Emergence of Body Image and Dichotomy of Sensory and Motor Activity

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Abstract

This paper reconsiders a boundary between an agent and its environment. The boundary between a simulated agent and its environment is convoluted in dynamic processes of sensory and motor devices. However the boundary is not a static but a dynamic interface. In order to study the dynamic property of the interface, the un-fixed sensory-motor distinction is introduced. Practically, a mobile arm passively or actively explores an object and attaining some discrimination tasks. We develop the discrimination ability by using a genetic algorithm. A conscious state towards an object is investigated with this framework.

1 Introduction

In order to reorganize the old and new psychological concepts such as ownership, agency and active perception, we need a radical new framework or modeling to supersede sensory-motor flow. Studies on embodied robots and simulations are based on the sensory-motor ideas (Walter, 1950, 1951; Braitenberg, 1984; Pfeifer and Scheier, 1999; Brooks, 1991a,b). For example, Walter discussed cognitive, play-like and social behaviours by synthesizing artificial vehicles. Braitenberg made conceptual robots to discuss the higher functioning of cognition. However, the ideas of ownership and agency are hardly met in this framework.

On the other hand, recent neuropsychological experiments are attacking the problem. Yamamoto and Kitazawa (2001) demonstrated with the arm-crossing experiment that the perceived temporal ordering of haptic stimuli was reversed when the successive stimuli were temporally close enough. Maravita and Iriki (2004) showed that Macaque monkey was trained to use tools to reach food, and showing that its body image was instantly extend to the tip of the tool bar. Ramachandran and Blakeslee (1998) showed that a human body image can be easily created or destroyed by using visual or auditory information. These experiments and others have revealed that body images and ownership have very dynamic nature, which we like to implement in our system.

Our body image and the ownership bridge the gap between the highly abstract sense of "self" and the physical world where our body is situated. Varela (1979) proposed a principle of autonomy stressing the idea of self-generated boundary. Varela exemplified autonomy as a "self" emerged from a chemical system through structural coupling with the environment. In his model, it was shown that some reactive particles created a boundary, which regulated internal reactions of the particles, and maintaining the boundary structure. This circularity of the physical boundary and the internal dynamics produces coherency of self state. The notion of "self" as a dynamic boundary must account for the origin of sensory-motor systems. One such challenge, with respect to a proto-cell system, can be seen in Suzuki and Ikegami (2004).

In this paper, we examine the idea of dynamic boundary in active perception; an agent actively touches an object to discriminate. We assume no explicit distinction between a sensor and a motor. An interface between an agent and its environment is only dynamically constructed. Nevertheless, an agent comes to categorize objects through evolutionary approach. We study the difference between active and passive touch by showing how perception is developed with motion structures.

2 Model

Agents are required to discriminate the number of fans of a windmill by spinning the fans. This task is inspired by a cookie-cutter experiment by Gibson (1962). Gibson developed a theory of perception based on the active/passive motion structure. In the present task, active or passive pattern is discriminated by the spontaneous motions of the windmill.

The agent has a straight arm which can rotate 180 degrees in a plane (Fig. 1). The arm can spin the windmill by pushing a fan at each impact. The motions of the arm and the windmill are calculated by the following equations;

$$M_a\ddot{\theta_a} + D_a\dot{\theta_a} + F_{arm} + F_{col}(\theta_a, \theta_w) = 0, \quad (1)$$
$$M_w\ddot{\theta_w} + D_w\dot{\theta_w} + F_{col}(\theta_a, \theta_w) = 0, \quad (2)$$

where θ_a and θ_w denote the angles of the arm and the windmill, respectively. F_{col} is a collision term giving a repelling force both to the arm and the fans. The collision is not an instant event but it has a finite width. F_{arm} is a force of the agent to rotate the arm.

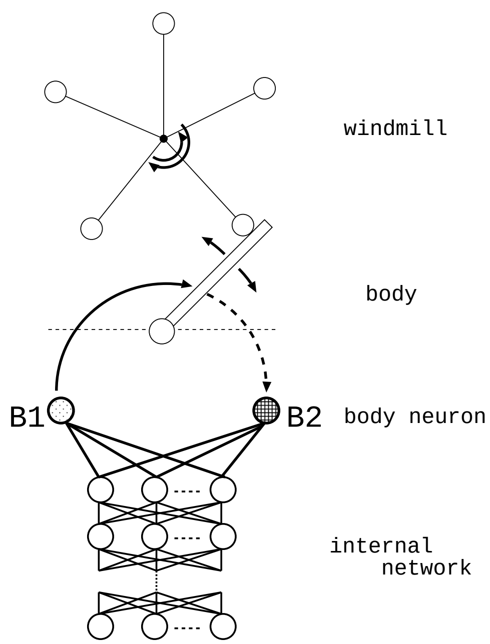

Figure 1: A schematic view of the windmill, the agent and its internal structures. The agent consists of a body with the straight arm whose length is L. The windmill has Q fans. The arm collides with each fan. As the agent's structures, there are body neurons and hierarchical internal neurons (concretely, see Sec. 2.1.). The distance between centers of the arm and of the windmill is determined to be a range $[-k : k]$ where the arm can touch fans. Q and k are assigned according to tasks and L is always set to 100.

2.1 Interface between body and internal dynamics

No explicit sensor-motor flow is pre-fixed so that the distinction between moving and being moved only appears from an internal viewpoint.

Practically, the arm state is assigned to two neurons, which are also connected to other internal neurons. We call these two neurons, 'body neurons.' They are activated or inhibited exclusively in response to the arm state. If one body neuron is more active than the other, one (*actor*) regulates the arm and the other (*observer*) will copy the state of the arm as its state. Each body neuron can potentially play a role of actor and observer depending on their relative activations. By restricting the observation to the state of the arm, we can naturally describe spontaneous moving and being moved by externals in our model, because both motions can be described as changes of arm states. However, the distinction between moving and being-moved becomes implicit. Whether arm motion is moved spontaneously or externally is internally evaluated by investigating the series of activations of the actor and the observer.

By doing this, the fixed sensor-motor relationship is removed. The dynamics of the boundary depends on the two body neurons. Formally, the following equations describe the model:

$$y_{B1} = g_{B1}^{-1}((1-\mu_1)S_1(\theta_a) + \mu_1 g_{B1}(y_{B1})), \quad (3)$$
$$y_{B2} = g_{B2}^{-1}((1-\mu_2)S_2(\theta_a) + \mu_2 g_{B2}(y_{B2})), \quad (4)$$

$$F_{arm} = \alpha\{\mu_1(g_{B1}(y_{B1}) - S_1(\theta_a)) + \mu_2(g_{B2}(y_{B2}) - S_1(\theta_a))\}, \quad (5)$$

$$\text{if} \quad g_{B1}(y_{B1}) - S_1(\theta_a) > g_{B2}(y_{B2}) - S_2(\theta_a), \quad (6)$$
$$\text{then} \quad \mu_1 = 1, \mu_2 = 0, \quad (7)$$
$$\text{else} \quad \mu_1 = 0, \mu_2 = 1, \quad (8)$$

where y_{B1} and y_{B2} are activations of the body neurons. S_1 and S_2 normalize the current arm state, θ_a, from 0 to 1. $g_{B1}(y_{B1})$ and $g_{B2}(y_{B2})$ represent the goal states of the arm, which is a position each body neuron desires to move to if it is the actor. The power of the arm, F_{arm}, is calculated from the difference between the current body state and the goal state of the actor (eq. (5)). The parameters, μ_1 and μ_2, decide which body neuron behaves as an actor or an observer. The body neuron with the larger difference between the goal states and the current state of the arm (eq. (6)) becomes the actor and another becomes the observer. The activations of the actor and the observer are updated as follows (eq. (3) and (4)). In case of the actor, the goal state of the arm, $g(y)$, is used for the force strength acting on an arm. The goal state will be fed back to the next neural state. In case of the observer, the next neural state will get the current state of the arm, S. Those next neural states are transformed to activations of the body neurons by an inverse function of $g(x)$, which is a transfer function used in a recurrent neural network.

The difference between spontaneous motions and being moved will be detected by a following way. When an arm is moving freely, the activation of the actor precedes that of the observers to the goal state of the actor. The actor and the observer can keep coherency while moving. However, if there is an obstacle or the arm is driven by external forces, the observer's activation can be different in response to the arm state. The coherency is broken at the event. This could be regarded as information flow from the environment to the agent.

The internal dynamics of the agent is controlled by a continuous-time recurrent neural network (CTRNN) (Beer, 1995). The time evolution of the states of neurons are expressed by :

$$\tau_i \dot{y_i} = -y_i + \sum_{j=1}^{M} w_{ji} g_j(y_j), \tag{9}$$

$$g_i(x) = 1/(1+e^{-x-b_i}), \tag{10}$$

where y is the activation of each neuron, τ is its time constant, b is a bias term, w_{ji} is the strength of the connection from the neuron, j, to i. We adopted a sparse connection among neurons. The neurons are hierarchically organized and the connections of neurons between different layers are only effective and the other connection weights are set to 0 (Fig. 1).

The neurons at the end of layer are connected to the body neurons in the same ways as eq. (9) and (10) (Fig. 1). As an output, the neural network has to choose one between two things in a task. We designed two specific neurons at the opposite side layer of the body neuron's. By comparing the activations of these two neurons, the alternative is represented.

2.2 Tasks : active touching and passive touching

There are four different tasks. In each task, the agent interacts with a 7- or 5-windmill and discriminate it by spinning the windmill (Fig. 1).

In active touch case, an agent can push to spin the windmill. When an arm touches a fan, the windmill rotates clockwise or anticlockwise. On the other hand, when the windmill rotates anticlockwise with a constant speed, an agent cannot control the windmill, and we call it passive touching case.

We use the abbreviations of A7, A5, P7, or P5 corresponding to the task conditions, active or passive, and 7 or 5 fans of the windmill. The parameter, k, is set to $\pi/4$ or $\pi/12$ under active or passive condition, respectively (see Fig. 1).

2.3 Genetic algorithm

Networks were trained by evolving connection weights using a standard evolutionary algorithm. Each artificial genome encodes parameters of the CTRNN: the weights w in [-4,4], time constant τ in [0.4,4], and bias b in [-3:3] as a continuous valued vector. The best agents are carried over to the next generation without any genetic modifications (elitism). Other agents are generated from the best agents by adding a small random values (mutation) from the range [-0.01:0.01]; no crossover is performed. We use 80 agents in this simulation.

Agents' performances are evaluated on the basis of the accuracy of discrimination during the evaluated period of time, which is fixed at 1000 time steps. The fitness value is calculated by multiplying the percentage of correct answers for each task.

3 Results

The best agents after approximately 4000 GA generations can approximately distinguish 7- and 5-windmills, in both active and passive cases. The agents before 2500 GA generations cannot distinguish them. From 2500 GA generations, the fitness is sharply improved as shown in Fig. 2. Each task cannot be achieved one by one at different generations, but all the tasks can be achieved around the same generation.

3.1 Behavior pattern

The best agent basically moves its arm left and right to spin a fan of the windmill. The behaviors under the four different conditions are briefly described as follows. Corresponding to the four conditions, the arm behaviors are given in Fig. 3.

In case of A7, the agent aggressively pushes the windmill when it touches a fan of the windmill, and the windmill rotates clockwise or anticlockwise. After pushing a fan and spinning, a next fan pushes the arm a little bit, and the agent pushing back the fan to the opposite direction.

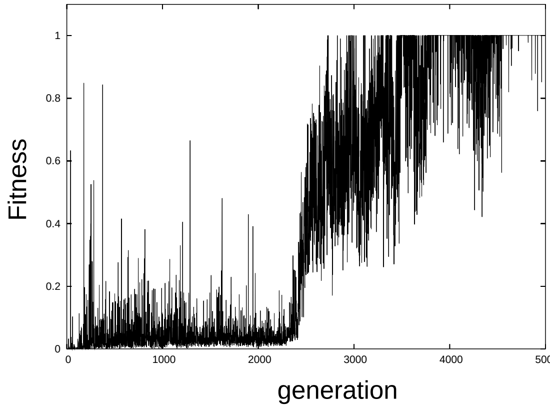

Figure 2: The fitness value of the best agent at each generation.

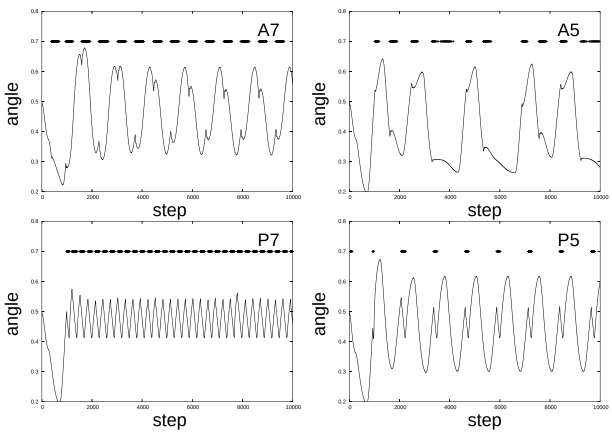

Figure 3: Behaviors of the best agent in its interaction with A7, A5, P7 and P5. In each graph, the time series of the angle of the arm, θ_a, are shown. The dots are plotted at 0.7 when the arm collides a fan.

In case of A5, the agent does not strongly push the fan compared with the condition A7. The arm touches alternately between left and right fans. The alternation periodicity is less frequent than A7 because of sparseness of fans.

In case of P5, in spite of the passive condition, the arm behaves like in case of A7 and A5. Because the number of fans is more sparse than those in P7, it is rare to collide with the fans of the windmill. The agent moves the arm left and right by itself, and the collision timing is regulated by the agent's motion.

Different from those 3 conditions, the arm is pushed into the same direction by the fans under the condition of P7. After being moved, the agent brings the arm back into the center and it is moved again by the next fan. Basically, the agent can tell whether it is 5 or 7 by being moved.

Under each condition, above processes are repeated for discrimination. Figure 4 shows the attractors of the internal dynamics formed at that time. The agent constitutes different attractors, according to the interacting task.

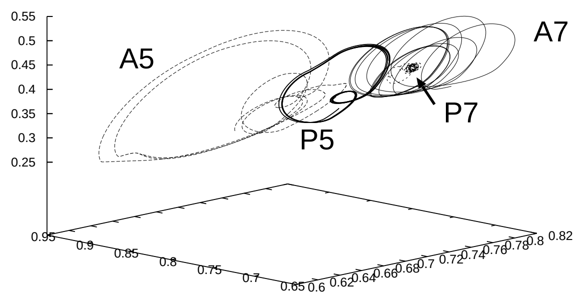

Figure 4: Attractors in the internal dynamics of the best agent in its interaction with A7, A5, P7, and P5. These are plotted by using activations of three internal neurons.

3.2 Dichotomy of sensor and motor

In order to investigate how the interface between the agent and its environment is constructed among different tasks, we perturb the coherency between two body neurons by giving a time delay in the body feedback. In eq. (3) and (4), the function $S(\theta_a)$ is given by the current state of the arm, but we replace it with an arm state several steps before.

Figure 5 shows the agent's performance with the time delay under the condition of A7, A5, P7, and P5. In case of A7, A5, and P5, the agent fails to discriminate depending on the time delay. As explained in the previous section, the task of P5 is basically achieved through the agent's motions although it is a passive condition. The boundary dynamics as an interface under these conditions, where the agent discriminates with active motions, is sensitive to the time delay, which causes a breakdown of the behaviors.

On the other hand, the discrimination can be achieved regardless of the time delay in case of P7. Different from the other three conditions, the coherency of two body neurons is not depending on the timing of being moved. This passiveness can be regarded as a static "sensor" given by the static nature of the boundary dynamics.

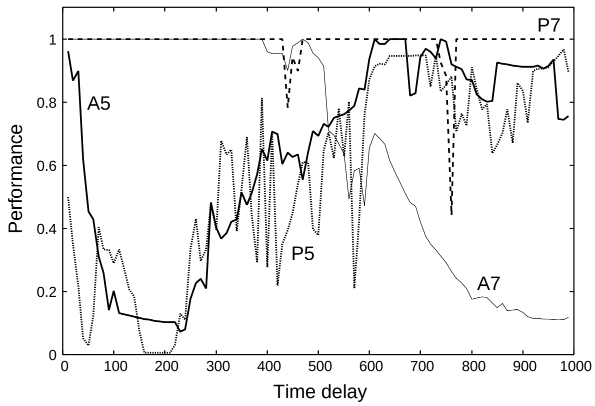

Figure 5: The ratio of the best agent's correctly categorizing under time delay in the body feedback. Horizontal axis means the length of the time delay.

4 Discussions

The ordinary sensory-motor categorization discriminates the sense-data into several domains (Pfeifer and Scheier, 1999). On the other hand, the present paper showed a new way of categorization. As no sense-data is given explicitly, what an agent discriminates is its own motion repertoire that is used to interact with an environment. Body image and ownership is, we believe, cannot be created by the static sense-data. That is why the sensory-motor categorization is not adequate for this matter.

At least two layers are prerequisite for understanding perception or conscious states. One is a physical layer where everything is driven by physical processes and no distinction between operator and operand exists. The other one is a phenomenological layer where everything is described from the first-person's view, based on the notion of "self" which enables subjective distinction between a sensor and a motor.

Two layers are complementary to each other, that is, one side understanding is not enough. A sensor and a motor are equivalent to operator and operand. To define a sensor and a motor first is equivalent to starting a discussion from the phenomenological layer. On the other hand, our present model assumes no distinction between a sensor and a motor apriori at the phenomenological layer. Sensor and motor only emerge with "self" as a result of complex interactions at the physical layer.

Emerging "self" also means an emergence of an interface between "self" and a world. The interface provides how to interact with the world. The world is not just an environment but a world that "self" perceives through the interface, that is, the surplus of signification (Varela, 1992). If we set up a fixed sensor and motor device, an emergence of "self" would not happen. What we want to see is how the subjective distinction such as "moving and being moved" (or tickle and being tickled) emerges and can be sensed. We showed a dichotomy of sensor-like interface from no distinction between a sensor and a motor in this paper. It inevitably requires a link between physical and phenomenological layers. Body image, ownership and active perception are the direct outcomes of this linkage.

Acknowledgements

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