

Self-Organization in a Mirror Neurons Model Using RNN Robot Experiments and Their Analysis

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1 Introduction

The most essential feature of the mirror neurons is that behavior generations and recognitions of the same behaviors are represented in the same activities in a set of neurons. In this extended abstract, we introduce a model of mirror neurons using recurrent neural network(RNN). The model have been implemented in different robotics platforms including Sony Humanoid robots by which we examined how a set of behavior primitives are self-organized in terms of the mirror system where their generation and perception are proceeded simultaneously. The results of the experiments are qualitatively analyzed from the views of dynamical systems. The next section describes a scheme called recurrent neural network with parametric bias (RNNPB) that is to represent the mirror neuronal system.

2 Model

RNNPB is a version of Jordan-type RNN where the PB units allocated in the input layer plays a role of the control parameters for modulating movement patterns. A set of movement patterns are learned in terms of forward dynamics of the RNNPB by self-determining both the PB values that are differently assigned for each movement pattern and a synaptic weight matrices that is common for all patterns. The information flow of the RNNPB in the learning phase is shown in Figure 1(a).

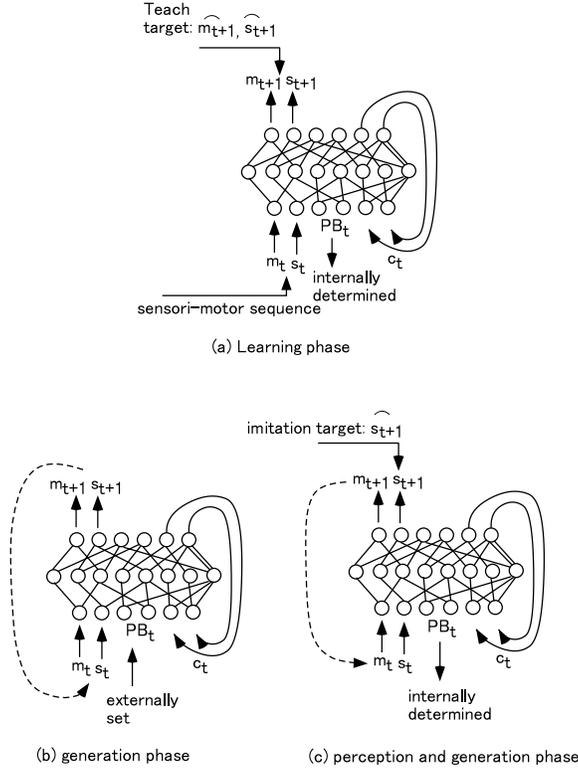


Figure 1: The system flow of RNNPB in learning phase (a) and testing phase (b).

This learning is conducted using both target sequences of motor values m_t and the sensory values s_t . With given m_t and s_t in the input layer, the network predicts their next time step values in the output layer as m_{t+1} and s_{t+1} . The outputs are compared with their target values \hat{m}_{t+1} and \hat{s}_{t+1} and the error generated is back-propagated for the purpose of updating both the synaptic weights and PB values. It is noted that the determined synaptic weights are common to all learning patterns but the PB values are differently determined for each pattern. c_t represents the context units where the self-feedback loop is established from c_{t+1} in the output layer to c_t in the input layer. The context unit activations represent the internal state of the network.

In the generation phase, the prelearned network is utilized without updating the synaptic weights. The network is operated either in the closed-loop mode in the generation phase shown in Figure 1(b) or in the open-loop mode in the perception and generation phase shown in Figure 1(c). In the closed-loop mode, the motor patterns are generated autonomously with feeding back the prediction outputs of the next step sensory image to the current step sensory inputs. In this case, the PB values are set

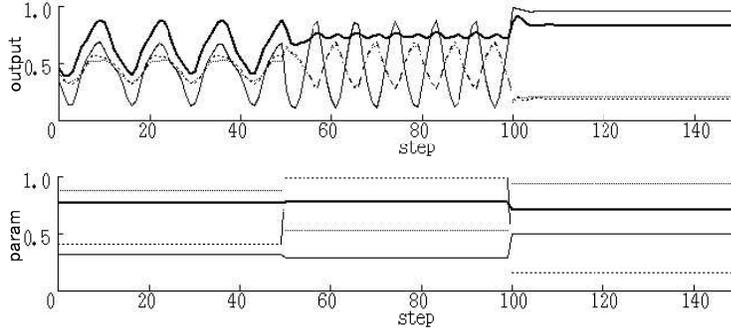


Figure 2: Generation of two oscillatory and one end-point behaviors.

from the external as determined in the learning phase and the corresponding movement patterns are generated.

The open-loop mode is utilized when the imitative interactions are taken place with the users. The perception and the generation of the movement patterns are proceeded simultaneously as the mirror system. The sensory inputs (that are hand positions of the user in the case of the humanoid robot experiments) are fed into the RNNPB as the target sequences. The RNNPB with receiving s_t attempts to predict its next value s_{t+1} . The generated prediction error from the target value s_{t+1} is back-propagated to the PB units and the PB values are updated in the direction of minimizing the error. Note that although the PB plays a role of the inputs for the forward computation, its values are slowly modulated in order to adapt to the current target sequence patterns. If prelearned sensory sequence patterns are perceived, the PB values tend to converge to the values that have been determined in the learning phase and then generate the associated motor patterns m_{t+1} as previously learned. Actually the PB units play the roles of mirror neurons for bridging between the perceptual dynamics and the motor generation dynamics.

3 Experiment-1

In this experiment, we examined how different behavior primitives are learned and generated using a 4 DOG arm robot. The robot is asked to learn 3 different end-point movements and 2 cyclic movements as embedded in a RNNPB with self-determining different PB value for each. Figure 2 shows that the robot after the learning can successfully generate the learned behavior patterns one by one while the PB values are changed externally. Further more it was observed that various behavior patterns other than learned ones can be generated when the PB values are externally manipulated.

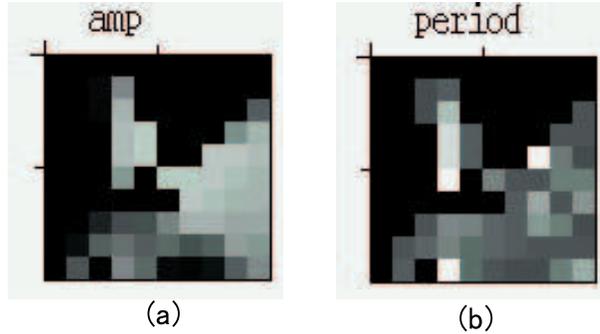


Figure 3: The phase plots for (a) the amplitude and (b) the periodicity for one of the motor outputs using 2 values of the parametric biases.

The phase analysis for two PB values were conducted where it was examined how amplitude and oscillation periodicity of the behavior patterns are modulated along with changes of the PB values. The results are summarized in Figure 3. In Figure 3(a) a black tile means that the amplitude is zero (a fixed point conversion) while a white tile means 1.0. In Figure 3(b) the periodicity is indicated by its log scale measure in which a white tile means the periodicity is more than 100 steps and a black one does a fixed point conversion. These two plots show that the parametric bias space is partitioned into the regions of fixed point dynamics and those of limit cycling dynamics with various periodicities. An important observation is that the landscape for the dynamic characteristics is quite lugged in some regions while it is smooth in other regions. Our analysis in the region of the fixed point dynamics revealed the fact that the end-point position changes smoothly in the 2 dimensional space of the PB with preserving topological relations between the positions and the PB values. On the other hand in the region of the limit cycle dynamics, the amplitude and the periodicity can change rather abruptly in some locations in the PB space. This observation suggests that the mapping between the parametric bias and the characteristics of generated behaviors is quite nonlinear.

4 Experiment-2

In this experiment, a Sony humanoid robot as shown in Figure 4 learns 3 different cyclic movement patterns of two arms (8 DOF) as associated with the hand movement patterns of the user (4DOF).

In this experiment the sensory inputs is the user hand positions perceived by the robot vision system. After the learning is converged, we examined how the robot can



Figure 4: A user is interacting with Sony humanoid robot SDR-4X.

follow the target patterns while the user switches to demonstrate learned patterns by turn. The time course of the interaction and the PB of the RNNPB are plotted in Figure 5.

In Figure 5, the plot at the top shows the target position of user hands, the plot at the second row shows the user hands position predicted by the RNNPB, the plot at the third row shows the robot joint angle generated by the RNNPB (Only 6 DOF are plotted among totally 8 DOF), the plot at the bottom shows the parametric bias of the RNNPB. It is observed that when the perceived user hand pattern is switched from one pattern to another, its predicted outputs are also switched while alternating the motor patterns. It is also observed that the synchronization between the user pattern and the robot one is once lost when the user pattern is switched to another but it is recovered with the switched pattern within several steps. It is said that recognition and generation of movement patterns in terms of the mirror system is achieved simultaneously by generating coherent dynamics between the user movement and the RNNPB activities.

5 Summary

A mirror neurons model is introduced which utilizes the RNN with the parametric biases for encoding multiple movement patterns. Our experiments using robots demonstrated that diversity of movement patterns can be embedded in the PB phase space. It was also shown that the recognition and the generation can be proceeded as synchronized while the robot and the user achieve the coherent state in their interactions.

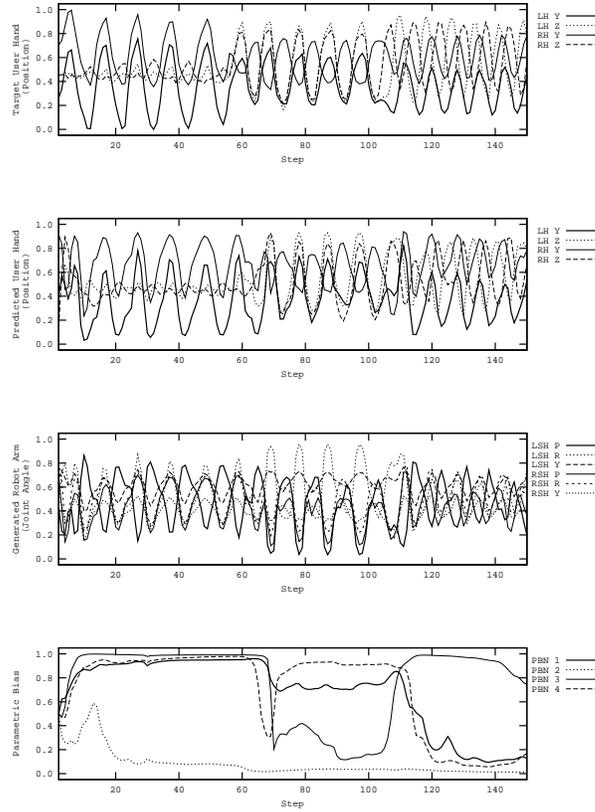


Figure 5: Switching of the robot movement pattern among three learned patterns as initiated by switching of user hand movement.