Learning both end-point and cyclic movements by RNNPB

1 Learning both end-point and cyclic movements

In the following experiment using an arm robot, we demonstrate that the robot can learn two different types of movement patterns, fixed end-point movements and cyclic movements, simultaneously in the RNNPB. End-point movement means that the robot reaches a target position and stops there. In cyclic movements, the robot repeats a periodic pattern. The focus of this experiment is to examine how the mapping from the PB vectors to movement patterns is generated for embedding different types of attractor dynamics.

1.1 Task setting

The robot used in the experiments has 4 degrees of freedom in its arm rotational joints. A hand attached to the arm can sweep over the task table horizontally as shown in Figure 1. The hand has a color mark and its position in X-Y coordinates on the table can be recognized by the vision camera mounted on the robot by using a color filtering scheme. A handle is attached to the hand so that a trainer can teach behavior to the arm manually.

The RNNPB deals with 4 DOF motor outputs and 2 DOF sensory inputs in terms of the visually perceived hand position. It has 20 hidden units and 8 context units. It also has 4 parametric bias units in the input layer. The robot was simultaneously trained for 3 different end-point movement patterns and 2 different cyclic movement patterns through manual guidance of the arm trajectories. Those 5 trajectories are shown in Figure 2. The BPTT learning for all the training sequences was iterated 20,000 times starting from randomly set initial synaptic weights.

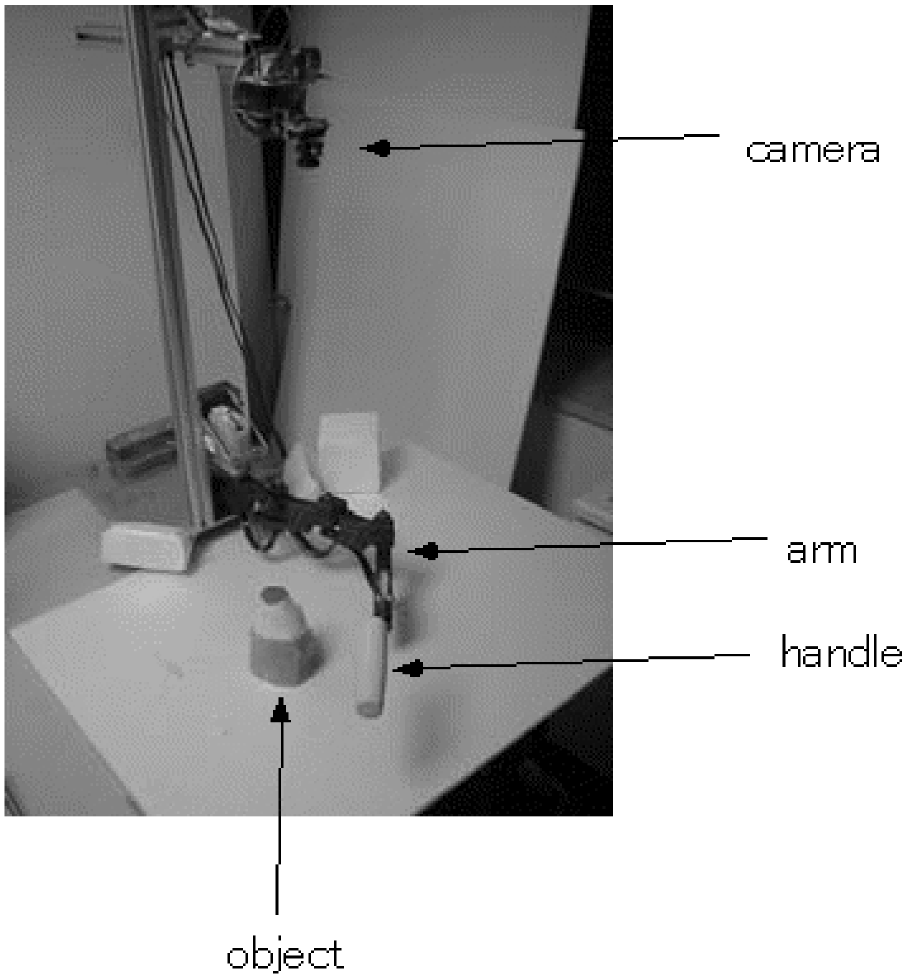

Figure 1: The arm robot with a vision system.

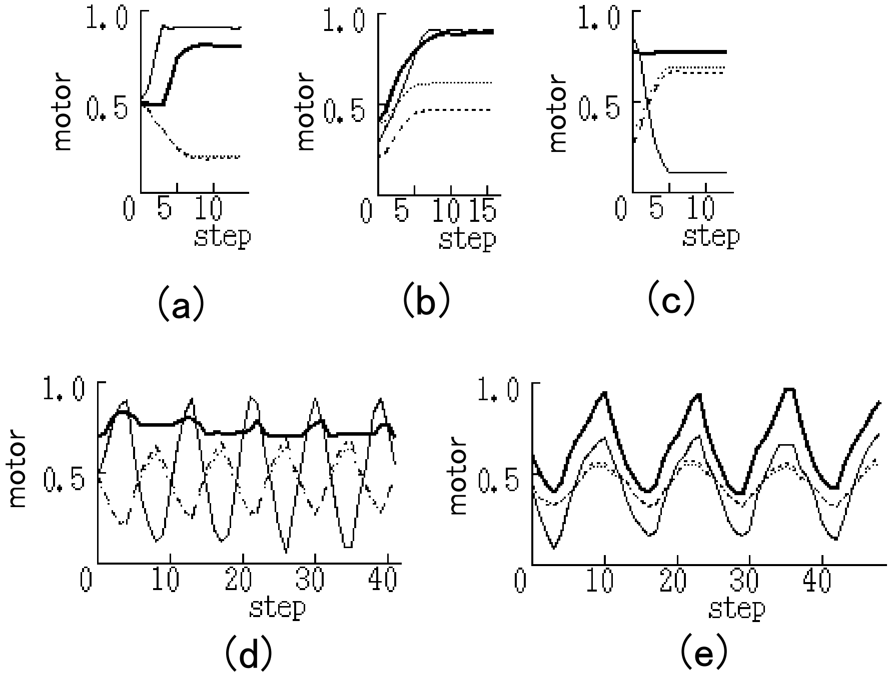

Figure 2: 4 DOF trajectories of 3 different end-point movements in (a), (b) and (c) and those of 2 different cyclic movements used in training.

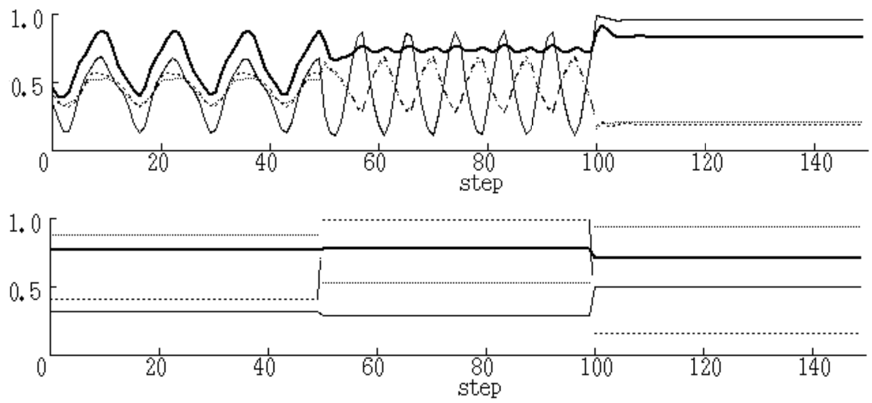

Figure 3: The results of generating two oscillatory movements followed by one end-point movement. The change over time of the motor outputs and the parametric biases are shown in the top and bottom rows, respectively. Time steps are shown in the abscissa.

1.2 Experiments and analysis

We tested the robot's ability to successfully regenerate each trained movement pattern by setting the corresponding PB vector. In this behavior regeneration test, the PB vectors are sequentially switched from those obtained for one cyclic movement pattern to those for another cyclic movement pattern, and then to those for an end-point movement. This sequential switching of the PB is done manually in the current experiment. Figure 3 shows motor pattern generation in the open-loop mode over time and the corresponding PB vectors in the top and bottom rows, respectively. Observe that the trained behavior patterns appear one by one, corresponding to the switching of the PB vectors. The results, indicate that different types of dynamic patterns, corresponding to end-point and cyclic movements, can be learned simultaneously in a single RNN by changing the PB vectors.

In addition to the regeneration experiments for learned movement patterns, we examined how the movement patterns are modulated when the PB vectors are changed from the ones determined in the learning phase. Figure 4 shows successive modulations of movement patterns as one value of the PB vector is varied from 0.0 to 1.0. Observe that the movement patterns can be modulated significantly even with small changes of the parametric bias, although they are less sensitive to change in different ranges of parametric bias.

In order to clarify the mapping structure between the PB vectors and the resultant movement patterns, phase analyses of the PB vectors were conducted. Figure 5 shows

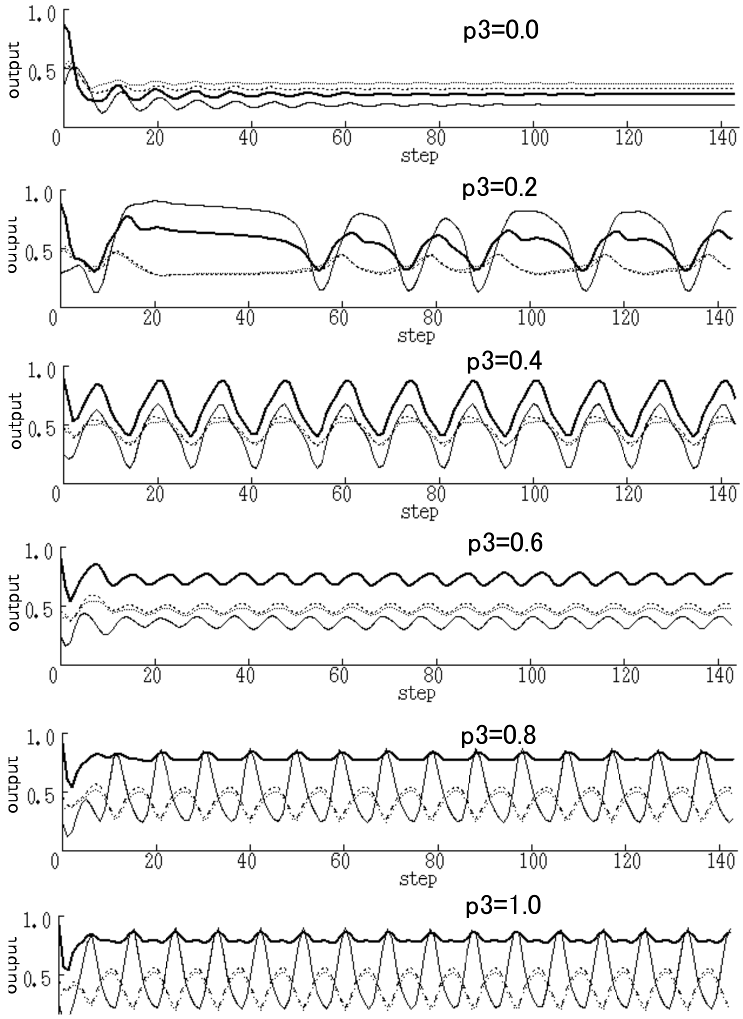

Figure 4: 6 motor activity patterns are plotted with a PB value incrementally increased from top to bottom. Ordinate: Motor Output; Abscissa: Time Step.

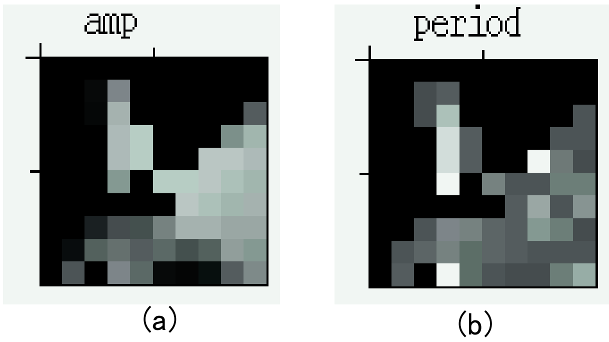

Figure 5: The phase plots for (a) the amplitude and (b) the period for one of the motor outputs using 2 values of the parametric biases.

how amplitude and period of one motor output in the generated movement patterns were modulated upon changing two values of the PB vector (the other two values were fixed). In Figure 5 (a), the degree of tile whiteness is directly proportional to the amplitudes of the movement patterns. The black tiles denote the regions of the end-point movement. The degree of tile whiteness is directly proportional to the period in Figure 5 (b). Again, the black tiles denote the regions of the end-point movement. When aperiodic movement patterns are generated, their amplitudes are measured by the difference between the maximum and minimum values in the sampling period. Their periods are regarded as infinite. These two plots show that the PB space is partitioned into regions of fixed-point dynamics, corresponding to end-point movements, and regions of limit cycling dynamics with various periods and amplitudes, corresponding to cycling movement patterns. An important observation is that the characteristic landscape is quite rugged in the region of the cyclic movement patterns. However, further analysis showed that the characteristics in the region of the end-point movement patterns are different. Figure 6 shows the variations of the end-point positions reached in the region of the fixed point dynamics in the 2 dimensional PB space. The end-point positions, in terms of the 1st and the 2nd joint angles of the arm, are represented by graded tile colors. It is observed that the end-point position angles fluctuate rather smoothly in the PB space. This observation suggests that the mapping between the parametric bias and the generated behaviors is quite nonlinear, in that the mappings in some regions fluctuate greatly while others are relatively smooth.

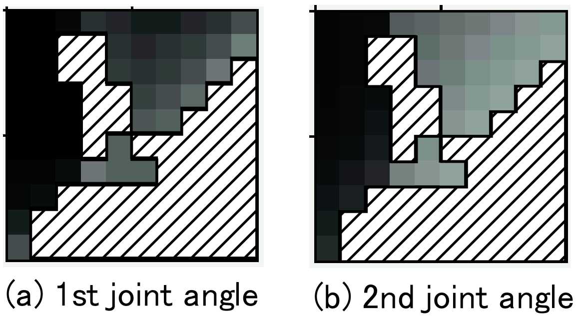

Figure 6: The phase plots for the end-point position in 2 dimensional PB space represented in terms of the first joint angle (a) and the second joint angle (b).