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Articulation of Sensory-Motor Experiences by "Forwarding Forward Model": From Robot Experiments to Phenomenology

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Abstract

This paper introduces the so-called "Forwarding Forward Model" network that explains how complex behavior can be learned and generated while its sensory-motor flow is hierarchically articulated. This model is characterized by a distributed representation of behavior primitives at each level, which contrasts with our prior models utilizing localist views. The model was examined through experiments using a 4-degrees of freedom arm robot with a vision system. The experimental results showed that behaviors can be generated both robustly and flexiblely going through the bottom-up and the top-down interactions between levels. The characteristics of the distributed representation are discussed. Our discussion is further extended to the phenomenological issue of subjective time perception. A novel idea for explaining the sense of "nowness" is derived by applying our idea of articulating experiences to Husserl's notions of retention and protention.

1 Introduction

It is generally understood that higher-order cognition involves structural information processing which deals with the level of abstraction. For motor systems, it is generally assumed that the lower level system stores motor primitives and the higher level manipulates them for generating complex behaviors [1] [2]. Previously, we proposed a neural network model [3] which is characterized by modular and level structures. Through the learning processes, each primitive for the sensory-motor representation and their abstract representation is self-organized in a local module in the lower and the higher levels, respectively.

In contrast with this localist scheme, the current study introduces a novel scheme, namely "Forwarding Forward model" (FF-model), which emphasizes its distributed representation scheme. The FF-model is characterized by two levels of forward models which interact with each other. The lower level forward model learns to generate various sensory-motor sequences with self-associating values of the so-called parametric bias. Multiple sensory-motor spatio-temporal patterns are distributedly represented in the lower level forward model where each sensory-motor profile can be evoked by switching of the parametric bias values. When the parametric bias is changed, the dynamic pattern generated in the lower level forward model changes structurally. This is analogous to the way that dynamical structures of nonlinear systems bifurcate as their parameters change. (Note that the time constant of the parametric bias change is much slower than that of the sensory-motor flow.) The higher level forward model, on the other hand, learns to generate the sequential changes of the parametric bias by which the desired sensory-motor sequence can be produced in the lower level.

Our experiment will clarify how complex behaviors are both recognized and generated as "articulated" through learning in this distributed representation scheme. Here, "articulated" means that the sensory-motor flow is recognized/generated as segmented/combined with reusable pieces or chuncks. It will be also shown that the bottom-up and the top-down interactions between levels are essential to generate both robust and flexible behaviors.

In the discussion, we attempt to make correspondences between our technical discussions and phenomenology, as we have been inspired by the neurophenomenology research program proposed by Varela [4]. More specifically, we will apply our ideas of the sensory-motor articulations to the phenomenological discussions of subjective time. By applying our dynamical systems views to Husserl's ideas of retention and protention in the formulation of a sense of "nowness", a novel view of nowness is introduced.

2 Model

We explain our model briefly. Figure 1 shows our proposed neural network architecture. The main architecture on the left-hand side consists of two Jordan-type recurrent neural nets (RNNs) [5] which correspond to

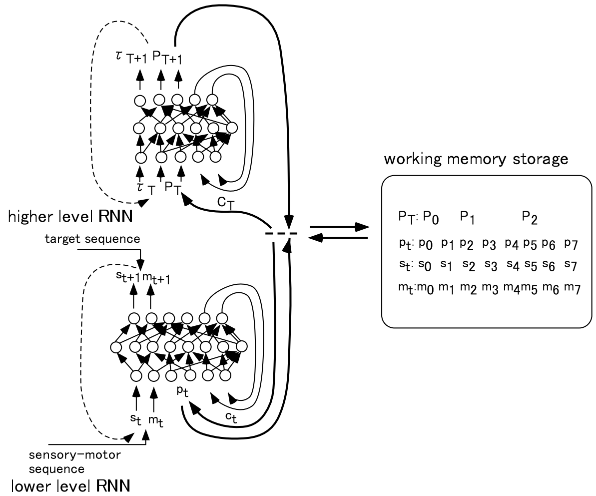


Figure 1: The FF-model utilizing two levels of RNNs.

the lower and the higher level networks. These RNN networks are operated through utilizing the working memory storage shown on the right-hand side of the figure. In the main architecture, the lower level RNN receives two types of input. One type is the vector of the current sensory-motor values (s_t, m_t); the other is the vector of the current parametric bias p_t. This RNN outputs the prediction of the sensory-motor values at the next time step $(\hat{s_{t+1}}, \hat{m_{t+1}})$. On the other hand, the higher level RNN receives p_t as inputs, then outputs its prediction at the time step $t+1$. It is also noted that the connection of p_t between the lower and the higher levels is bi-directional depending on the operational processes. The working memory storage is used to store the sequences of the parametric bias and the sensory-motor inputs/outputs where computation of regression as well as motor planning take place as will be described later.

In the top-down process, the sequence of p_t is generated in the higher level RNN by means of its forward dynamics and its sequence is fed into the parametric bias units in the lower level RNN. Then, the lower level RNN generates the sensory-motor sequence as corresponding to the inputs of p_t. As will be described later, p_t tends to change stepwisely from time to time in the sequence. Such stepwise changes in p_t cause dynamic changes of the sensory-motor profile generated in the lower level. It is said that command-like signals of p_t sent from the higher level trigger to generate detailed sensory-motor flows in the lower level. The higher level is said to play a role of the 2nd order forward model, as its forward model learns to predict how characteristics of the lower level forward model changes in terms of the parametric bias. With closing the loop between the outputs of the sensory-motor state and its inputs, lookahead prediction is made for future sensory-motor sequences in the lower level. This mechanism is utilized for generating motor program.

The bottom-up processes are utilized in the processes of recognizing its own sensory-motor sequence experienced from certain steps before to the current step. Now, let us consider that the system experiences a sensory-motor sequence while its arm is moved with a specific patten through manual guidances. If the system already learned this pattern previously, the lower level RNN can re-generate this target sequence with adapting the parametric bias sequence to adequate one. The sequence of p_t is searched by means of the inverse problem of minimizing the errors between the target and output sequences with the smoothness constraints on the p_t sequence. Actually, p_t is obtained by back-propagating the error obtained during the regression and the delta error in the parametric bias node is utilized to update p_t. Here, the details of the update mechanism is described more specifically. The temporal profile of p_t in the sequence is computed via the back-propagation through time (BPTT) algorithm (Rumelhart, Hinton, & Williams, 1986), utilizing the sequence of the internal values of the parametric bias ρ_t, the target and the regenerated outputs of the sensory-motor sequences in the working memory storage. The total number of steps of these sequences in the working memory is L_p. For each iteration, the forward dynamics of the RNN are computed for L_p steps through establishing closed sensory-motor loops. Once the L_p steps of the sequence are regenerated, the errors between the regenerated outputs and the target ones are computed and then back-propagated through time in order to update the values of the parametric bias at each step in the sequence. The update equations for the ith unit of the parametric bias at time t in the sequence are:

$$\delta{\rho_t}^i = k_{bp} \cdot \sum_{t-l/2}^{t+l/2} {\delta_t^{bp}}^i + k_{nb}(\rho_{t+1}^i - 2\rho_t^i + \rho_{t-1}^i) \quad (1)$$

$$\triangle\rho_t^i = \epsilon \cdot \delta{\rho_t}^i + \eta \cdot \triangle\rho_{t-1} \quad (2)$$

$$p_t^i = sigmoid(\rho_t/\zeta) \quad (3)$$

In Eq. (1) the δ force for the update of the internal values of the parametric bias ρ_t^i is obtained from the summation of two terms. The first term represents the delta error δ_t^{bp} back-propagated from the output nodes to the parametric bias nodes which is integrated over the period from the $t-l/2$ to the $t+l/2$ steps. By integrating the delta error, the local fluctuations of the output errors will not affect the temporal profile of the parametric bias significantly. The parametric bias should vary only corresponding to structural changes in the sensory-motor sequences. The second term plays the role of a low pass filter through which frequent rapid changes of the parameter values are inhibited. ρ_t is updated by utilizing the delta force obtained from the steepest descent method, as shown in Eq. (2). Then, the current parameters p_t are obtained by means of the sigmoidal outputs of the internal values ρ_t. A parameter ζ is employed such that the gradation of the parametric bias can be controlled. With setting ζ as relatively small values, the parametric bias tends to have more extreme values of either near to 0 or near to 1. Its value changes stepwisely only when the profile of the sensory-motor flow changes significantly.

When the robot actually behaves, the motor plan for the future L_f steps is generated in the top-down process while the past L_p steps sensory-motor sequence is regressed in the bottom-up process as described above. These computation of regression and planning are conducted as on-line iteratively for the window of $L_p + L_f$ steps which is shifted to forward at each time step while the robot actually behaves. Since this regression of the past can re-interpret and update p_t sequence, the on-line planning for future, which depends on the p_t sequence, can be generated as contextually depending on the past. The actual p_t from the past to the current step is determined utilizing both forces of the top-down prediction and the bottom-up regression with k_{top} as an arbitration coefficient between these two.

Finally, the learning is a process to search for optimal synaptic weights in both of the lower and higher level RNN and the parametric bias sequences by which the target teacher sensory-motor sequences (given through the manual guidances) can be regenerated in the outputs with minimum errors. Firstly, the lower level RNN is trained with a set of target teacher sequences. After determination of corresponding p_t sequences and the synaptic weights, the higher level RNN is trained to be able to regenerate these p_t sequences. For the reason of simplifying the learning scheme, p_t sequence is segmented with their stepwisely changing points and the resultant segmented sequence of P_T is learned associated with each segment step length τ_T in the higher level. The update of the synaptic weights are conducted by utilizing the back-propagation through time algorithm [6]. The update of the parametric bias sequence follows Eq. (2).

3 Experiments

We utilized an arm robot with 4 degrees of freedoms equipped with a vision system as shown in Figure 2. The arm sweeps horizontally on the surface of the task table on which a colored object is located. The positions of the object as well as the arm hand are perceived by a real time vision system. A handle is attached in the arm top by which the trainer can guide the arm for specific behaviors.

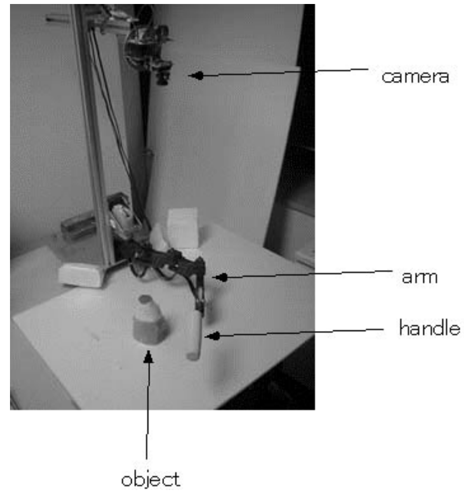
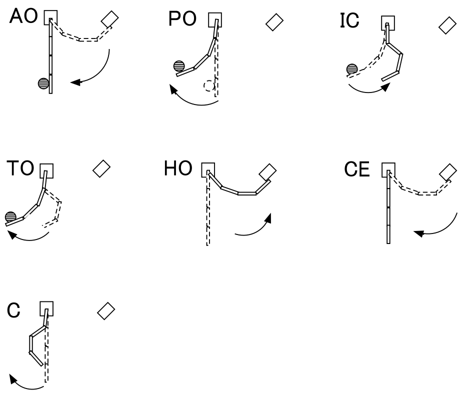


Figure 2: The arm robot.

We conduct three types of experiments. In the first experiment we examine how the robot learns to generate a set of behavior patterns by focusing on the ways of self-organizing primitive representations in the network. Nextly, we examine how the system can imitate to generate novel behavioral patterns by combining the pre-learned primitives. In the last experiment, we investigate how the motor plans can be dynamically modified in the course of their execution in response to situation changes in the environment. This experiment provides us with an opportunity to examine the roles of the bottom-up and the top-down interactions in on-line behavior generation.

These experiments are conducted using the proposed neural network model of the same specification. The network sizes as well as the parameters were determined by try and error base in order to find robust conditions for the robot experiments. The lower level RNN has 8 input nodes which are allocated for the 4 motor positions of the arm and the two dimensional cartesian positions of the hand and of the object obtained through the video camera image processing, for the current time step. The output nodes are allocated in the same way as the input nodes, but with the values for the next time step. All values are normalized to between 0.0 and 1.0. The lower level RNN has 20 hidden nodes and 8 context nodes. It also has 4 parametric bias nodes in the input layer. The higher level RNN has 4 input and output nodes which are allocated to the parametric bias of the current and the next time step respectively; it also has 10 hidden nodes and 6 context nodes.



(a)

(1) AO–PO–IC–TO–HO
(2) AO–PO–IC–TO–IC–TO–HO
(3) AO–PO–HO
(4) AO–HO–AO–HO–AO–HO
(5) CE–C–CE–HO
(6) CE–C–CE–C–HO
(7) CE–HO–CE–HO

(b)

Figure 3: (a)A set of primitive behaviors and (b) the behavior sequences learned to imitate.

3.1 Learn to articulate

Before the first learning experiment, the trainer prepares a set of primitive behaviors , as shown in in Figure 3(a), for which he himself practices to guide the robot arm until his manual guidances become stable enough. Those primitives are AO: approach to object in the center from the right-hand side, PO: push object from the center to the left-hand side, IC: perform inverse C shape, TO: touch object, HO: back to home position, CE: go to the center from the right-hand side, and C: perform C shape. Then, the robot is guided with seven sequences as shown in Figure 3(b) each of which is generated by combining the primitives prepared in sequences. Note that the training sequences are carefully designed such that they do not include any deterministic sub-sequences of the primitives. For example, after AO either PO or HO can follow. If PO were always to follow after AO, the AO-PO sequence could be regarded as an alternative primitive. The objective of this experiment is to investigate how the system seeks the segmentation structures hidden in the training sequences by self-organizing primitives in the proposed network architecture.

The learning experiments are repeatedly conducted for various integration step lengths l since this parameter is assumed to affect significantly the ways of segmenting the sensory-motor flow. We examined how the behavioral primitives are acquired as articulated in the training patterns by observing the relationship

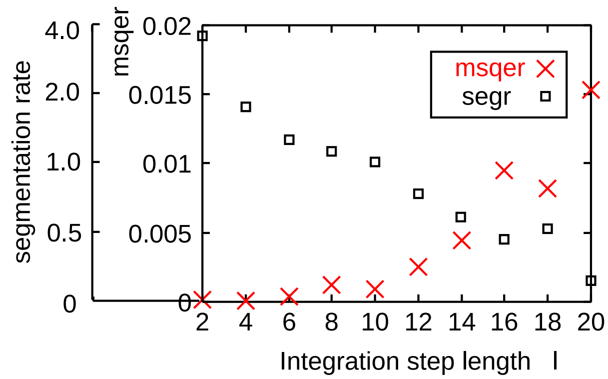


Figure 4: The mean square error (msqer) and the segmentation rate (segr, logscale) plotted as a function of l in the repeated learning trials.

between the training error and the segmentation rate with parameter l variation. The segmentation rate is calculated as the average ratio of the actual number of the segments generated in the learning processes to the actual numbers of primitives combined in the training sequence patterns. The results are plotted in Figure 4 in which the mean square error and the segmentation rate (on a log scale) are plotted as a function of the integration step length. It is observed that the mean square error becomes higher and the segmentation rate becomes lower as the integration step length increases. This means that the learning error can be minimized if fragmentation of the segmentation is allowed to be generated, while the error with typically increase if such fragmentation is not permitted through control of the parameter l.

We inspect the results in more detail for the case in which l is set to 6, as a representative example. Figure 5 shows how the parametric bias is activated in the learning results, for three of representative training sequences. The plots in the top row in this figure show the activation of four parametric bias units as a function of the time step; the activation values from 0.0 to 1.0 are represented using the gray scale from white to black, respectively. The plots in the second and the third rows represent the temporal profile of motor and sensor values for each training sequence. The vertical dotted lines indicate the occurrence of segmentation when the behavior sequence switches from one primitive to another in generating the training sequence. The capital letters associated with each segment denote the abbreviation of the corresponding primitive behavior. In this figure, it is observed that the switching of bit patterns in the parametric bias takes place mostly in synchronization with the segmentation points known from the training sequences although it is observed that some segments are fragmented. Our examinations for all the trained sequences showed that the bit patterns in the parametric bias correspond uniquely to primitive behaviors in a one-to-one relationship in most cases.

3.2 Imitate novel combinations of the primitives

Next, we examine how the robot can imitate behavioral patterns which are prepared as novel combinations of the pre-learned primitive behaviors. Two behavioral patterns are prepared. Each behavioral pattern is taught in which only the connective weights in the higher level RNN are allowed to adapt, while those in the lower level RNN are unchanged, assuming that the internal representations for primitives are preserved in the lower level RNN. More specifically, the sequences of the parametric bias p_t are obtained by iterative computation using Eq. (1) for the lower level RNN in which the learning rate of the connective weights ϵ is set to 0.0. Subsequently, the higher level RNN is trained using the articulated sequences of the parametric bias P_T.

After the learning in the higher level RNN converges, the robot attempts to regenerate each behavioral pattern. The actual behavior of the robot is generated based on the scheme of the motor planning and regression processes described previously. Figure 6 shows the comparison of the temporal profiles between the taught patterns (the top row) and the regenerated patterns, as the robot actually behaves (the bottom row) associated with the sequence of the parametric bias (the middle row), for each sequence. It is observed that the sensory-motor profiles are successfully regenerated from the patterns taught without any significant discrepancies. These results suggest that the robot successfully learned to generate the guided behavior sequences as articulated.

3.3 On-line motor plan modification

In the next experiments, the characteristics of on-line motor plan adaptation are examined by focusing on the bottom-up and the top-down interactions. The robot is trained with two different behavioral patterns each of which is associated with a specific environmental situation. The training is conducted only for the higher level RNN while the synaptic weights in the lower level RNN are preserved as acquired in the previous experiment. The first behavior is that the arm repeats a sequence of approaching to touch the object and then returning home while the object is located in the center of the task space. The second behavior is that the arm repeats a sequence of centering, making a C-shape, and then returning home while the object is located to the left-hand side of the task space.

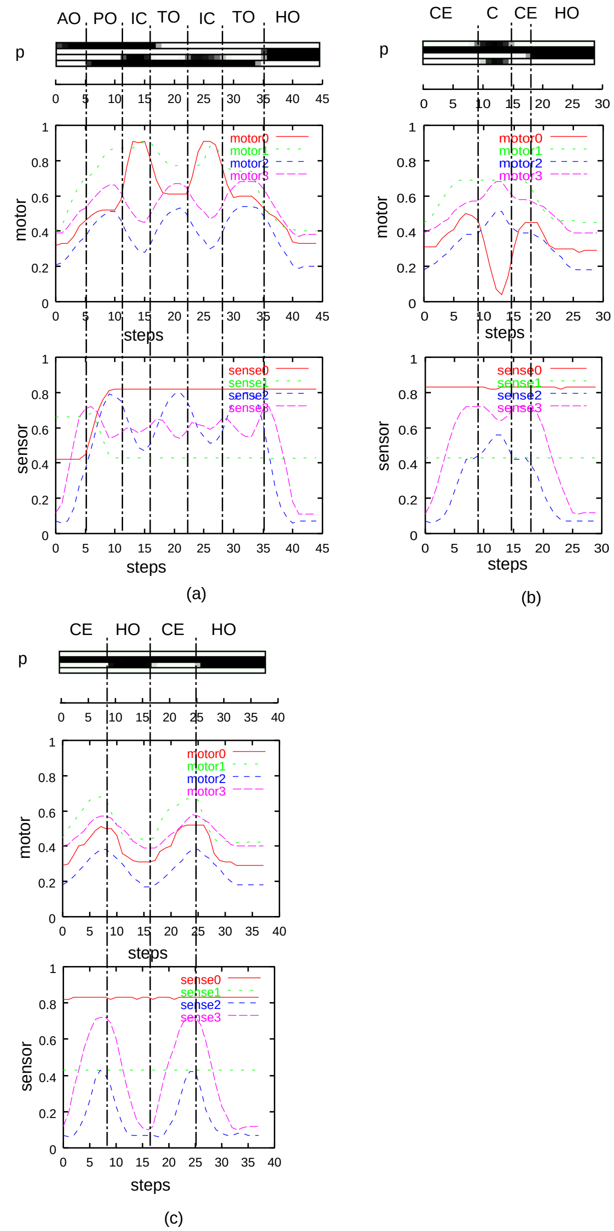


Figure 5: For the three representative training sequences (a)-(c), the temporal profiles of the parametric bias, the motor outputs are plotted in the second row and the sensor inputs are plotted in the third row. The vertical dotted lines denote occurrence of segmentation when the primitive behaviors switched. The capital letters associated with each segment denote the abbreviation of the corresponding primitive behavior.

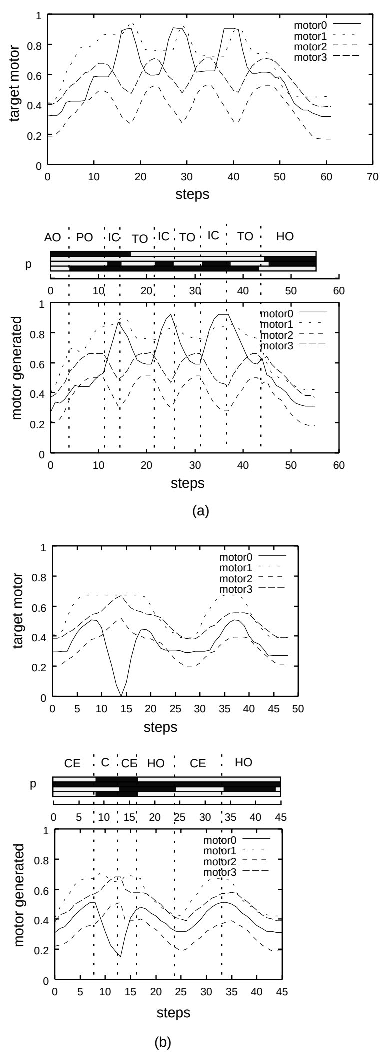


Figure 6: Two of imitated sequences.

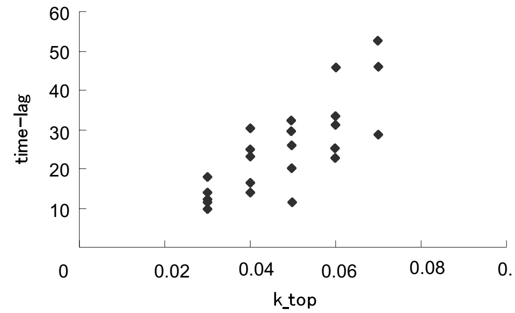


Figure 7: The time lag in the behavior switching plotted as a function of the top-down coefficient k_{top}.

The test is then to examine how the behavioral patterns are switched between when the position of the object is suddenly moved from the center to the left-hand side of the task space in the middle of executing the first behavior. As the position of the object is moved, certain errors are generated in the prediction of the visual sensory inputs in the lower level RNN as a result of which the parametric bias tends to be modulated in the bottom-up way while the higher level RNN continues to proceed with the current behavior pattern, generating the same top-down signal for the parametric bias. Here, we expect to observe a transient dynamic during the switching as caused by interactions between the bottom-up and the top-down processes for determining the parametric bias.

As it is assumed that the balance between the top-down and the bottom-up processes affects the system's behavior to a large extent, the experiments on behavior switching are conducted repeatedly, changing the strength of the top-down effects by varying the coefficient k_{top} from 0.0 to 0.1 with 0.01 increment. In particular, we examine the smoothness of the behavior switching by observing the time lag from the moment the object is moved to the moment when the second behavior is activated. The switching trial was repeated for 5 times for each setting of k_{top} value. Other conditions such as the timing of the object move were set as the same for all the trials. Figure 7 shows the plot of the time lag versus the coefficient k_{top}.

It was observed that the first behavior pattern was not accomplished when k_{top} was set to less than 0.03: the parametric bias was not activated as learned since the top-down force was too weak. When the top-down behavior plan in terms of the parametric bias sequence is executed as on-line, the sequence was easily affected by even small predcition error in the lower level which was caused by noise in the robot operation. When k_{top} was set to between 0.03 and 0.07, behavior switching from the first behavior to the second behavior took place. There was a tendency that the time lag increased as k_{top} was increased. This indicates that the

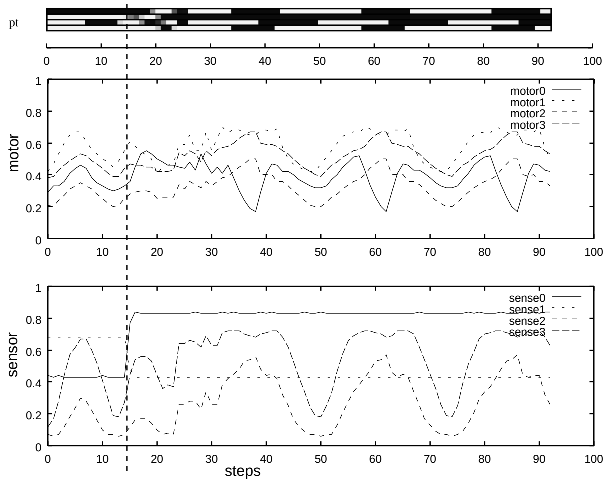


Figure 8: The temporal profiles of the parametric bias, the motor outputs and the sensory inputs in the behavioral switching trial.

motor plans tend to be less sensitive to the sensation of the situation changes in the environment when the top-down effects become larger, as expected. An important observation, however, is that there is relatively large distribution of the time lag for each k_{top} value. This suggests that the transient behavior patterns are generated diversely during the switching. When k_{top} was set to larger than 0.07, no behavior switching was observed. The parametric bias was not affected anymore by the bottom-up sensations since the top-down influence on the parametric bias was too strong.

Figure 8 shows the temporal profile of the behavior generated in the case where k_{top} was set to 0.05. The profiles of the parametric bias, the motor outputs and the sensor inputs are plotted in the top, in the second and in the third rows, respectively. The vertical dotted line denotes the moment when the object is moved from the center to the left-hand side of the task space. It is observed that it takes 20 steps until the second behavior pattern is initiated after the object is moved to the left-hand side. It is also observed that the parametric bias, the motor outputs as well as the sensory inputs fluctuate during this transition period. The fluctuation is initiated because of the gap generated between the top-down prediction of the parametric bias and the reality as it appears in the bottom-up process. The fluctuations in the parametric bias result in generating complex motor patterns in the lower level by means of the top-down pathway which turns out to generate the sensory prediction error that is again fed-back to the parametric bias by means of the bottom-up pathway. In the 5 times of repeated trials in this parameter setting, the profiles of the traisient patterns were never repeated, as have been suggested by the large distribution of the delay time. The observed fluctuation seems to play the role of a catalyst in searching for the diverse transition path from the steady attractor associated with the first behavior pattern to that for the second behavior pattern. Once the transition is complete, the second behavior pattern proceeds steadily.

4 Discussion

4.1 Distributed or local representation

There are continuing discussions about whether primitives should be represented locally or distributedly in the networks. Tani and Nolfi [3] as well as Wolpert and Kawato [7] showed localist view models in which complex behaviors could be decomposed into a set of reusable behavioral patterns each of which is stored in a specific local neural network module. Our FF-model contrasts with this localist view in a sense that various behavior primitives are represented in a distributed manner in a single RNN at each level. A specific difference between two schemes is that number of the primitives in the local representation scheme is constrained by the number of local modules while that in the distributed one is by the number of possible bit combination in the parametric bias. It is, furthermore, assumed that an infinite number of different patterns could be generated if the parametric bias is allowed to take a graded value. In such situation, it would be furthermore interesting to ask what type of mapping is generated between space of the parametric bias and that of the behavior pattern. It is intuitively assumed that patterns could be generated by linearly interpolating learned patterns by changing the parametric bias. However, our recent studies [8] showed that the attractor patterns bifurcates nonlinearly with the linear change of the parametric bias. It was found that the nonlinear interferences among trained patterns results in generating a distorted mapping between the parametric bias and the patterns to be generated. Therefore, diverse behavior patterns could be generated which cannot be explained by the linear interpolations of learned patterns. Such example was shown in the behavior generation during the transient period in the experiment of the behavior switching. It can be said that the diversity is gained by taking advantage of the nonlinear interferences caused by the distributed representation in the network.

Which is better between the distributed and the local representation scheme? This is supposed to be a trade-off problems between the diversity and the stability in generating and learning patterns. In the distributed representation, if a novel pattern is learned in the network, it cannot be avoided that this pattern interferes with the memory patterns stored previously to some extents, since each pattern shares the same resources in the network. On the other hand, although number of patterns generated could be limited to that of local networks in the localist scheme, learning of novel patterns would not affect the memory of previously learned patterns since they do not share the resources in the networks. Our future research goal is to explore possible scheme which reside in between these two extremes.

4.2 The subjective time

In this sub section, we attempt to apply our ideas of sensory-motor articulation to the phenomenological problem of subjective time perception. First of all, we would like to explain why our research, which mostly focuses on technical issues, has been extended to the region of phenomenology. The reason is that current disciplines such as neuroscience, cognitive modeling, and phenomenology seem to be not yet powerful enough to obtain satisfactory answers for various questions of cognition. For example, our modeling of sensory-motor articulation might seem to be plausible in the view of nonlinear dynamics cognitive modeling but we cannot expect to obtain neurobiological evidence for the scheme so soon. In such a situation, Varela [4] proposed the so-called neurophenomenological hypothesis which states as follows: *Phenomenological accounts of the structure of experience and their counter parts in cognitive science relate to each through reciprocal constraints.* He considered that the following three ingredients play equally an important role: (1) the neuro-biological basis, (2) the formal descriptive tools from nonlinear dynamics, and (3) the nature of lived temporal experience studied under phenomenology. He expected that mutual interactions among those three, where effects of constraint and modification can circulate effectively, could induce substantial novelty in the exploration of lived cognition. Following this idea, we conducted reciprocal analysis between the neuro-mechanism of articulation and the experiences of subjective time.

Our question is that how we sense the temporality in our experiences. The major agreement concerning the time perception in phenomenology is that time does not flow like linear sequence as defined in physics, but having complex texture and structures [9]. Such complex structures are apparent in our awareness of the present. William James [10] pointed out the apparent paradox of human temporal experience as: on the one hand there is the unity of the present, an aggregate we can describe where we reside in basic consciousness, and on the other hand this moment of consciousness is inseparable from a flow, a stream. Intuition is that although "nowness" is perceived as a static concrete object, it is still a part of flow. Consider video, where each frame is a distinct object but also part of the larger sequence.

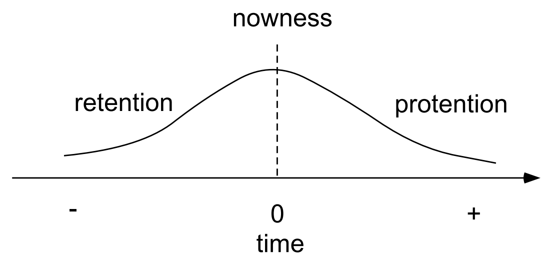


Figure 9: Husserl's idea of retention and protention. The nowness includes fringes of the immediate past and future while the physical present time is a point denoted by the dotted line.

Husserl [11] introduced an idea of retention and protention for explaining this paradoxical nature of "nowness". He used an example of hearing a sound phrase as like "Do Mi So" for explaining the idea. When we hear the note of "Mi", we would still perceive lingering impression of "Do" and at the same time we would anticipate to hear the next note of "So". The former is called as retention and the latter as protention. Those terms are to designate the dynamics that follows impression in the present which intends the just-past and the immediate future. Those effects are a part of automatic processes and they cannot be controlled consciously. Husserl considered that the subjective experience of "nowness" are extended to include fringes both in the past and the future in terms of the retention and pretension. (Figure 9 shows a sketch for this idea.)

After coming to understand Hussearl's idea of "nowness", a question is arisen. We ask where the "nowness" is bounded? Husserl seems to argue that immediate past does not belong to a *re-presentational* conscious memory, but just to an impression. Then, how can the immediate past which is experienced just as impression slip into a distant past which can be evoked only through conscious memory retrieval? What kind of mechanism qualitatively changes an experience as from just impression to consciously retrieval episodic memory? Here, we consider that the idea of the articulation could be a key to answer the question. Our main idea is that the "nowness" can be bounded where the flow of experience is articulated. A sequential notes of "Do Mi So" constitutes a chunk within which a perfect coherence is organized in the coupling between the neural dynamics and the sound stimulus flow. Within the chunk, everything proceeds smoothly, automatically and unconsciously. However, when we hear a next phrase of "Re Fa La" after "Do Mi So", a temporal incoherence emerges in the transition between two phrases since this second phrase is not necessarily predictable from the first one. In our neural network model, the prediction error is generated at this moment which triggers the stepwise change in the parametric bias, then after a coherent state is achieved again in the system. It is supposed that at the very moment of this transition from one chunk to another, the system becomes conscious about passing of time in terms of event transition.

Our argument could be clarified further more when the issue is discussed as related to the notion of the momentary self [10]. William James [10] considered that we are conscious about ourselves not continuously in time but only discontinuously. This observation would correspond to Strawson's [12] view in which he suggests the image of a string of pearls, as an image of a self. He claims that each self should be considered as a distinct existence, an individual thing or object, yet discontinuous as a function of time. This unity of momentary self can be interpreted as the dynamical state of coherence in our system, as have been discussed also in [13]. And when the system state become incoherent where the flow is segmented, we first time becomes conscious about this unity which has already become a part of retrieval episodic memory. It can be said that the nowness is noticed only in a posterior manner after that part of flow is articulated into consciously manipulable object.

One of Husserl's goal was to explain the emergence of the objective time from the immanent time of the retention and protention level [11]. Husserl seems to consider that the sense of objective time would emerge as a natural consequence when each experience has been organized into one line of consistent sequence. The idea seems to be applicable also to a question how a consistent self can be sensed not only for momentary experiences but also those extended in time [14]. An idea of so-called narrative self explains that a coherent self emerges through making his or her story by interweaving momentary episodes experienced in the past [15]. This idea, in an abstract sense, would be explained by the memory consolidation [16] known in neuroscience. It is said that each momentary experience once stored in the short-term memory are later transfered into the long-term memory where it is consolidated into a web of organized episodic memory. Our system level explanation for this is that the chunks segmented in the lower level are learned to be a line of sequence in the higher level network.

However, if we say that the higher level deals with the formation of consciously retrieval episodic memory, another problem would arise. Let us think that we repeatedly hear "Re Fa La" after "Do Mi So" as a sequence. In such case, we can think of generating a new chunk in the further higher level which ties these two phrases into a familiar sequence. Then, the problem is that when we hear the phrase of "Do Mi So", we would have retention of "Re Fa La". Question is that if the nowness is bounded inside of "Do Mi So", or "Re Fa La" is also included in the nowness in this situation. For this problem, we assume that nowness would be sensed hierarchically as like the experience can be articulated in multiple levels in our scheme. Let us suppose a situation that we hear a phrase "Ci Re So" instead of "Re Fa La" after "Do Mi So". Then, we would feel a sense of incompatibility in this new phrase which was not anticipated after "Do Mi So" and we would say that "now" I hear a strange phrase. However, it will be different if we hear a phrase like "Re Re Fa" in which the second note is generated by a mistouch. The sense of incompatibility comes from the note level in this situation and we would say that "now" I hear a strange note. Our discussion is that our sense of nowness could be directed in different levels depending on of which level coherence is broken. Since we recognize our experience as hierarchically articulated, the subjective time should have the corresponding hierarchical structures.

In the end of this section, our arguments are summarized. We considered that the phenomenology of the subjective time perception is deeply related to the sensory-motor level behavioral structure. In order to make sense of the world, the sensory-motor experience should be articulated structurally utilizing a set of reusable schema or primitives. The experience is consciously recognized at the very moment of switching between different schema. In other words, the present experience becomes a consciously manipulable object after it is articulated into an event. Therefor, we can sense "nowness" for such event only as a posterior manner. It is also natural to assume that the sense of nowness is organized in a hierarchy since the experiences are recognized utilizing the sensory-motor level hierarchical structures.

5 Conclusions

In this paper, we have proposed the FF-model which is characterized with its distributed representation scheme. Our experiment demonstrated that complex behavior can be learned and generated as articulated by self-organizing behavior primitives by utilizing the distributed representation scheme in the lower level. It was also shown that the bottom-up and the top-down interactions are essential for the system to adapt environment both robustly and flexiblely. We discussed that the proposed mechanism of the sensory-motor articulation would explain the phenomenology of the subjective time. It was explained that the nowness is sensed hiererchically as we recognize our experiences as articulated in multiple levels.

References

[1] E. Bizzi, N. Acornero, W. Chapple, and N. Hogan, "Posture control and trajectory formation during arm movements", *J. Neurosci.*, vol. 4, pp. 2738–2744, 1984.

[2] A. Feldman, "Superposition of motor programs, I. Rhythmic forearm movements in man", *Neuroscience*, vol. 5, pp. 81–90, 1980.

[3] J. Tani and S. Nolfi, "Learning to perceive the world as articulated: an approach for hierarchical learning in sensory-motor systems", in *From animals to animats 5*, R. Pfeifer, B. Blumberg, J. Meyer, and S. Wilson, Eds. Cambridge, MA: MIT Press., 1998.

[4] F. Varela, "Neurophenomenology: a methodological remedy for the hard problem", *J. of Conscious Studies*, vol. 3, no. 4, pp. 330–350, 1996.

[5] M.I. Jordan, "Attractor dynamics and parallelism in a connectionist sequential machine", in *Proc. of Eighth Annual Conference of Cognitive Science Society*. 1986, pp. 531–546, Hillsdale, NJ: Erlbaum.

[6] D.E. Rumelhart, G.E. Hinton, and R.J. Williams, "Learning internal representations by error propagation", in *Parallel Distributed Processing*, D.E. Rumelhart and J.L. Mclelland, Eds. Cambridge, MA: MIT Press, 1986.

[7] D. Wolpert and M. Kawato, "Multiple paired forward and inverse models for motor control", *Neural Networks*, vol. 11, pp. 1317–1329, 1998.

[8] J. Tani, "Self-organization of behavioral primitives as multiple attractor dynamics: a robot experiment", in *Proc. IJCNN'2002*, 2002, pp. ??–??

[9] F. Varela, "Present-Time Consciousness", *J. of Conscious Studies*, vol. 6, no. 2-3, pp. 111–140, 1999.

[10] W. James, *The principles of psychology*, Dover Publ. (reprinted 1950), 1890.

[11] E. Husserl, *The phenomenology of internal time consciousness, trans. J.S. Churchill*, Indiana University Press, Bloomington, IN, 1964.

[12] G. Strawson, "The self", *J. of Consciousness Studies*, vol. 4, no. 5-6, pp. 405–428, 1997.

[13] J. Tani, "An interpretation of the "self" from the dynamical systems perspective: a constructivist approach", *Journal of Consciousness Studies*, vol. 5, no. 5-6, pp. 516–42, 1998.

[14] S. Gallagher, "Philosophical conceptions of the self: implications for cognitive science.", *Trends. CogSci.*, vol. 4, no. 1, pp. 14–21, 2000.

[15] D. Dennet, *Consciousness explained*, Little Brown Co., 1991.

[16] L.R. Squire, N.J. Cohen, and L. Nadel, "The medial temporal region and memory consolidation: A new hypothesis", in *Memory consolidation*, H. Weingartner and E. Parker, Eds., pp. 185–210. Erlbaum, Hillsdale, N.J., 1984.