Embodied language project

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In this study, we attempted to bind the simple linguistic processes of combining verbs, objects, and the simple behavioral processes of object-related actions by using the RNNPB scheme (Sugita & Tani, 2003). The study was inspired by Arbib (2002)'s hypothesis that mirror neurons, which become active both for generating and recognizing object handling behaviors, play crucial roles in language development, especially in pairing verbs and objects.

Modeling and task setting

Figure 1 (a) illustrates the RNNPB scheme used in the co-learning of 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 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 1 (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 2, 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. (See Figure 2 (b) for a trained trajectory corresponding to "HIT red".) 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

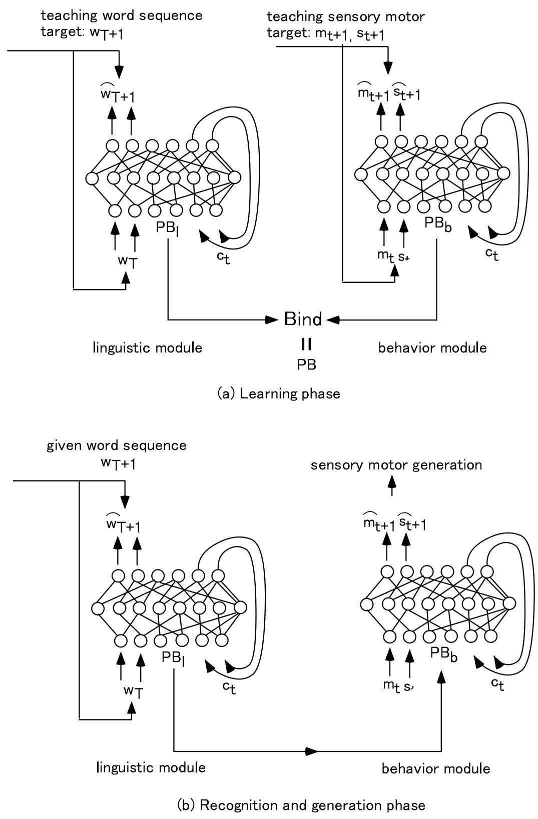

Figure 1: (a) Model for co-learning of word sequences and corresponding behaviors, (b) model for recognizing word sequences and generating corresponding behaviors.

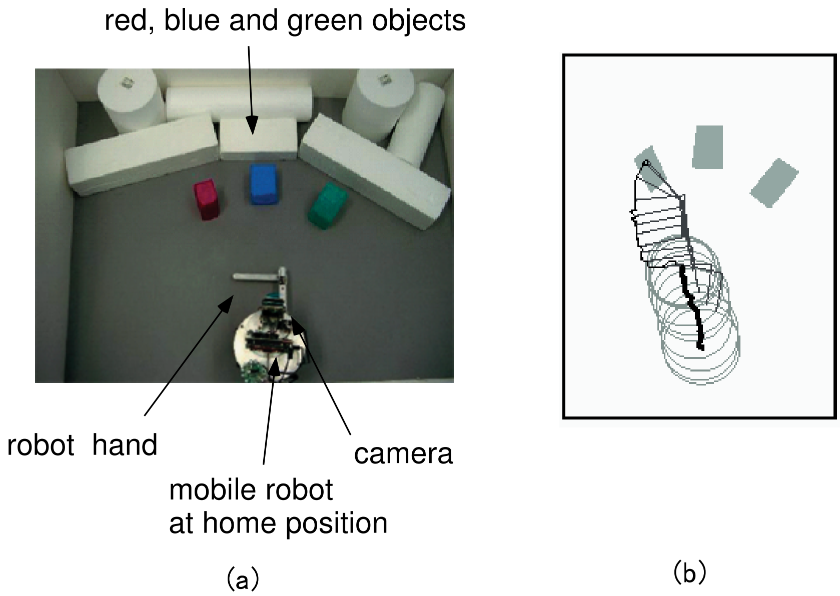

Figure 2: (a) The task environment consists of red, blue and green objects placed in left, center, and right positions, respectively. The mobile robot is at the starting position. (b) A trained behavior trajectory of "HIT red".

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.

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 3 (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 3 (b) shows the PB_b vectors that are determined for 90 behavior sequences in the co-learning phase. Figure 3 (c) shows the averaged PB_b vector for each of 9 behavior categories.

There are some interesting findings in these figures. First in Figure 3 (a), two

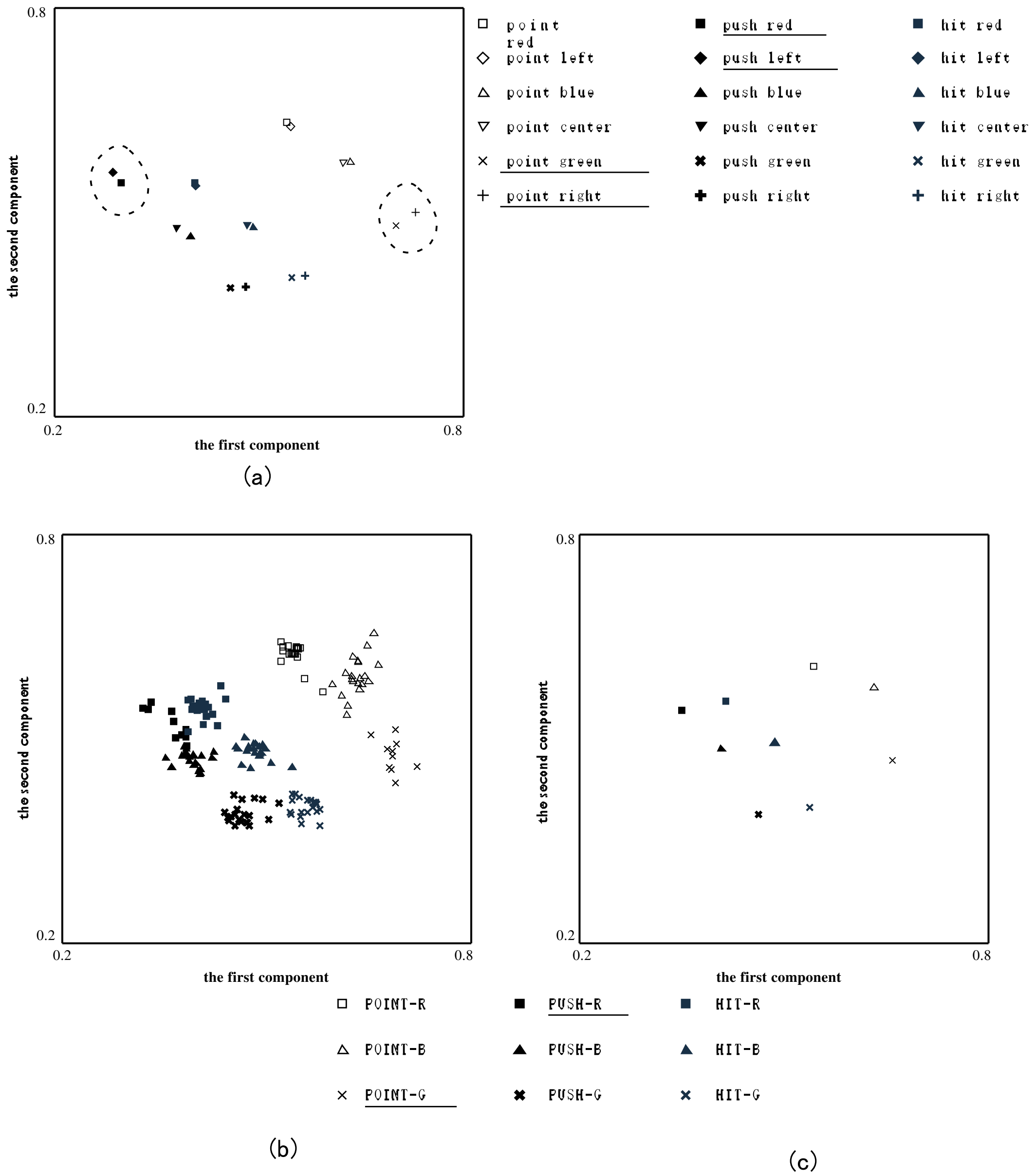

Figure 3: In each plot, the PB vectors for recognized sentences in the bound linguistic module (a), the PB vectors for training behavioral sequences in the bound behavioral module (b), and the averaged PB vectors of (b) over each behavioral category (c) are plotted. All the plots are projections of the PB spaces onto the same surface determined by the PCA method.

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 3 (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 3 (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. 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 3 (a), the PB points for pairs of sentences ending with "red" and "left", "blue" and "center", and "green" 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 adequate structures in the PB mapping, utilizing both linguistic and behavioral constraints.

References

Arbib, M. (2002). The mirror system, imitation, and the evolution of language. In *Imitation in animals and artefacts* (pp. 229–280). Cambridge: MIT Press.

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