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Review of a Dynamic Neural Network Scheme for Synthesizing Cognition of Robots and Humanoids

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This paper describes our recent cognitive robotics projects using a neural network learning scheme. By reviewing those projects that focus on various issues including self-organization of behavior primitives, chucking of sensory-motor flow, behavior-linguistic association learning and humanoid imitative interactions, the essential characteristics of embodied cognition based on our proposed dynamic neural network scheme are elucidated.

Keywords: Cognition; neural nets; robots.

1. Introduction

Cognitions in robots and humanoid requires two different aspects which seem to conflict with each other in various contexts. On the one hand, the sensory-motor processes have to deal with detailed interactions with the environment for the purpose of precise control of bodily movements. On the other hand, higher level cognition would require abstractions of those lower level sensory-motor processes, manipulating them compositionally for conducting goal-directed planning, inference, etc. This conflict seems to be related to the symbol grounding problem by Harnad (1990), in which it is argued that symbol systems consisting of arbitrary tokens cannot be grounded because they are not constrained by physical interactions with the external world.

We have explored the possibility that equivalent structures of symbol systems are self-organized in neuronal dynamics through iterative sensory-motor interactions with the external world. We presumed that the gap between higher cognitive processes and the sensory-motor level might be reduced significantly if both share the same metric space of analog dynamical systems, and if dense bi-directional bottom-up and top-down interactions can be achieved there.

Local vs. distributed representation

Based on these thoughts, the authors have studied dynamic neural network models which can generate as well as recognize spatial-temporal pattern of sensory-motor flow based on its learning. Firstly, we focused on the problems of how to organize and manipulate behavior primitives (Arbib, 1981). In the conventional approach each behavior primitive is allocated as a local and independent entity and sequencing of those primitives are conducted by the higher level system. In such approaches, the primitives can be represented by symbolic graph structures (Inamura, Nakamura, Ezaki, & Toshima, 2001), hidden markov models (Amit & Mataric, 2002) or mixture of expert networks (Wolpert & Kawato, 1998; Tani & Nolfi, 1998). The potential problem on using local scheme for representing the primitives is lack of generalization. In the localist approach, whenever novel movement pattern is experienced, it is added to the primitive repertory without generalization among them. (Generalization might be done but only by externally using preassumed functions such as linear interpolations of stored patterns.) It would end-up with extensive numbers of the primitives for covering varieties of behavior patterns required.

Facing this problem, we have investigated the possibility of the distributed representation for the primitives as an alternative scheme where different primitives are learned and embedded in the same neural network by sharing the same synaptic weights among them. We investigated a novel scheme called as the recurrent neural network (RNN) with parametric bias (PB) (Tani, 2002, 2003; Tani & Ito, 2003) in which the PB vector works as dynamic parameters for encoding different sequence patterns in a single RNN. The same PB values accounts for both of generating and recognizing sensory-motor sequence patterns which could be a possible modeling of mirror neurons (Rizzolatti, Fadiga, Galless, & Fogassi, 1996). The essential differences of this distributed representation scheme from the localist scheme are that each memory of a different pattern are stored as relational one among others. Our primal focus has been what sorts of generalized structures can be self-organized and how diversity as well as robustness can be attained in generating patterns in the distributed representation scheme.

Level structures

It is generally considered that certain level structures are necessary in order to manipulate the behavior primitives in compositional ways. We formulated a model in which the higher cognitive level and the lower sensory-motor level are interfaced by the PB vector (Tani, 2003). We focused on two problems in this model. One is the problem of chunking that asks how a set of movement primitives can be acquired as segmented from continuous sensory-motor flow through iterative experiences. The second problem concerns with the bottom-up and top-down interactions between the levels. It is expected that adequate interactions could enable the higher cognitive level to preserve compositionality in manipulating the lower sensory-motor level without loosing their tight coupling with the outer world.

Cognitive robotics projects

For the purpose of examining the above mentioned ideas and thoughts, several cognitive robotics projects have been conducted. It is important to note that our experiments do not just peruse the performance in terms of engineering but rather focus on analysis of dynamic structures appeared in the experiments. Such analysis would gain our understanding in essential aspects of embodied cognition, including local and distributed representation, bottom-up and top-down interactions, articulation of sensory-motor flow and behavior primitives, imitation and joint attention, behavior-linguistic binding, self-organization of hierarchy.

The arm robot platform was utilized to examine the basic characteristics of the RNNPB (Tani & Ito, 2003). The issues of generalization and diversity in learning, generating and recognizing behavior patterns are experimentally examined. The experiments with the RNNPB with levels (Tani, 2003) showed how complex behavior patterns can be decomposed into sequences of behavior primitives where our interest is how such behavior primitives are acquired as segmented from continuous sensory-motor flow of experienced.

The embodied language project (Sugita & Tani, 2003) have focused on bidirectional interactions between behavioral and linguistic processes. The RNNPB is regarded as a mirror system in which behavioral modality in terms of continuous sensory-motor flow and linguistic modality in terms of word sequences is binded by utilizing the PB vector. The experiments were conducted in a task space where a mobile robot with a vision system can act on some objects. The analysis of the self-organized structures in the RNNPB illustrated how the compositionality as well as the generalization in learning are achieved in the system.

The studies of imitative interaction (Ito & Tani, 2003b) have been conducted by using a small Humanoid robot developed by Sony Corp. The RNNPB is employed as a mirror system for recognizing the human subject's movement patterns and generating its own corresponding behavior. The experiments in the imitation game using the humanoid robot showed that joint attention as well as turn taking behaviors are generated which are explained in terms of synchronization and desynchronization between the robot and the subjects.

In the following sections, firstly our proposed model of the RNNPB will be described briefly. Nextly, several robotics experiments using the RNNPB will be reviewed. Finally, we will show the future research directions are discussed.

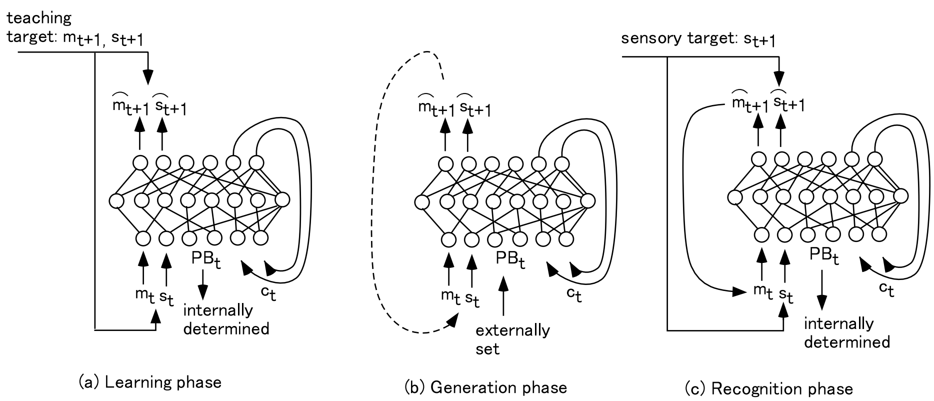

Fig. 1. The system flow of RNNPB in learning phase (a), generation phase (b) and recognition phase(c).

2. The RNNPB modeling

This section presents the main ideas behind our proposed model RNNPB. For details of the modeling, please refer to our prior publications (Tani, 2002, 2003; Tani & Ito, 2003).

The role of learning is to self-organize the mapping between the PB vector and behavioral spatio-temporal patterns. It is important to note that the PB vector for each learning pattern is self-determined in a non-supervised manner, without teacher signals. Another feature of the RNNPB is that the system works as both a behavior recognizer and generator as a mirror system after learning. When given a fixed PB vector, the RNNPB generates the corresponding dynamic patterns. On the other hand, when given target patterns to be recognized, the corresponding PB vectors are obtained through an iterative inverse computation.

In the learning phase, a set of movement patterns are learned through the forward model of the RNNPB by self-determining both the PB vectors, which are assigned differently for each movement pattern, and a synaptic weight matrix, which is common for all the patterns. The information flow of the RNNPB in the learning phase is shown in Figure 1(a). This learning is conducted using both target sequences of motor values m_t and the sensory values s_t. When given m_t and s_t in the input layer, the network predicts their values at the next time step in the output layer as $\hat{m_{t+1}}$ and $\hat{s_{t+1}}$. The outputs are compared with their target values m_{t+1} and s_{t+1} and the error generated is back-propagated (Werbos, 1990; Rumelhart, Hinton, & Williams, 1986) for the purpose of updating both the synaptic weights and PB vectors. Note that the determined synaptic weights are common to all learning patterns, but the PB vector is differently determined for each pattern. The manner of determining the PB vectors will be detailed in later sections. 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.

After the learning is completed, the sensory-motor sequences can be generated by means of the forward dynamics of the RNNPB with the PB vectors fixed as shown in Figure 1(b). The PB vectors could be given from another network, as in the behavior-language association task described later, or self-determined through the recognition process, as in the imitative interaction task with the humanoid robot. In the generation phase, the RNNPB can be operated in a closed-loop mode where the next step's sensory-motor prediction outputs are fed back to the current step as inputs, as denoted by a dotted line on the left-hand side in Figure 1(b). Thus, the RNNPB can generate imaginary sensory-motor sequences without receiving the actual sensory inputs from the environment.

Figure 1(c) illustrates how the PB vectors can be inversely computed for the given target sensory sequences in the recognition phase. The RNNPB, when receiving the current sensory inputs s_t, attempts to predict their next vectors, $\hat{s_{t+1}}$, by utilizing the temporarily obtained PB vectors. The generated prediction error from the target value s_{t+1} is back-propagated to the PB units and the current PB vectors are updated in the direction of minimizing the error. The actual computation of the PB vectors is conducted by using the so-called regression window of the immediate past steps, by which the PB vectors can be modulated smoothly through the steps. (This mechanism will be detailed in the next section.) If pre-learned sensory sequence patterns are perceived, the PB vectors tend to converge to the values that were determined in the learning phase.

3. Learning different dynamic movement patterns

In this section, we will describe how multiple movement patterns of different types of attractor dynamics can be learned simultaneously using the RNNPB. We will examine characteristics of generalization in learning as well as diversity in pattern generations in this scheme through our specific dynamical systems analysis.

3.1. *Arm robot experiments*

The RNNPB was used to learn two different type of movement patterns, end-point movements and cyclic movements, simultaneously by using an arm robot shown in Figure 2. The arm robot has 4 degrees of freedom and it has a vision to identify the position of the arm tip. 3 end-point movement patterns and 2 cyclic movement patterns were successfully learned with minimizing the error. Figure 3 shows a profile of generating movement patterns with manually switching the PB values.

3.2. *Analysis*

In order to examine the mapping self-organized between the PB vector to movement patterns, the phase space analysis was conducted for the PB vector. Figure 4

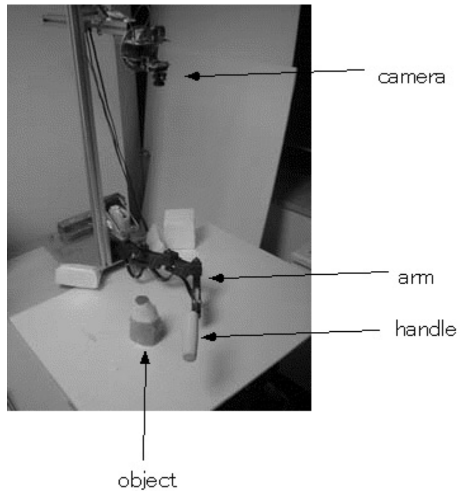

Fig. 2. The arm robot with a vision system.

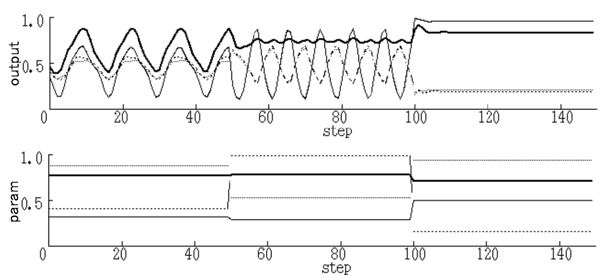

Fig. 3. The results of generating two oscillatory movements followed by one end-point movement. The change over time of the motor outputs and the parametric biases are shown in the top and bottom rows, respectively. Time steps are shown in the abscissa.

(a) and (b) show how amplitude and periodicity of generated oscillatory patterns modulate while the PB values are changed in 2 dimensions. The sub-regions of black colored represent the region for end-point movements and other regions do for cyclic movements. 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 were different. Figure 4 (c) and (d) show the variations of the end-point positions reached in the region of the fixed point dynamics in the 2 dimensional PB space. It is observed that the end-point position angles modulate rather smoothly in the PB space.

These experimental results indicate important aspects of the RNNPB concern-

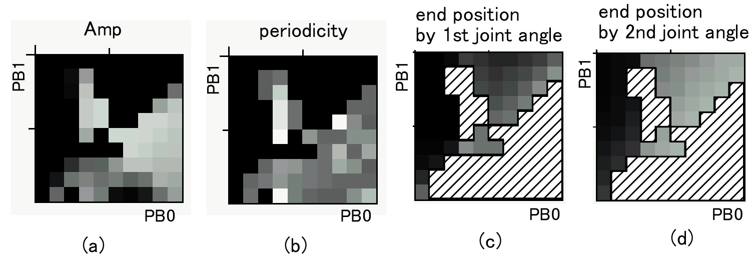

Fig. 4. The phase plots for (a) the amplitude and (b) the period of generated movement patterns in 2 dimensional PB space. The end positions in terms of 2 joint angles are shown in (c) and (d) for the analysis of the end-point movement region.

ing generalization and diversity in self-organizing distributed memory for movement patterns. Firstly, it was shown that two types of movement primitives, end-point movements and cyclic movements, are organized in the separated regions in the PB space. The end-point movements are said to be generalized in terms of their smooth modulation characteristics observed in the PB space. It is explained that end-point movement patterns can be structurally shared as shown by Bizzi, Acornero, Chapple, and Hogan (1984). On the other hand, cyclic movement patterns are not well generalized in terms of their fluctuated modulations, however it can generate diverse cyclic movement patterns including aperiodic ones. This is because a shared structure among cyclic movement patterns in the training set cannot be found easily and thus the PB mapping is nonlinearly distorted in the processes of embedding those unrelated patterns in one network. This sort of characteristics appear because each memory pattern is stored as relational to others in the distributed representation of the RNNPB. We have discussed these essential characteristics of the RNNPB repeatedly in different task contexts (Ito & Tani, 2003a; Sugita & Tani, 2003).

4. Sensory-motor flow chunking by the level structured RNNPB

The following will describe how we addressed the problems of how the sensory-motor flow can be learned by chunking. In the current paper, the problems of the bottom-up and top-down interactions in behavior generation based on top-down plans cannot be addressed because of the limited space. This should be referred to (Tani, 2003).

4.1. *The RNNPB with multiple levels*

The RNNPB is extended to have multiple levels by which it can deal with generation and recognition of more complex behavior patterns. Figure 5 shows the extended architecture. The higher level and the lower level RNNS are bi-directionally interfaced using the PB vector. The prediction of the PB vector sequences generate top-down plan of action sequences while the recognition of the sensory flow gen-

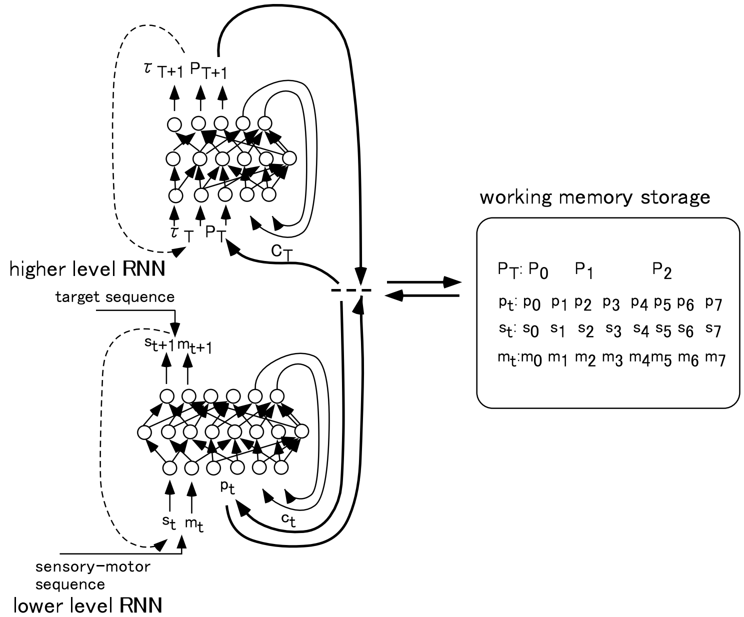

Fig. 5. The complete architecture. Two levels of RNNs on the left-hand side and the working memory on the right-hand side.

erate the feedback of the PB vector corresponding to the actual experience in the environment.

4.2. *Chunking experiment*

The experiments were conducted in the task of simple object manipulation using the arm robot shown in Figure 2. In this task, the robot receives the center position of the object and the arm tip position perceived by the robot camera as the sensory inputs. The extended RNNPB with two levels are forced to learn multiple behavior episodes in a supervised way. Each episode consists of a sequence of behavior primitives such as approaching the object, pushing the object, and then return to home position. It is noted that there are no signs of segmentations in the sensory-motor flow which the robot experiences. The network has to discover how to segment the flow by attempting to decompose the sensory-motor flow into a sequence of segments (behavior primitives) which are reusable in other episodes to be learned.

The learning results are shown in Figure 6. It is observed that 7 episodes are learned by decomposing them into sequences of 7 behavior primitives. Those are shown in Figure 6 with abbreviations with AO: approach to object in the center from the right-hand side, PO: push object from the center to the left-hand side, TO: touch object, IC: perform inverse C shape, HO: go back to home position, CE:

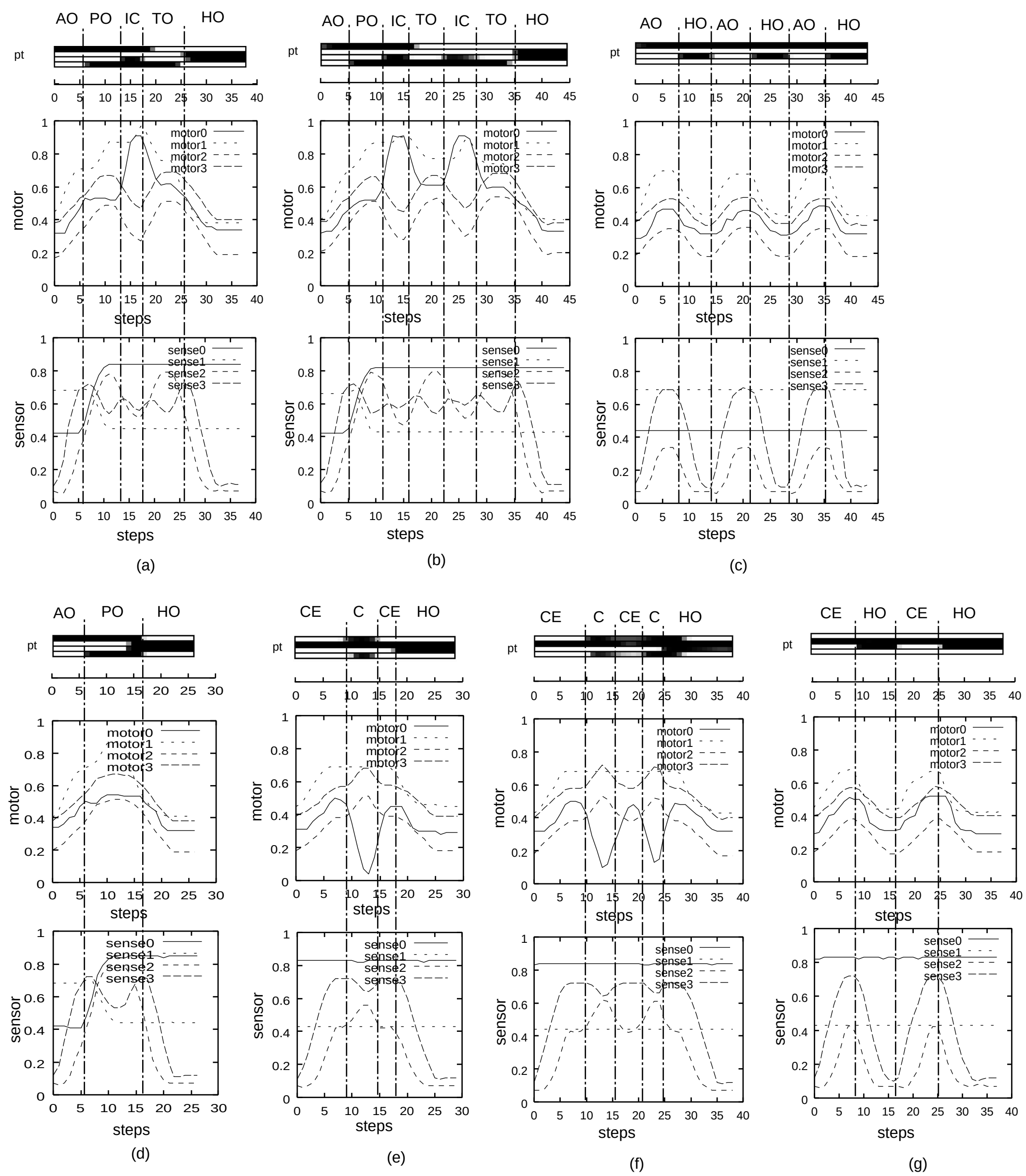

Fig. 6. For the seven training sequences (a)-(g), the temporal profiles of the parametric bias which resulted from learning are plotted in the top row, the motor outputs are plotted in the second row and the sensor inputs are plotted in the third row. The vertical dotted lines denote the occurrence of segmentation when the primitive behaviors switched in the training sequences. The capital letters associated with each segment denote the abbreviation of the corresponding primitive behavior.

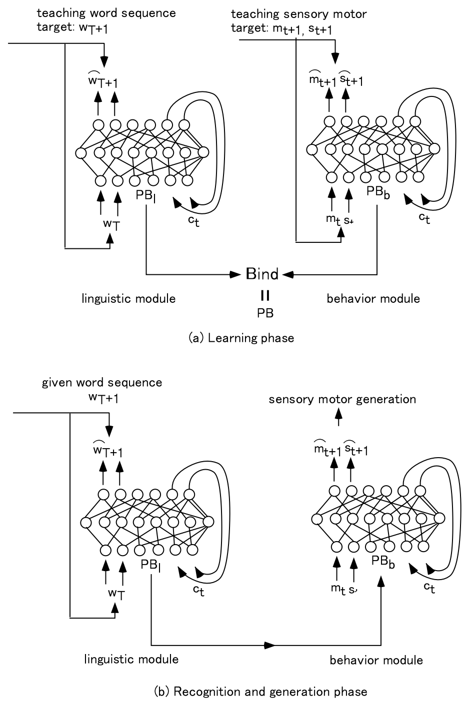

Fig. 7. (a) Model for co-learning of word sequences and corresponding behaviors, (b) model for recognizing word sequences and generating corresponding behaviors.

go to the center from the right-hand side and C: perform C shape.

5. Embodied language project

In this study, we attempted to bind simple linguistic processes of combining verbs and objects and simple behavior processes of object related actions by using the RNNPB scheme. The study was inspired by Arbib (2002)'s hypothesis that the mirror neurons, which become active both for generating and recognizing object handling behaviors , had played crucial roles in language development especially in pairing verbs and objects.

5.1. *Modeling and task setting*

Figure 7 (a) illustrates the RNNPB scheme used in the co-learning of the word sequences and their corresponding behavior patterns. The linguistic module on the left-hand side receives word sequences, beginning with a "start symbol" for each sequence. The behavior module on the right-hand side receives sensory-motor sequences. During co-learning, word sequences are bound to the corresponding behavior sequences. More specifically, PB_l in the linguistic module and PB_b in the

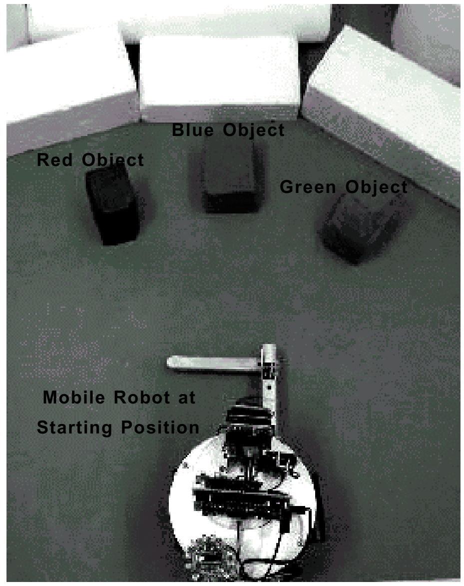

Fig. 8. The task environment consists of red, blue and green objects placed in left, center, and right positions, respectively. The mobile robot is at the starting position.

behavior module are simultaneously updated, under the constraint that the difference between these two vectors be minimized for each bound sequence. In the ideal situation, PB_l and PB_b become equal at the end of co-learning for each sequence. Figure 7 (b) illustrates the RNNPB scheme utilized in the recognition and generation phases. The PB_l in the linguistic module is determined by recognizing a given word sequence. Its vector is set to PB_b in the behavior module for generating the corresponding behavior.

The mobile robot experiment is conducted in the environment shown in Figure 8, where red, blue, and green objects are located in the left, center, and right positions respectively in front of a white rear wall. The robot learns to "POINT" with its arm, "PUSH" with its body, and "HIT" with its arm these three objects repeatedly associated with corresponding sentences. Each sentence consists of two words, a verb followed by a noun. The verbs used are point, push, hit, and the nouns are red, blue, green, left, center, right. There can be 9 different combinations of behavior categories and 18 different sentences in this setting. Note that "red", "blue" and "green" turn out to be equivalent to "left", "center" and "right", respectively, in this task context. In order to investigate the generalization capability, especially in the linguistic learning, only 14 sentences out of 18 possible sentences are trained.

5.2. *Results and analysis*

Recognition and generation tests were conducted after learning was completed. The appropriate corresponding behaviors were generated for all 18 word sequences, including the 4 unlearned ones. In order to analyze the internal structures self-organized in the co-learning process, a phase space analysis was conducted for PB_l and PB_b. In this analysis, the original 6-dimensional PB space was projected onto the 2-dimensional surface determined by principal components analysis. In Figure 9 (a) the PB_l vectors, corresponding to all possible 18 word sequences, are plotted in the 2-dimensional space. The PB_l vector is inversely computed during the recognition of each word sequence in the linguistic module. The PB_l vectors for 4 unlearned word sequences are surrounded by dashed circles. Figure 9 (b) shows the PB_b vectors that are determined for 90 behavior sequences in the co-learning phase. Figure 9 (c) shows the averaged PB_b vector for each of 9 behavior categories.

There are some interesting findings in these figures. First in Figure 9 (a), two congruent sub-structures can be observed among the PB points corresponding to word sequences. There are 6 word sequences, each of which has the same verb followed by one of 6 nouns. All 3 of the hexagons, made up of the 6 PB points for each verb, seem to be congruent. Similarly, 6 congruent triangles can be seen for the 3 verbs preceded by the same noun. This doubly congruent structure is crucial for representing the compositionality hidden in the learned sentences i.e.– each verb can be followed by one noun in the same noun set. The combinatorial relationship between the verbs and the nouns is well represented in the multiplication of these two congruent structures. An interesting fact is that this structure was self-organized without using all possible combinations of word sequences during learning. However, 4 PB points, corresponding to unlearned word sequences, are actually found to come to the right positions in the structure when they are inversely computed in the recognition processes (thus correct behaviors can be successfully generated for them). This sort of generalization became possible because each word sequence is learned not as an independent instance, but rather in the form of relational structures among others, which is the compositionality of nouns and verbs in the current case.

Second, a cluster structure can be seen in the PB_b vectors in the behavior module, as shown in Figure 9 (b). Although there are certain distributions in each cluster due to the perturbations in the sensory-motor sequences in the learning set, the layout of the averaged center of those clusters seems to have the same congruent structures as the linguistic module, as shown in Figure 9 (c). It is interesting to note that this sort of congruent structure cannot self-organize when the behavior module is trained without binding with the linguistic module (Sugita & Tani, 2003). The linguistic structure affects the behavior module, allowing generation of the observed congruent structure. On the other hand, the behavior constraints can also affect the structure self-organized in the linguistic module. In Figure 9 (a), the PB points for pairs of sentences ending with "red" and "left", "blue" and "center", and "green"

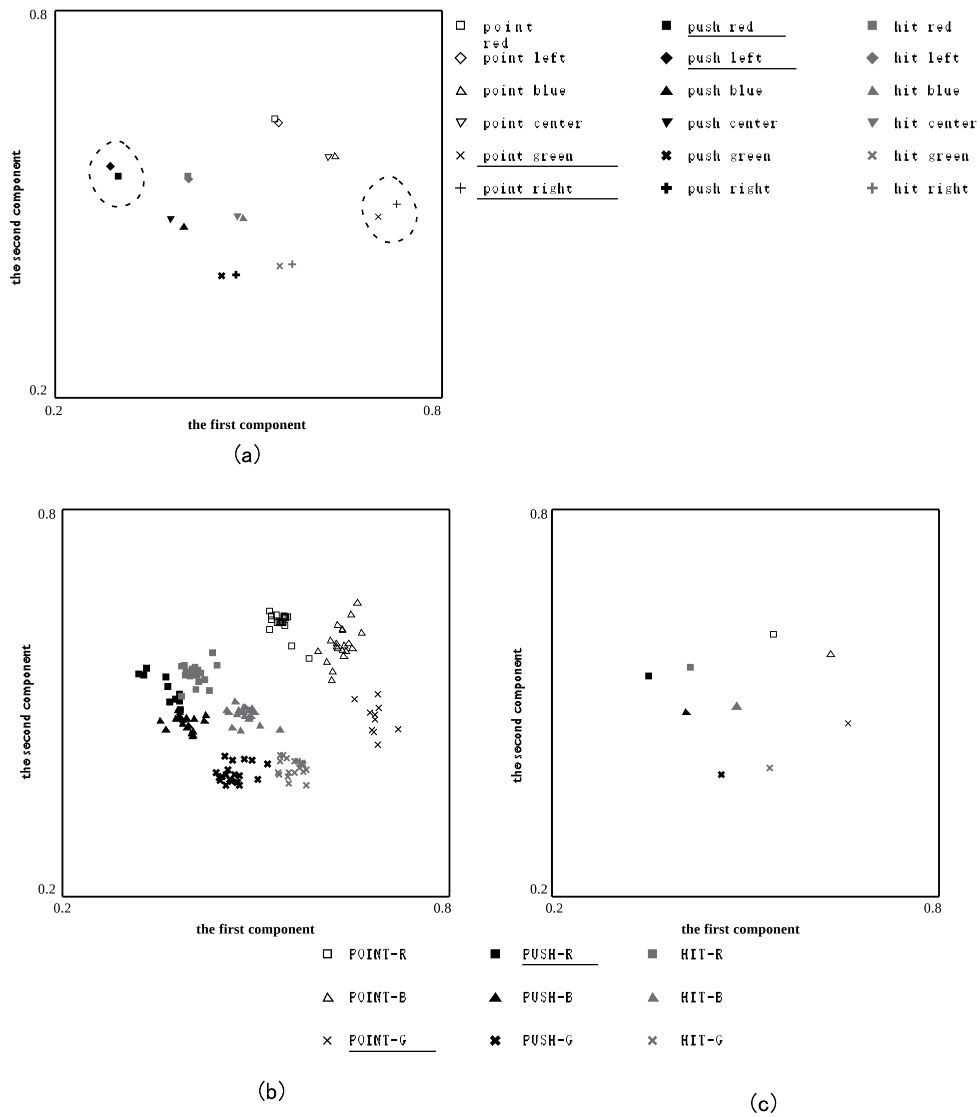

Fig. 9. In each plot, the PB vectors for recognized sentences in the bound linguistic module (a), the PB vectors for training behavioral sequences in the bound behavioral module (b), and the averaged PB vectors of (b) over each behavioral category (c) are plotted. All the plots are projections of the PB spaces onto the same surface determined by the PCA method.

and “right”, are quite close in the space. This is due to the fact that those pairs of nouns have the same meaning in the behavioral context in the current task.

Based on these observations, one may conclude that certain generalizations are achieved in recognizing sentences and generating behaviors by self-organizing ade-

Fig. 10. A user is interacting with the Sony humanoid robot QRIO SDR-4XII.

quate structures in the PB mapping, utilizing both linguistic and behavioral constraints.

6. Imitative interactions between a humanoid robot and users

The last experiment introduced in this review paper is about man-machine interactions using a small humanoid robot developed by Sony Corp. We will discuss the issues of the joint attentions as well as turn taking based on this experiment.

6.1. *Model and task setting*

The Sony humanoid robot QRIO SDR-4XII have been used as the experimental platform in the 1st experiment (see Figure 10).

In this experiment, the robot learns multiple movement patterns shown by user's hand movements in the learning phase. The RNNPB shown in Figure11 (a) learns to predict how the positions of the user's both hands change in time in terms of the sensory mapping from s_t to s_{t+1} and also it learns how to change the motor outputs correspondingly in supervised ways. The positions of the user's hands are sensed by means of color tracking of colored balls in his or her hands. In the interaction phase, when one of learned movement patterns is demonstrated by the user, the robot arms are expected to move by following the pattern. When the hand movement patten is switched from one to another, the robot arm movement pattern should switch correspondingly. This sort of on-line adaptation can be done by conducting the generation and the recognition processes simultaneously as a mirror system (see Figure11 (b)). When the prediction of the user's hand movement generates error, the PB vector is updated toward directions of minimizing the error in real time while the motor outputs are generated depending on the current PB values.

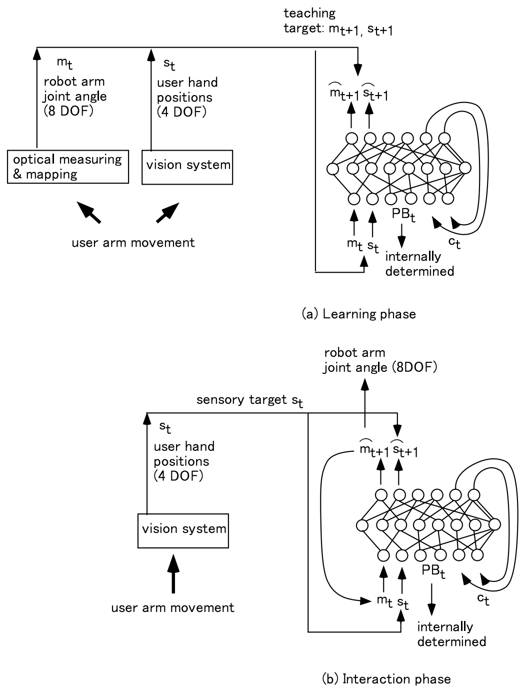

Fig. 11. System configurations in learning phase (a) and interaction phase (b).

The results of the experiment are plotted in Figure 12. It is observed that when the user hand movement pattern is switched from one pattern to another, the patterns in the sensory prediction and the motor outputs are also switched correspondingly by accompanying substantial shifts in the PB vector. Although the synchronization between the user hand movement pattern and the robot movement pattern is lost once during the transitions, the robot movement pattern is re-synchronized to the user hand movement pattern within several steps. The experiments also showed that the patterns once synchronized were preserved robustly against slight perturbations in the repetitions of the user's hand movements. Our further analysis concluded that the attractor dynamics system with its bifurcation mechanism by the PB makes the robot system to be manipulatable by the users as well as robust against possible perturbations.

6.2. *Mutual imitation game*

The previous experiments focused mainly on the adaptation in the robot side. We conducted another experiment which focus on bi-directional adaptation in mutual interaction between the robot and users. In this new experimental set-up, after the robot learns multiple movement patterns in the same way as described previously, subjects who are ignorant of what the robot learned are faced with the robot.

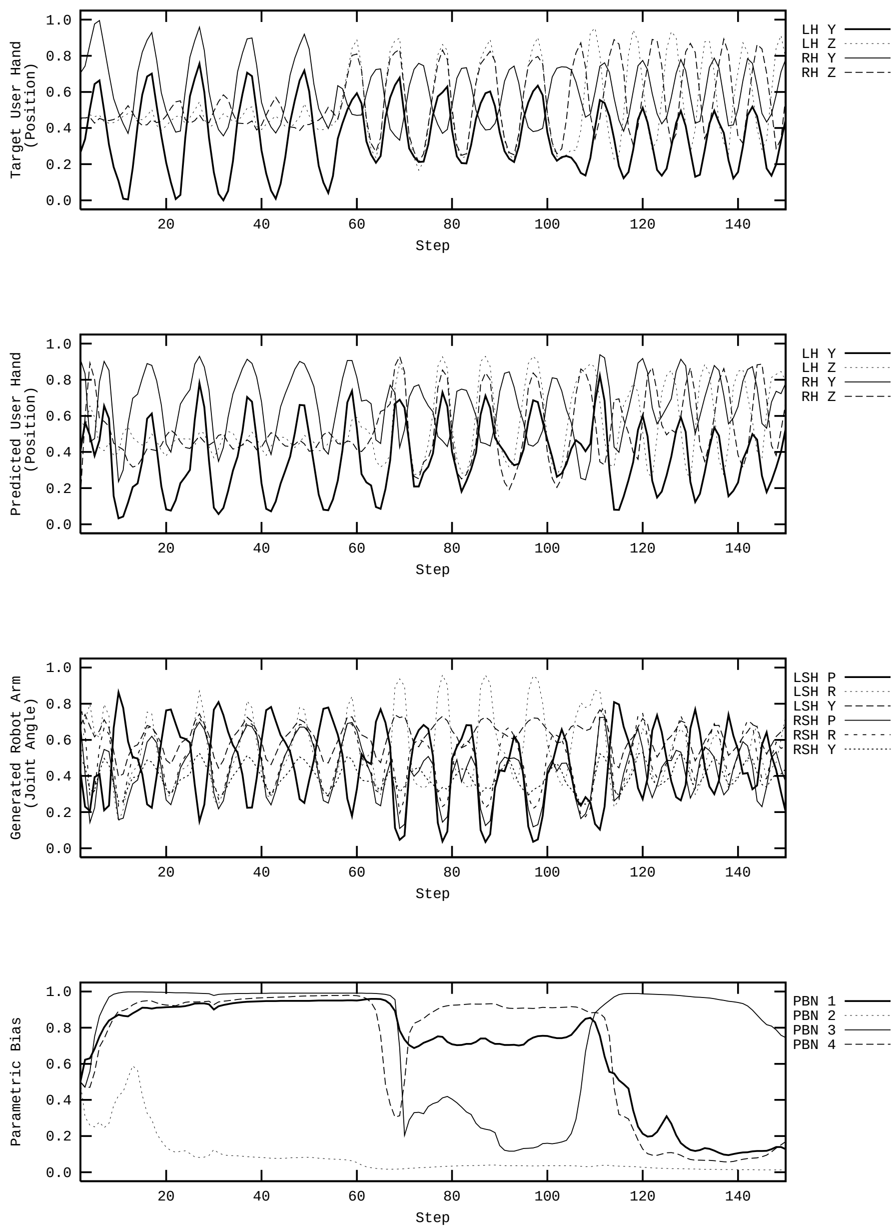

Fig. 12. Switching of the robot movement pattern among three learned patterns as initiated by switching of user hand movement. User hand position and its prediction by the robot are shown in the first and the second row, respectively. The third row an the fourth row show motor outputs and PB vector, respectively.

The subjects are then asked to find as many movement patterns as possible for which they and the robot can synchronize together by going through exploratory interactions. Five subjects participated in the experiments. Although most of the subjects could find all movement patterns by the end, the exploration processes were not trivial for the subjects.

There are interesting points in this new experiment as compared to the previous one. First, the master-slave relation, which was fixed between the subjects and the robot in the previous experiments, is no longer fixed but is instead spontaneously switched between the two sides. Second, there are autonomous shifts among synchronized patterns between the robot and the subject. Once a synchronized pattern is achieved which, after while, breaks down, and then another pattern of synchronization appears. One example of the interaction in imitation game is plotted in Figure 13. It is observed that joint attention to a certain movement pattern between the

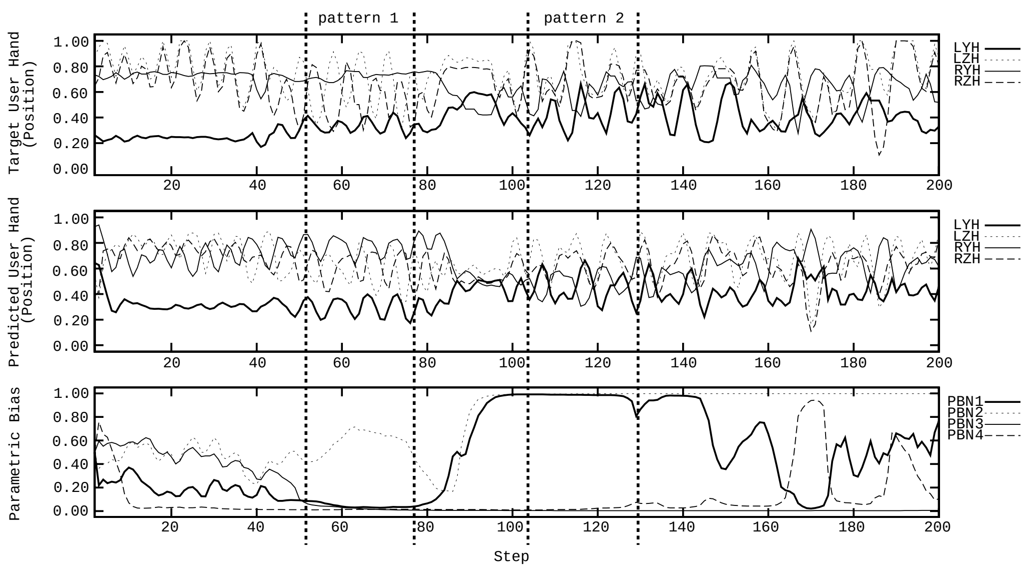

Fig. 13. Joint attention as synchronization between the robot and the subject in imitation game. User hand position and its prediction by the robot are shown in the first and the second row, respectively. The third row shows PB vectors of the RNNPB.

robot and the subject as synchronization is achieved after some exploratory phase. It is also observed that this joint attentional state is break down once but joint attention to another pattern is achieved again.

We speculate that appropriate analysis of these observed phenomena might shed a ray of light on the mechanism of joint attention as well as turn taking behaviors (Baron-Cohen, 1996; Moore & Corkum, 1994) . Although joint attention itself might be explained simply by synchronization (Andry, Gaussier, Moga, Banquet, & Nadel, 2001; Ijspeert, Nakanishi, & Schaal, 2003), a more interesting question is how a joint attention can break down and flip to another one spontaneously as well as how the roles of following and followed turn take autonomously between the robot and the subject. We propose that the coexistence of stable and unstable characteristics in the system dynamics might be the main cause for the spontaneous shifts. The stability originates from the synchronization mechanisms for shared memories of movement patterns between the robot and the subjects while the instability arises from the potential uncertainty in predicting each other's movements. (The subjects cannot be completely sure about the pre-learned patterns of the robot and the robot cannot predict well subject's own minded patterns.)

In the mutual interaction experiments, most of the subjects reported that they occasionally felt as if the robot had its own "will" because of the spontaneity in the generated interactions. It is speculated that the spontaneity originated from the total system dynamics including the users in the loop might play an important role in attracting people to play with entertainment robots.

7. Discussion and summary

The current paper reviewed the RNNPB, which can learn multiple behavior schemata distributively encoded in a single network. The scheme is characterized by the PB vector, which plays essential roles both in generating and recognizing patterns as a mirror system by self-organizing adequate structures internally. The model was implemented in three different robot platforms. Learning to generate different types of dynamic movement patterns, chunking by organizing multiple levels, linguistic-behavior binding and imitative interactions were demonstrated.

The hallmark of the current study was explaining how internal memory structures self-organized, and how such structures could account for the compositionality, generalization and behavioral diversity observed in each experiment. The proposed scheme differs significantly from the localist scheme in this aspect. In the localist scheme, no structures exist for memory organization since each behavioral schema is memorized as an independent template in a corresponding local module. On the other hand, in the proposed distributed representation scheme, learning is considered as not just memorizing each template of behavior patterns, but as reconstructing them by extracting the structural relationships among them.

Nevertheless, it is also true that local representation schemes have their advantages. They have fewer memory interference problems (McCloskey & Cohen, 1989). Such a characteristic is advantageous when the system is required to learn in a dynamic environment (Wang & Yuwano, 1996). One important future research direction is to explore an intermediate representation scheme between the two extremes of distributed and local representations. The degree of distribution in the representation might be controlled by modulating the sparseness of activated neurons in the network. If the activations become more sparse, the overlap of activated neurons among learned patterns becomes smaller, possibly reducing interference between them. The degree of distribution should be determined in the trade off between generalization and fast learning capabilities. Such learning schemes should be investigated in future studies.

Another important issue which is missing in the current studies is the "goal-directedness" in generating or recognizing behaviors. Although the current implementation has achieved only trajectory level repetitions of given movement patterns, its extensions to imitation through understanding others' goals as well as one's own (Tomasello, 1999) are important future research topics. It is also true that many mirror neurons are found in rather goal-directed task settings, where they seem to encode not exact movement patterns, but their abstraction or goals (Rizzolatti et al., 1996). Although it is speculated that our proposed level structured scheme might be able to achieve such abstraction, further intensive studies should be required.

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