Evolution of Plastic Sensory-motor Coupling and Dynamic Categorization

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Abstract

We study the dynamic categorization ability of an autonomous agent that distinguishes rectangular and triangular objects. The objects are distributed on a two-dimensional space and the agent is equipped with a recurrent neural network that controls its navigation dynamics. As the agent moves through the environment, it develops neural states which, while not symbolic representations of rectangles or triangles, allow it to distinguish these objects. As a result, it decides to avoid triangles and remain for longer periods of time at rectangles. A significant characteristic of the network is its plasticity, which enables the agent to switch from one navigation mode to another. Diversity of this switching behavior will be discussed.

Introduction

Gibson reports blind touch experiments with a cookie cutter where a subject can tell the shape of a cutter when he moves it by himself (Gibson, 1962). O'Regan stresses the importance of active vision and argues perception as mastering sensory-motor coupling (O'Regan and Noë, 2001).

The significance of Gibson's perception theory that deals with perception associated with action is that it highlights the difference between memory and experience. For example, to know a paper crane having seen one in a photograph is qualitatively different from making a paper crane yourself. The difference is due to the fact that our representation of "paper crane" isn't a simple, static labeling. One's experience of constructing a paper crane, a non-trivial task, involves a number of complex perceptive experiences which are organized to give a representation of a paper crane. In other words, a mental representation is a combination of diverse somatosensory experiences. For real-world situations, one imagines that such representations are not static and algorithmic but rather more dynamic in nature.

In ECAL95, Pfeifer and Scheier reported a study on evolutionary robots that could perceive the size of an object by their bodily movements (Scheier and Pfeifer, 1995). They prepared two sizes of cylinder, one of larger diameter than the other. Robots were small vehicles with a single arm that could grasp only the smaller cylinders. By training the internal network of the robots, robots could eventually categorize the large and small cylinders. When a robot successfully grasped an object, it assumes it is small, otherwise it thinks it is large. As a result, the robot neglects a cylinder it can't grasp and spends more time with smaller ones. It looks as if a robot could obtain a representation of sizes of cylinder. This example clearly shows that categorization is established by his embodied active perception. Recently, there have been reported many such examples of dynamic categorization (Tani and Nolfi, 1998; Marocco and Floreano, 2002; Nolfi and Marocco, 2002).

The simulation results presented here provide another example of such dynamic categorization. In contrast to existing models, our model exhibits a dynamic repertoire of seemingly purposeful, lifelike behaviors whilst categorizing objects. In particular, while agents are trained to ignore triangles and linger at rectangles, they are also required to fill in the area inside rectangles. When doing this, our agents show a behavior that is distinct to that of finite state machines coupled with random noise, because long-term correlations with previous object interactions may be observed.

Model Description

The basic idea of our model is inspired by the active vision system of (Kato and Floreano, 2001). The differences are:

1) Categorization is not a direct task but a required feature to perform the task.

2) Objects and sensory area are rotatable. Therefore direction independent categorization should be required.

3) Focusing or leaping feature of sensory area is not considered here. The size of sensory area is fixed and moves continuously in the space.

4) No noise in the environment. Agent should use his internal dynamics to move in a non-deterministic way.

Field and Task

The field is a two-dimensional discrete lattice space of 100×100 points. Each point is in one of two states, empty(0) or occupied(1). An agent is situated in a point in the field and

Figure 1: Examples of the field conditions and trajectories of an evolved agent.

has a direction of the heading. He receives sensory inputs from the point he stays and the 8 neighboring points. The positions of sensory inputs can be distinguished relative to his direction. Therefore 9 bits of information in total can be used to decide the next movement. On every discrete time step the agent changes the position to a neighboring point and change the direction of the heading according to the motor output. Motor output can be one of the 3 directions, namely, straight, left, and right.

If an agent crosses a boundary of the field, he appears from random position of the opposite boundary with the same direction of the heading. [1]

There are some objects classified as rectangles or triangles in the field. This classification is determined by the global arrangement of the occupied points. Using upright and slanted edges, we designed 2 types of triangles and 4 types of rectangles. Possible shapes of objects are enumerated in Fig. 4–7 in the latter section. The size of the objects are distributed between 5 and 15 units each side.

The task upon agents is to fill more points in rectangles and less in triangles. This task implicitly requires the categorization of objects. Because they can see only 3×3 points in the field simultaneously, the categorization is required to be dynamic.

Fig. 1 shows examples of an object arrangement in the field and a trajectory of an evolved agent. The internal structure of the agent is explained in the next subsection.

Network Architecture

An agent is equipped with a recurrent neural network to decide the next movement from the current states. Recurrent neural network is interpreted as a mapping of internal variables depending on the inputs as parameters in terms of dynamical systems. Activations of context neurons represents the internal variables which can be used to keep memory such as "I've turned to left at the corner 2 time steps before".

Fig. 2 depicts the internal network structure. The activations of neurons are updated internally as follows:

$$y_i(t) = g\left(\Sigma_j w_{ij} y'_j(t-1) + b_i\right), \quad (1)$$

$$g(x) = \left(1 + \exp(-\beta x)\right)^{-1}, \quad (2)$$

where $y'_i(t)$ is the actual activation of the ith neuron at the time t, $y_i(t)$ is the value generated by the internal dynamics. w_{ij} is the weight of connection from the jth neuron to the ith neuron, and b_i is the bias of the ith neuron. The summation is taken over all neurons which have a connection into the ith neuron. $g(x)$ is the sigmoid function. As a result, the activations take the value from $(0,1)$. β is the nonlinearity coefficient and 1.0 in this paper.

Actual activations of input neurons are modified as follows:

$$y'_i(t) = (1-\mu)s_i(t) + \mu y_i(t), \quad (3)$$

where s_i is the raw sensory input and take one of two values, namely 0(empty) or 1(occupied). For context and output neurons $y'(t) = y(t)$. The meaning of Eq.3 is that the actual activations of input neurons are modified by the value which is generated from the internal dynamics. In this paper, we used $\mu = 0.3$. Therefore the activation of an input neuron takes the value from $(0,0.3)$ or $(0.7,1.0)$, depending on the state of the corresponding position in the field. When the value from internal dynamics is close to the sensory inputs, actual activations of input neurons get distinguishable clearly.

In addition, we introduced the plasticity of weights. Weights from input neurons and context neurons into input neurons change during the interaction with the environment so that input neurons can play a role like a prediction. These weight are updated according to the following difference:

$$\Delta w_{ij}(t) = \eta\left(s_i(t) - y_i(t)\right) y'_j(t-1), \quad (4)$$

where $\eta(= 0.01)$ is the learning rate. By introducing the plasticity in this way, the value y_i corresponding to the input neurons, which is generated from the internal dynamics, has the tendency to get closer to s_i in general.

Genetic Algorithm

To get the agents that have relevant sensory-moter coupling for dynamic categorization, the genetic algorithm is used.

Weights and biases of neural networks are binary encoded with 8-bit strings. In this model every genotype of individual has 8×195 bits of length. Gene strings are decoded to

[1] The reason why we used such a strange boundary condition is not essential but practical. Evolved agents tend to go straight when no objects are seen. Therefore, if the boundaries are precisely periodic, he often fail to find any object and get no score in experiments. Of course if we assume the boundary condition to be periodic, more intelligent agents that can explore the field more broadly might evolve. But in our simulations no such agents evolved. That's possibly because of the cheapness of their internal network structures.

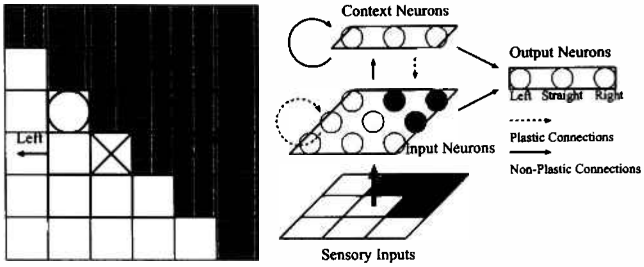

Figure 2: An agent situated in the environment and his neural network architecture: 9 sensory inputs are connected to corresponding input neurons. 3 context neurons are used to keep short term memory in unit cubic space. Colors of the circles in front of the agent show the value of context neurons and indicate his internal state. Movements are decided by the most activated neuron of the 3 output neurons related to moving Straight, Left and Right. Connections into input neurons are plastic and updated according to sensory inputs.

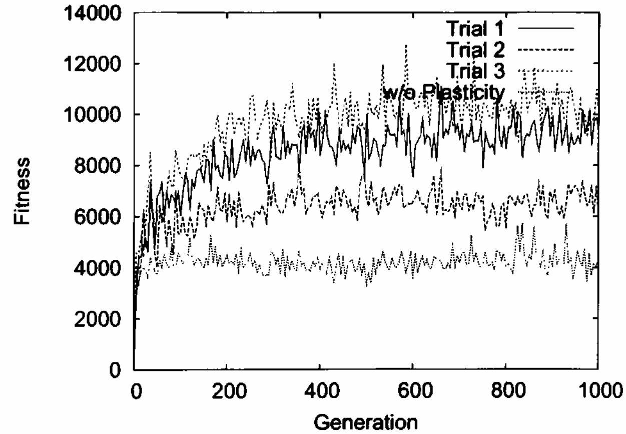

Figure 3: Fitness of the best individual from each generation. Trial 1,2,3 are the cases with neural plasticity. The last line shows the case without plasticity. Without plasticity, fitness saturate to lower value. The difference of the saturated value in the cases with plasticity depends on the dynamic repertoire of the movements discussed later by examples.

real values in the range $[-4,4]$. In the case of plastic connections, values decoded from gene strings are interpreted as the initial values of the weights.

The number of population is 100. In each generation the performance of every agent is evaluated in 100 patterns of object arrangement randomly generated. The movement is simulated from the random initial position and direction for 1000 time steps. Weight values of plastic connections are reset to the initial values when the agent is put in the new environment. The score of the agent is determined by the number of footprints on rectangles minus the number of footprints on triangles. Footprints on the same position are not counted again. Scores in 100 arrangements are summed up to the fitness of the agent.

To create the next generation, bottom 30 individuals are killed and top 30 individuals are duplicated. In addition, 20 pairs of individuals exchange part of their genes by one point crossover and 50 individuals suffer point mutation. The mutation rate is 5 % for every bit.

Experimental Results

Fig. 3 shows the increase of the fitness of the best individual from each generation. Those grow faster in early generations and saturate in about 1000 generations. In the case without plasticity, fitness saturates to lower value than the cases with plasticity. Because the volume of genotype space are equal, we can say that this kind of plasticity has a good effect in this categorization task.

Fig. 4–7 are the collection of moving patterns of agents. They are the best individuals from the 1000th generation of 3 GA trials with plasticity and 1 trial without plasticity corresponding to Fig. 3. In general, the reaction to an object depends on the entrance point and direction. Some typical entrance patterns to the first object the agent meet in the field are enumerated. The dark line shows the trajectory of the agent. In some figures the position of the agent is on the boundary. It means that the agent has left from the object. More explanations are found in each figure caption.

Fig. 8 shows the internal distinction between objects by the best individual in the trial 1.

Discussion

Although agents' predictive ability due to neural plasticity is not itself a component of agent fitness, it improves the fitness indirectly. While interacting with objects, agents form expectations based on the continuity of the object and their movement. The difference between these expectations and actual sensory input changes the internal dynamics and gives rise to the variety of behavior observed. Such relatively long time-scale dynamics (compared to the internal dynamics) should be a common feature of perceptual experience. We claim that the coupling between the short time scales of sensory-motor interaction and long time scales of adaptation and learning mechanisms plays an important role in cognitive processes. With this in mind, we can discuss the relationship between learning process and evolutionary process of adaptive systems.

The previous section does not show all the agent movement patterns. Agents may change their pattern of movement depending on what they previously interacted with. To solve the shape discrimination problem algorithmically, this kind of instability might be harmful. But our evolved agents can solve the problem reliable in spite of their intrinsic instability, indeed appearing as if they are able to autonomously

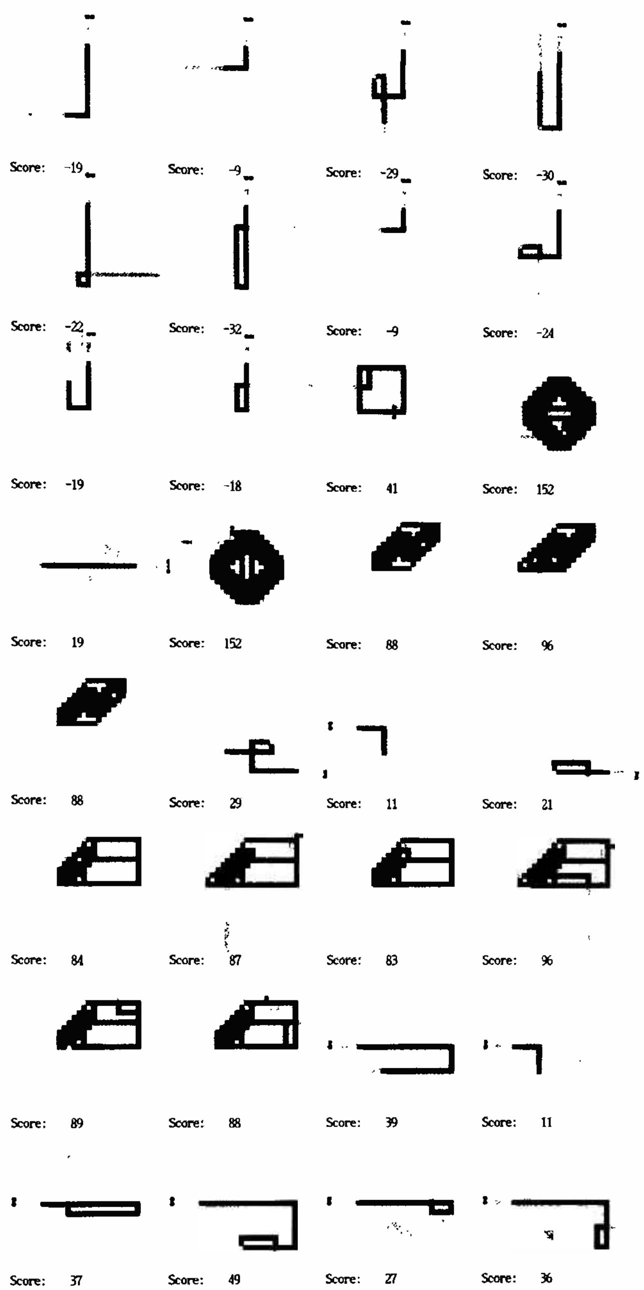

Figure 4: The best individual of the 1000th generation in the trial 1: Showing the movement patterns when the first object is found. This agent tries to distinguish the shape of object by moving along the edges of the object. After he categorized the object as “a rectangle”, he tries to fill broad area near slanted edges by the rolling movement. He eventually enters to periodic movement and never leaves “a rectangle”. The switching mechanism of this agent from the viewpoint of internal dynamics is shown and discussed later.

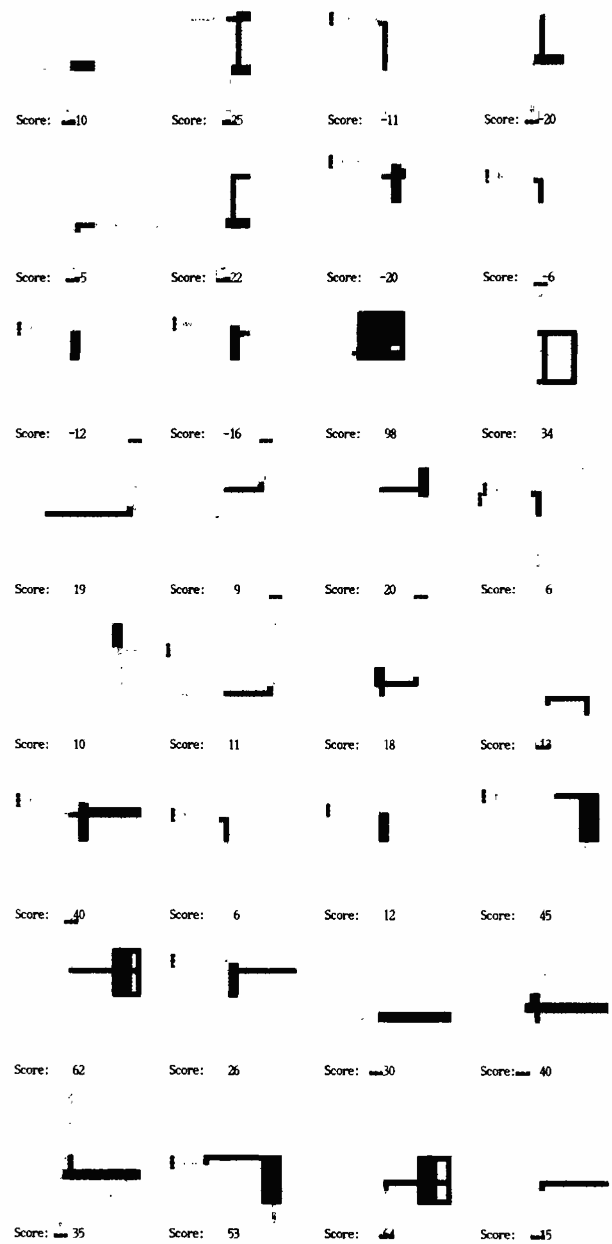

Figure 5: The best individual of the 1000th generation in the trial 2: Showing the movement patterns when the first object was found. This agent tries to fill between upright edges by turning into the object from random position. If the object is a upright square, he stays on the object forever. But if the object is a trapezoid, he leaves the object from a slanted edge. To realize the random movement while filling rectangles, chaotic or quasi-periodic internal dynamics is used.

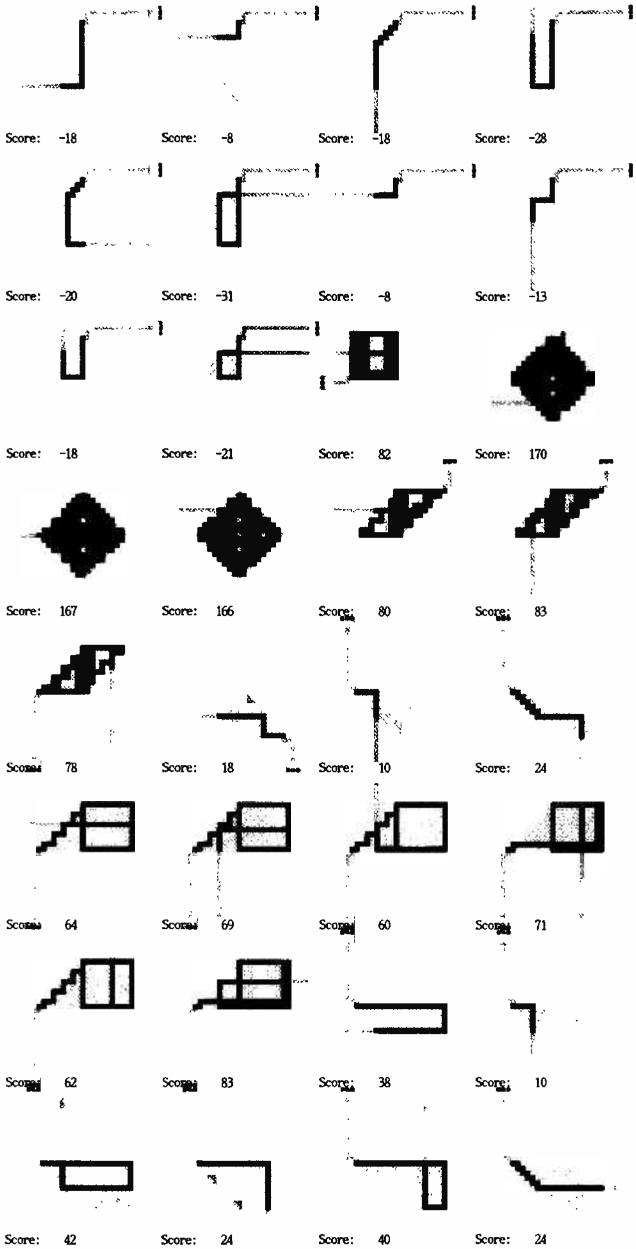

Figure 6: The best individual of the 1000th generation in the trial 3: Showing the movement patterns when the first object was found. This agent takes more flexible strategy compared to the other 2 agents before. Fitness is slightly higher than others. He leaves upright squares, parallelograms, and trapezoids after staying for a while. In addition, He can fill almost all the points of slanted squares. He moves as if wondering from one object to others and stay relatively short time around triangles and long time around rectangles. Actually, the trajectories in Fig. 1 is the movements of this agent. It can also be seen that after leaving an object, his internal states differ depending on the object.

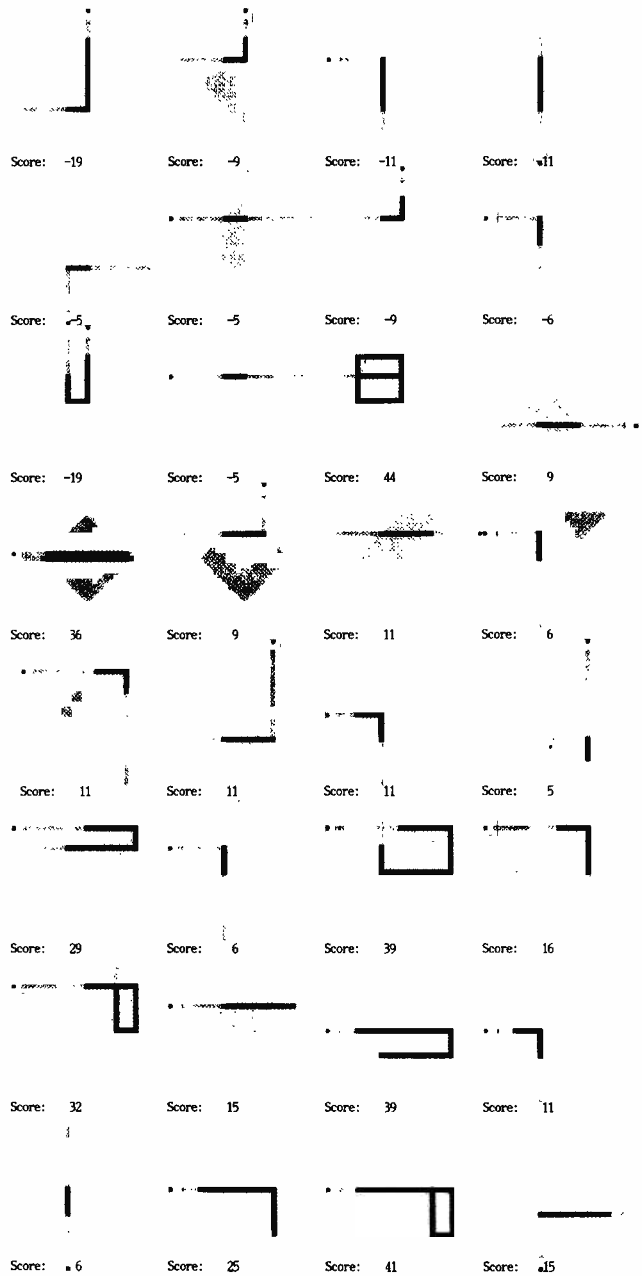

Figure 7: The best individual of the 1000th generation in the trial without plasticity: Showing the movement patterns when the first object was found. Without plasticity, evolved agent shows quite simple pattern of movement which can be realized without internal states or dynamics. That seems not only because it's hard to switch the movement by the internal dynamics. It may be harmful to have an unstable internal dynamics and switch the movement without memorizing long-term correlation.

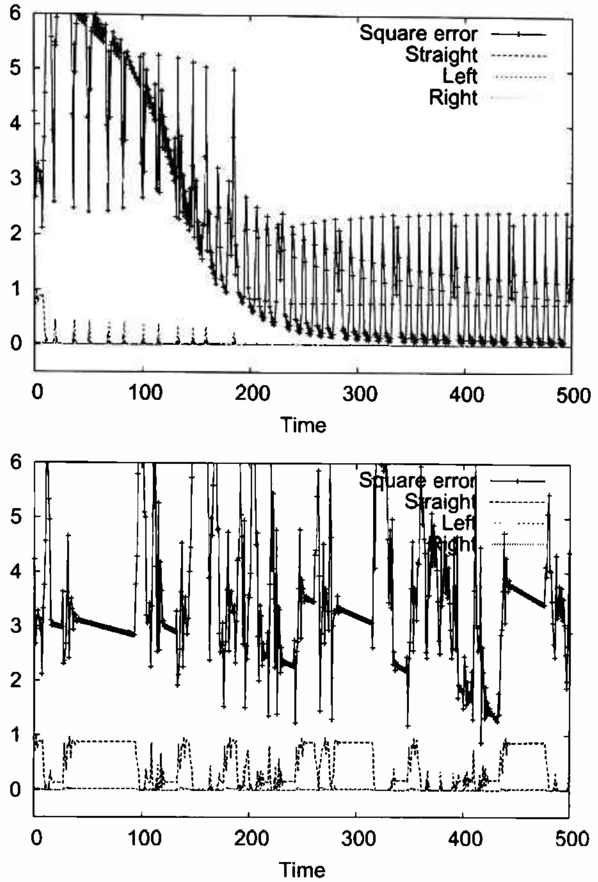

Figure 8: The dynamics of the square error of prediction and the activations of output neurons. Square error of prediction is defined as $\Sigma(s_i - y_i)^2$ by the difference between the raw sensory inputs and the generated values from internal dynamics. Although it is hard to read the actual movement from the activities of output neurons, the change of the pattern of activities shows the change of the pattern of movements. The agent is the best one from the trial 1 which shows the clear difference between interactions with a rectangle and a triangle. The top figure shows the dynamics while interacting with the slanted square. Square error decreases smoothly. The movement have changed from traveling along the edges of the square to rolling to fill the broad area along the edges around 200 time steps. The bottom one shows the dynamics while interacting with many triangles. In this environment the agent repeats entering and leaving triangles. Square error doesn't decrease smoothly. Internal dynamics is perturbed while moving around a triangle , but the switching to filling movement doesn't occur.

decide their movements, and at times even seem bored. In Kato and Floreano's active vision system, the environment is noisy and the agent tries to stabilize its movement to discriminate objects successfully. This is the main difference between our approach and theirs.

The agents presented here cannot discriminate objects perfectly; different agents have difference preferences. We feel that this is a positive result attributable to the autonomous and embodied characteristics of living systems. In particular, exploring behavior should be investigated as one way of understanding the difference between living systems and machines. In the narrow context here, generation of radial categories (Lakoff, 1987) with dynamics having both stable and unstable directions is a possible candidate for lifelike categorization.

Acknowledgments

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