Microslip as a dynamical system

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Abstract. A simple recurrent neural network was constructed to simulate a novel action selection dynamics. The selection process becomes complex when more than two action repertoires are possible. Even with a simple task, one often experiences making an unintentional form of movement or slip of action. One example is called a microslip, named and reported by Reed and Schoenherr. We propose a model of such slip-like behaviour based on the dynamical systems viewpoint.

Keywords: microslip, neural network, action selection, embodiment, adaptation

1 Introduction

We studied the fluctuation of action selection dynamics. Fluctuation in action selection occurs more frequently when more than one equivalent action choice exists. It has been reported that the characteristic slip of action pattern appears in situations of hesitation, called microslips (Reed & Schoenherr 1992). For example, while making a coffee, one may mistakenly grasp a coffee cup rather than a spoon. Microslips are a kind of action slip, or false action, that are frequently observed when one is under mental or time pressure. The systematic study of the mechanism of microslips has not yet been undertaken.

In this paper, we built a simple toy model to explain microslips, using a two-layered recurrent neural network. A novel aspect of our model is that the network has action-switching neurons. A possible action sequence is selected by the state of those switching neurons.

In §2, we briefly introduce Gibson's theory with respect to the microslips phenomenon. Then we describe our agent architecture in §3. Several dynamics' properties of our system are reported in §4. The possible interpretation of our results in terms of microslips is described in §5.

2 Microslips

By investigating video recordings of normal adults performing daily tasks—for example, coffee making—Reed and Schoenherr reported that action slips occurred, on average, every minute (Reed & Schoenherr 1992). Such unintentional slips of action are called microslips. Microslips, however, are not mere error actions. Whenever microslips occur, they are corrected almost automatically. The microslips reveal a basic aspect of our cognitive function, which supports Gibson's theory of ecological psychology (Gibson 1979).

Reed categorized microslips into four types. They were hesitations, trajectory changes, hand shape changes and touching behaviours. Hesitations are detected when actions—for instance, reaching for or grasping something—are observed. Trajectory changes are detected by the abrupt change of action. Action slips may come in the form of a discernable hand shape change. The fourth category is more subtle but describes a touching or holding action without purpose. Suzuki and Sasaki recently replicated their findings (Sasaki 2003). In particular, Sasaki studied microslips by videorecording the temporal changes in behaviour of a woman recovering from brain damage. Recently, Nagashima and Mogi quantitatively analysed singular trajectory changes by measuring the curvature of action orbits (Nagashima & Mogi 2002).

Based on the phenomenological studies on microslips, Reed and Suzuki argued that the main causes of microslips are the complexity of the environment and the hierarchical action structure. The complexity of the environment is measured by the number of disturbances of a task (for example, similar cups or similar tasks). The hierarchy of action suggests that each action pattern is composed of sub-action patterns. For example, coffee making is comprised of five distinguishable patterns: grasping the cup, adding hot water, adding cream, adding sugar, and stirring. Furthermore, each pattern is comprised of lower level actions. For example, adding hot water is comprised of reaching for a pot, grasping the pot, moving the pot towards a cup, and pouring from

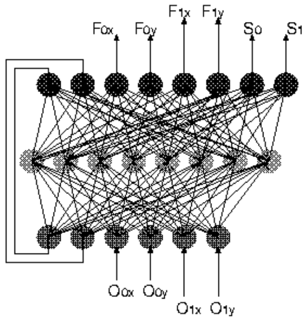

Figure 1. The recurrent neural network in our model. This network has inputs of two objects' relative positions. It acquires two outputs for each object as actions, and the switching dynamics of the outputs as plans for adaptation for the tasks.

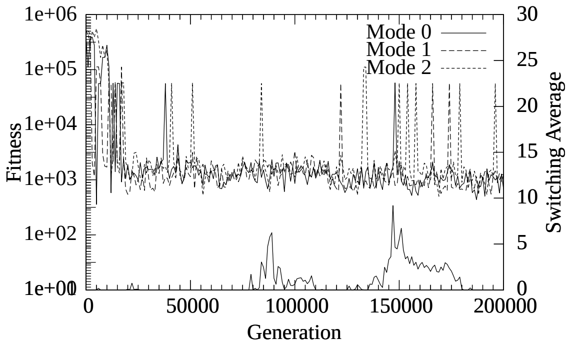

Figure 2. Improvement of agent's fitness and average times of switching action. The upper three lines represent "Mode 0", "Mode 1", and "Mode 2". "Mode 0" denotes the fitness in case of a single object 0, "Mode 1" denotes the single object 1, and "Mode 2" denotes the two-objects case. Lower fitness agents are selected as better agents in GA. The lower line represents the switching average; that is, the average times of changing the switching neuron in trials.

the pot. In addition, the order of higher level actions is more variable than that of lower level actions. It is argued that microslips rarely occur between the lower level actions, and frequently occur between the higher level actions.

Microslips raise many fundamental questions. In ordinary psychology, the production of microslips is thought of as a mere consequence of a failure of a designed plan or schema. Alternatively, Reed claimed that action planning is more like a selective process among coexisting wishes/plans (Reed 1996). Microslips allow for the flexibility of switching between actions to generate hierarchical action structures to deal with the complexity of the environment. Microslips treat a plan and action as a non-separate and non-sequential process. This is one of Gibson's original ideas of perception. He suggested that any action can be understood as a bundle of parallel action patterns.

Recently, some studies using agent models have used action selection based on the dynamical system (Okada, Nakamura & Nakamura 2003)(Pfeifer & Scheier 1997). For example, Tani studied the articulated behaviour of robot arm systems through the use of a hierarchical neural network (Tani 2003). In past models, functions of the model relating to action are separated from those relating to planning. In this study, we investigated the relationship between planning and action by an agent that has non-separate planning and action functions.

We simulated a model made confusing by the introduction of two choices and studied the behaviour of a simple mobile agent. We used two scenarios: when there is one object, an agent can reach the object without any confusion; when there are two equivalent objects, two intentions may be confused. As a result, we expect complex fluctuations of action selection by the agent. This will enable better understanding of microslips.

3 Model Description

A simple neural system with a recurrent connection is applied here (Figure 1). The entire network is composed of three layers where we have $eight$ hidden neurons and two recurrent ones.

An agent navigates on a two-dimensional plane to reach objects on the plane. Here we have two targets on the plane. The network receives the inputs from the targets on the plane to determine its output pattern. The sensory inputs are given XY coordinates of the two objects. Two pairs of input neurons, $(O_{0x}(n), O_{0y}(n))$ and $(O_{1x}(n), O_{1y}(n))$, denote the relative XY coordinates of the two targets 0 and 1, respectively.

On the other hand, the output provides a navigation forward vector. Two outputs are used as the driving force $(F_{0x}(n), F_{0y}(n))$ and $(F_{1x}(n), F_{1y}(n))$.

One of the outputs is selected to navigate the agent. The selection criterion is given by another neural state, hereafter called a switching neuron ($s_0(n)$ and $s_1(n)$). When $s_0(n)$ is larger than $s_1(n)$, F_0 is chosen, otherwise F_1 is chosen. Therefore, a resulting action sequence is expressed as, e.g., $F_0F_0F_1F_1F_1F_1F_0\cdots$. If agents move by the force F_0, then they can reach object 0 through this sequence and if by the force F_1, then they can reach object 1 through it.

The whole neural dynamics including $s_0(n)$ and $s_1(n)$ is given by the following equations.

$$u_{(i+1)j}(n) = g(\sum_{k=0}^{M} w_{ijk} u_{ik}(n)) \tag{1}$$

In the Equation(1), u_{ij} is the value of the jth node in the i layer, and w_{ijk} denotes the weight of the network, where the function $g(x)$ is given by the sigmoid function (Equation(2)).

$$g(x) = \frac{1}{1 + e^{-\beta x}} \tag{2}$$

In this study, we adopted a standard genetic algorithm (GA) to train the network weight to perform better with respect to the fitness function E (Equation(3)). The fitness concerns how fast it can reach objects in three different situations: a single target 0, a single target 1 and both targets at the same time. In the case of a single-target environment, only one input and one output is used. In the two-targets case, an agent is required to reach either one of the targets. In Figure 2, we call the tasks “Mode 0”, “Mode 1” and “Mode 2”, respectively.

The fitness function E is a function of the time needed to reach a target (T), the distance from a target when it fails to reach either of the targets within a given time (D), and a punishment (P). Agents whose fitness is lower are selected as better agents in GA. The punishment (P) value is much greater than the time (T) and distance (D). Moreover, if the agent succeeds in reaching the target, distance (D) and punishment (P) are 0. Agents that steadily and speedy reach either target are selected. A total fitness value is computed and averaged over N trials for each agent. Here the N is set at 10.

$$E = \sum_{i=1}^{N} (T_i + D_i + P_i) \tag{3}$$

For most simulations, we use 20 agents. In each GA generation, we select the $four$ best agents according to the fitness function E and create a new population from the $four$ with mutations. We use a normal distribution (Equation(4)) to mutate the parent’s net weights.

$$\phi(x) = \frac{1}{\sqrt{2\pi}\sigma} exp\Big\{\frac{-(x-m)^2}{2\sigma^2}\Big\} \tag{4}$$

In Figure 2, the improvement of agents is depicted as a function of GA steps. After a few thousand GA steps, agents can successfully reach most targets, and after about 20000 generations, fitness is steady, with only occasional failures. In Mode 0, the neural output 0 is trained for the object 0. In Mode 1, the neural output 1 is trained for the object 1. Incidentally, switching actions are not indispensable for Mode 2, which is the two-target case. Agents can accomplish two-target cases by using either action. Nevertheless, it has been shown that some agents combine alternative actions to reach targets by the switching average from the about 80000th generation to the about 180000th generation in Figure 2. In the next section, we observe the agent that combines alternative actions.

4 Simulation Observations

4.1 Choice structure

Figure 3 shows a basin structure of an evolved agent’s choice from the 160000 GA steps. Fixing the initial internal states of the neural network, we computed the choice of an agent by changing the relative location of the targets. The choice is the object that the agent reached.

The agent’s action selection is highly sensitive to the relative spatial pattern of the objects. We verified the sensitivity of the action selection by measuring the boundary dimension. As is depicted in Figure 4, the basin boundary of the object 0 and 1 becomes fractal. That is, the agent’s choice is highly sensitive to the initial portion relative to the objects there.

4.2 Time complexity

The amount of time to reach an object is another measure of complexity of the reaching behaviour. When a single object is presented, almost all portions of an object are reached within a few hundred steps after 160000

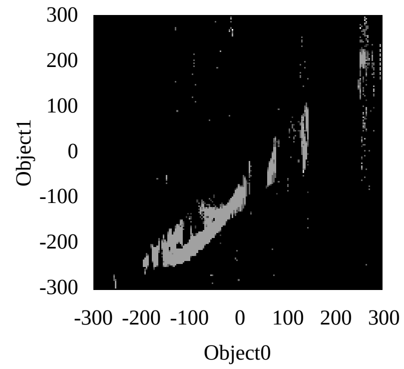

Figure 3. A basin structure of agent's choices from the GA steps 160000. Fixing the Y coordinate of the objects, we vary the X coordinates of two objects, which are the vertical and horizontal axis, respectively. The black area is the choice of the object 0 and the grey area is the object 1. The area unreachable within time T (which is fixed at 1000) is coloured white; however, most of the area is within reach of the agent.

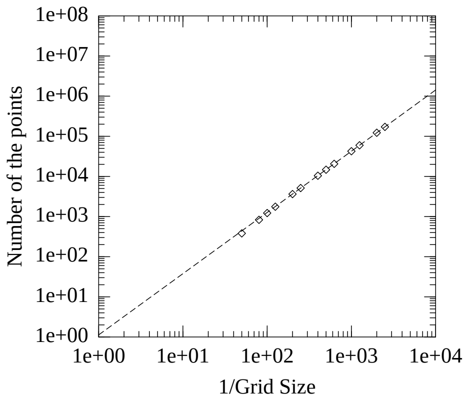

Figure 4. A dimension of the boundary in area $((100, 0) - (200, 100))$ of Figure 3 is computed by changing the grid size. The coefficient of the line gives the dimension value. The points are linearly fitted with $f(x) = 1.12677x^{1.52539} + (1e - 30)$.

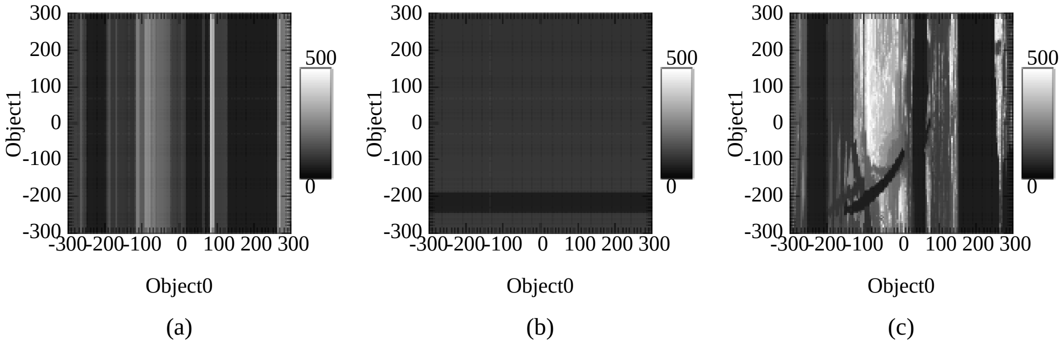

Figure 5. Time used by the agent to reach object. (a) A single object 0, (b) a single object 1 and (c) two objects are presented. The horizontal and vertical axes represent the X coordinates of the objects 0 and 1. The Y coordinates of the objects 0 and 1 are fixed. To have a clear pattern, the reaching time less than 500 steps is depicted.

GA steps (Figure 5). In Figure 5a and b, the agent can see only one object. The initial state dependency becomes a striped pattern. Those dependencies become complicated when both objects are presented.

In Figure 5c, we see some vertical boundaries. Because the object 0 is preferred by this agent, those vertical lines reflect the single object's case. However, owing to the inputs from the object 1, the time required to reach the objects is perturbed. In particular, the upper middle and right requires more time to reach the object 0. Compared with Figure 3, we notice that the object 1 is only within reach immediately at the central crescent area. Moreover, between the two areas where each object is within immediate reach, the agent's choices show a fractal structure.

This complexity of time structure is partly understood by investigating the switching dynamics and the navigation pattern in the next section.

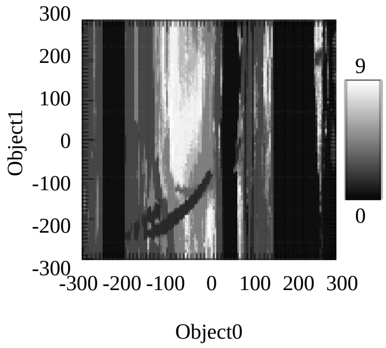

Figure 6. The number of alternations between two actions before reaching an object. This figure's XY coordinates are the same as those in Figure 3 and Figure 5.

4.3 Dynamic alternation of action pattern

Figure 6 show times of switching action. In right and left vertical lines, the agent does not switch the action. In addition, Figure 6 is similar to Figure 5. Nevertheless, the agent changes action pattern in response to the time used by the agent to reach the object.

Figure 7a and b are actions at the central crescent area in Figure 6, This is a successful case, and in this area, an agent can reach the object immediately. In contrast, Figure 7c and d are actions at the upper middle area in Figure 6. This is a failed case, and in this area, the agent takes a long time to reach the object. These two cases are similar to each other by time 100, but in Figure 7d switch 0 time extends increasingly. Therefore, the agent moves around the object 0 later. Additionally, it is shown by Figure 3 and Figure 5c, that the object 0 is easy to select when the agent takes a long time to reach the object at the upper middle area. That is, the agent can reach the object stably by using switch 0 later at the upper middle area. Thus, the agent's choice is intricately constructed by the relationship of actions.

5 Conclusions and Discussion

The fluctuation of action selection is discussed in terms of the complexity of the basin boundary, of time structure and of action sequence. It is always possible to provide a criterion for choosing actions. However, from the agent's point of view, such a criterion should be generated by him/herself.

The resulting basin structure of which objects to take shows a fractal boundary. A certain area, relative to the portion of two objects, becomes singular; i.e., an agent's final decision is sensitive to the spatial arrangements of objects. The sensitivity causes the wandering behaviour between two actions. When there is only one object, no such wandering behaviour emerges.

In comparison with a separate plan–action engineering point of view, an autonomous agent has to choose an action without having a complete plan. A disadvantage for this unstable behaviour (e.g., from the optimist's point of view) may be compensated for by its possible explorative actions. The exploration is not a special task. We consciously/unconsciously execute it in our daily life. Microslips are a subtle but significant property of such exploratory behaviour underlying cognitive behaviour. To take account of this exploration dynamics, we can build a theory to explain active touch and other subjective phenomena.

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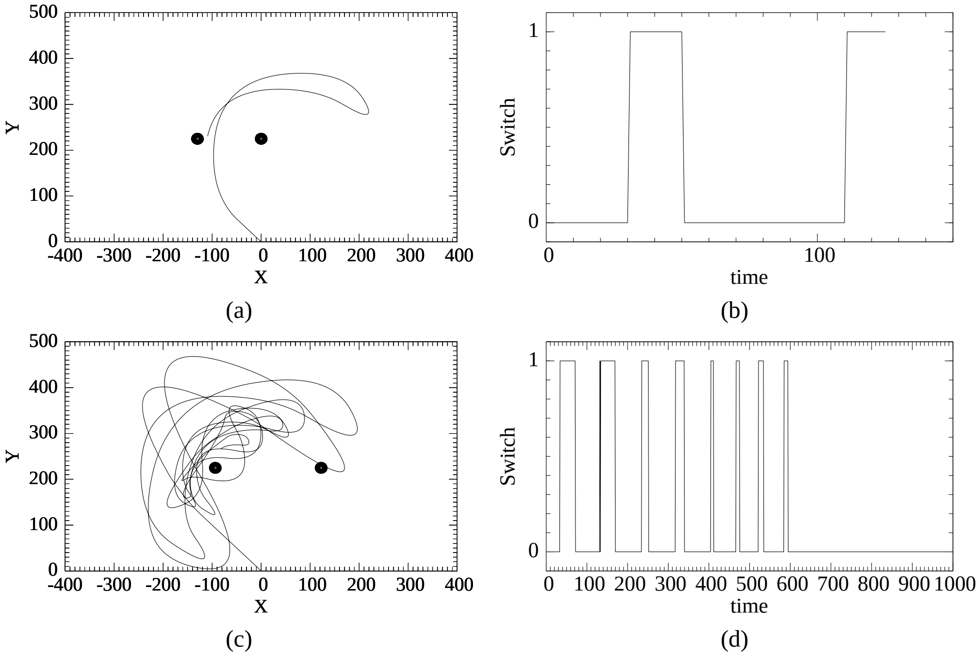

Figure 7. Spatial navigation patterns for reaching an object by alternating the basic action patterns (a) and the associated switching time course are depicted (b). In this time, the objects' positions are $(0, 225)$ and $(-130, 225)$. When it fails to reach any objects within a given time, the corresponding navigation pattern (c) and the switching time course are also depicted (d). The objects' positions are $(-93.6, 225)$ and $(122.4, 225)$. In (c) it seems that the agent passes the object 1, but then it uses object 0 action, and thus it fails.

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