population cluster of daisies on the body surface constitutes a sensory system of this agent and a temperature regulation mechanism at the same time.

Using the environment in Fig. 10, we have tested the agent's behavior in an "inhomogeneous" environment with several heat sources distributed in a space. Each

heat source radiates a heat flux radially whose amplitude decays exponentially as a function of distance, and each portion of the agent's body surface integrates all the heat flux from the environment. In a homogeneous environment, each portion receives the same heat radiation. A temperature caused by the integrated heat flux is inserted as T_e in the above Eq. (1). Therefore, when an agent moves around, T_e will vary accordingly. Here, the controlling parameters are the maximum heat amplitude (h_{max}), the half-decaying distance (r_h), the radius of the agent body (b_d), and the amplitude of the navigation force vector (k_1 and k_2) in Eqs. (4) and (5). Depending on the heat distribution, and those parameters, the agent demonstrates several kinds of navigation patterns, which are controlled by the daisy population dynamics. The navigation behavior is terminated when the daisy dynamics fallsdown to a simple attractor.

When the dynamics is in a fully chaotic state, the navigation space is highly limited. The agent's behavior becomes a random fluctuating pattern around a single heat source. Our concern here is the emergence of explorative behaviors because the exploration is a paraphrase of trial and error, which can be a cause of Ashby's second feedback dynamics. In this experiment, the explorative behavior is defined as an itinerant behavior from one heat source to the other. To have this behavior, the agent first approaches a heat source, then it must change its internal state and leave that source. This navigation process is sustained by the itinerant behavior between partial soliton turbulence and two three-soliton states. Therefore, the itinerant behavior is terminated when the daisy dynamics attains the chaotic attractor or the dead state.
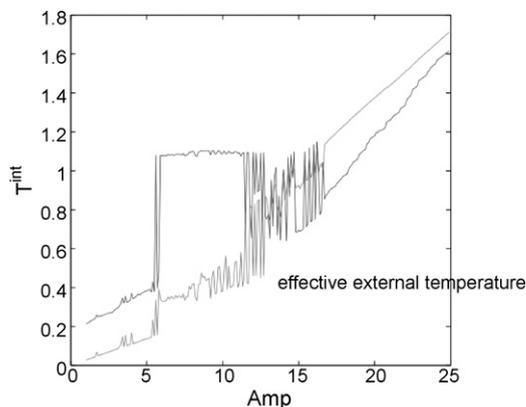
Fig. 11. The surface temperature as the function of the maximal heat amplitude .16 heat sources, and each source is put regularly in a space. The effective T_e perceived by the agent is overlaid in the figure.

As indicated in Fig. 11, dynamic states with a region that show fluctuating average temperatures after a flat temperature region are the candidates for such explorative navigation. The fate of the itinerant behavior is determined by the environment and the internal dynamics. An agent can develop various spatio-temporal attractors on its surface, which create the profile (long term memory) of the agent. In other words, the agent's exploration behavior differs depending on its previous sensory experience in an environment. The length of this memory effect is determined by the size of the agent and the environmental structures.

So far, we have focused on the regulation mechanism driven by the population dynamics of the Daisyworld because the population dynamics is sufficiently unstable to break the homeostatic state and cause the explorative navigation. But it should be remarked that daisy population dynamics is not strictly determined by the surface temperature. This weak correlation is a prerequisite for ultrastability.

7. Discussion

In the middle of the 20th century, a movement of cybernetics drew attention to a new theory of life. Cybernetics was the first interdisciplinary science that attracted not only biologists but also mathematicians, physicists, psychologists and people from many other fields. A main message from cybernetics was to take homeostasis as a basis of life forms. But we still have a missing link from the homeostatic state to cognitive behaviors.

When building a machine, we design sensorimotor coordination to produce a desired action pattern. But we can barely give a motivation or intention to the machine, because the entire desired action pattern is given from the external designer. A light-seeking machine merely stops moving when there are no lights. Therefore we have to go back to the origin of life and pursue the evolutionary process all the way up to cognitive states.

Autopoiesis is a theory that deals with an organization of physical membranes or a metabolic (re)cycling of essential chemicals. But autopoiesis does not simply study physical chemical properties. It provides a hint to think about a self-boundary without any inputs or outputs. Ashby's ultrastability is about a homeostatic mechanism with two kinds of feedback, which are somehow missing in Autopoietic theory. In particular, a second feedback loop through a viability constraint is an important mechanism often neglected in autopoiesis. The viability constraint is, as we redefined in the first section, a physiological range that supports the homeostatic state of a system. A second feedback loop determined by the viability constraint is uncorrelated with a sensorimotor coupling between a system and its environment. Because of this uncorrelated relationship, sensorimotor coupling is repaired without sacrificing the homeostatic state.

We have developed the idea a step further. In order to bootstrap evolution from the homeostatic state, we insist on autonomous movement. By having autonomous movement, a system can distinguish likes from dislikes and prey from predators. But more important, a system should develop a new type of homeostasis conserved under the autonomous movement. Because autonomous movement perturbs the system in qualitatively different ways, the latter must distinguish which is its own motion and which is not. A boundary between self and an environment is varied by autonomous movement. Therefore, the viability constraint is expected to be updated. This picture is what we have examined with our computational models.

Ashby argued, "almost any machine or physical system will break if its variables are driven far enough away from their usual values", and he then went on to say that a "widespread tendency for systems to show changes of step-function form if their variables are driven far from some usual value". (Ashby, 1960, p. 93). This happens for both models by changing a membrane shape in the first model or by changing the population dynamics in the second model. However, when a system moves around, the same viability condition is no longer available. In the first model, only an autonomous mobile agent with a round membrane shape can survive. In the second model, an autonomous mobile agent must sacrifice the chaotic attractor to explore. But the explorative behavior risks killing the Daisyworld. Therefore, Ashby's second feedback loop is realized by the homeodynamic process.

It is difficult to make a direct link between cognitive functions and homeostatic behaviors. There is an intricate step from homeostatic proto cells to self mobile and homeostatic cells, which we call homeodynamic cells. The transition from homeodynamic cells to those with sensors is what we have to understand in the next step. Then the homeodynamic cells elaborate to have sensori-motor coordination, which is when we expect high cognitive functions to appear. In this paper, we have only demonstrated a possible step of the first transition from a homeostatic to a homeodynamic self.

Acknowledgments

References

Ashby, W.R., 1960. Design for a Brain: The Origin of Adaptive Behaviour, 2nd ed. Chapman and Hall, London.

Braitenberg, V., 1984. Vehicles: Experiments in Synthetic Psychology. MIT Press, Cambridge, MA.

Brooks, R.A., 1999. Cambrian Intelligence: The Early History of the New AI. MIT Press, Bradford Books, Cambridge, MA.

Costall, A., 2007. Bringing the body back to life: James Gibson's ecology of agency. In: Zlatev, J., Ziemke, T., Frank, R., Dirven, R. (Eds.), Body, Language and Mind, vol. 2. Mouton de Gruyter.

Di Paolo, E.A., 2003. Organismically-inspired robotics: homeostatic adaptation and natural teleology beyond the closed sensorimotor loop. In: Murase, K., Asakura, T. (Eds.), Dynamical Systems Approach to Embodiment and Sociality. Advanced Knowledge International, Adelaide, pp. 19–42.

Di Paolo, E.A., 2000. Homeostatic adaptation to inversion of the visual field and other sensorimotor disruptions. In: Meyer, J.-A., Berthoz, A., Floreano, D., Roitblat, H., Wilson, S. (Eds.), From Animals to Animats 6: Proceedings of the Sixth International Conference on the Simulation of Adaptive Behavior. MIT Press, Cambridge, MA.

Gacs, P., 2001. Reliable Cellular Automata with Self-Organization. J. Stat. Phys. 103, 45–267.

Gallagher, S., 2005. How the Body Shapes the Mind. Oxford University Press.

Gibson, J.J., 1962. Observations on active touch. Psychol. Rev. 69, 477–491.

Gibson, J.J., 1979. The Ecological Approach to Visual Perception. Houghton Mifflin, Boston.

Gray, P., Scott, S.K., 1983. Autocatalytic reactions in the isothermal, continuous stirred tank reactor: isolas and other forms of multistability. Chem. Eng. Sci. 38 (1), 29–43.

Harvey, I., 2004. Homeostasis and rein control: from daisyworld to active perception. In: Pollack, J., Bedau, M., Husbands, P., Ikegami, T., Watson, R.A. (Eds.), Proceedings of the Ninth International

Conference on the Simulation and Synthesis of Living Systems, ALIFE'9. MIT Press, Cambridge, MA, pp. 309–314.

Ikegami, T., Zlatev, J., 2007. From pre-representational cognition to language. In: Zlatev, J., Ziemke, T., Roz, F., Dirven, R. (Eds.), Body, Language and Mind, vol. 2. Mouton de Gruyter, Berlin, pp. 241–283.

Ikegami, T., Kaneko, K., 1992. Evolution of host-parasitoid network through homeochaotic dynamics. CHAOS 2, 397–408.

Kaneko, K., Ikegami, T., 1992. Homeochaos: dynamical stability of symbiotic network with population dynamics and evolving mutation rates. Physica D 56, 406–429.

Langton, C.G., 1984. Self-reproduction in cellular automata. Phisica D 10, 135–144.

Lovelock, J.E., 1972. Gaia as seen through the atmosphere. Atmos. Environ. 6, 579–580.

Madina, D., Ikegami, T., 2004. Cellular formation in a 3D molecular dynamics system with chemistry. In: Artificial Life IX: Proceedings of the Ninth International Conference on the Simulation and Synthesis of Living Systems. MIT Press, pp. 461–465.

Moreno, A., Etxeberria, A., 2005. Agency in natural and artificial systems. Artif. Life 11, 161–175.

Morimoto, G., Ikegami, T., 2004. Evolution of plastic sensory–motor coupling and dynamic categorization. In: Pollack, J., Bedau, M., Husbands, P., Ikegami, T., Watson, R.A. (Eds.), Artificial Life IX: Proceeding of the Ninth International Conference on the Simulation and Synthesis of Living Systems. MIT Press, Cambridge, MA, pp. 209–214.

Neumann, J.V., 1966. Theory of Self-Reproducing Automata. University of Illinois Press Urbana, Illinois.

Ono, N., Ikegami, T., 2000. Self-maintenance and self-reproduction in an abstract cell model. J. Theor. Biol. 206, 243–253.

Ono, N., Ikegami, T., 2003. Selection of Catalysts through Cellular Reproduction in Artificial Life VIII, Standish, R.K., Bedau, M.A., Abbass, H.A. (Eds), MIT.

O'Regan, J.Kevin., Noë, A., 2001. A sensorimotor account of vision and visual consciousness. Behav. Brain Sci. 24 (5).

Pfeifer, R., Scheier, C., 2001. Understanding Intelligence. MIT Press, Cambridge, MA, USA.

Reggia, J.A., Armentrout, S.L., Chou, H.H., Peng, Y., 1993. Simple systems that exhibit self-directed replication. Science 259, 1282–1287.

Salzberg, C., Antony, A., Sayama, H., 2003. Genetic diversification and adaptation of self-replicators discovered in simple cellular automata. In: Proceedings of the Sixth International Conference on Humans and Computers (HC-2003). University of Aizu, Japan, pp. 194–199.

Salzberg, C., Sayama, H., 2004. Complex genetic evolution of artificial self-replicators in cellular automata. Complexity 10 (2), 33–39.

Sasaki, M., 2000. Chikaku ha Owaranai [Perception Never Stops—Introduction to Affordance] Tokyo: Seidosha. 2002 Sentai-Shinrigaku no Kousou [Grand Design of Affordance]. University of Tokyo Press, Tokyo.

Sayama, H., 1998. Introduction of structural dissolution into Langton's self-reproducing loop. In: Artificial Life VI: Proceedings of the Sixth International Conference on Artificial Life. MIT Press, Cambridge, MA, pp. 114–122.

Sayama, H., 1999. A new structurally dissolvable self-reproducing loop evolving in a simple cellular automata space. Artif. Life 5 (4), 343–365.

Scheier, C., Pfeifer, R., 1995. Classification as sensory–motor coordination. In: Proceedings of the European conference on artificial life, ECAL-95, pp. 656–667.

Staley, M., 2002. Darwinian selection leads to Gaia. J. Theor. Biol. 218, 35–46.

Steels, L., 1994. The artificial life roots of artificial intelligence. Artif. Life 1 (1/2), 76–110.

Suzuki, K., Ikegami, T., 2006. Spatial pattern induced evolution of self-replicating loop net-work. J. Artif. Life 12 (4), 461–485.

Suzuki, K., Ikegami, T., in press. Shapes and Self-Movement in Proto-Cell System Artificial Life.

Tempesti, G., 1995. A new self-reproducing cellular automaton capable of construction and computation. In: F.M., et al. (Ed.), Advances in Artificial Life, LNAI-929, Springer-Verlag, pp. 555–563.

Toyota, T., Tsuha, H., Yamada, K., Takakura, K., Yasuda, K., Sugawara, T., 2006. Fluorescence microscopic investigation on morphological changes of giant multilamellar vesicles induced by amphiphilic additives. Langmuir 22, 1976–1981.

Turing, A.M., 1952. The chemical basis of morphogenesis. Philos. Trans. R. Soc. London B 237, 37–72.

Tyrrell, T., 1999. The relative influence of nitrogen and phosphorus on oceanic primary producton. Nature 400, 525–531.

Varela, F.R., 1992. Autopoiesis and a biology of intentionality. In: Proceedings of a workshop on Autopoiesis an Perception, pp. 4–14.

Varela, F.R., 1979. Principles of Biological Autonomy. North Hollandk, New York.

Varela, F.R., Maturana, V., Uribe, V., 1974. Autopoiesis: the organization of living systems, its characterization and a model. Bio. Syst. 5, 187.

Watson, V., Lovelock, J.E., 1983. Biological homeostasis of the global environment: the parable of daisyworld. Tellus 35B, 284–289.

Zeng, X., Pielke, R.A., Eykholt, R., 1990. Chaos in Daisy-world. Tellus 42B, 309–318.