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Development of Compositional and Contextual Communication of Robots by using the Multiple Timescales Dynamic Neural Network

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***Abstract*— The current paper introduces neurorobotics experiment on acquisition of complex communicative skills with human via learning. A dynamic neural network model which is characterized by its multiple timescale dynamics characteristics was utilized as a neuronal model for controlling a humanoid robot. In the experimental task, the humanoid robot was trained to generate specific sequential movement patterns as responding to various sequences of imperative gesture patterns demonstrated by the human subjects by following predefined compositional semantic rules. The experimental results showed that (1) the MTRNN can learn to extract compositional semantic rules with generalization in the higher cognitive level, (2) the MTRNN can develop further higher-order cognition capability for controlling the internal contextual processes as situated to on-going task sequences without being provided with cues for explicitly indicating task segmentation points. The analysis on the dynamic characteristics developed in the MTRNN through learning indicated that the aforementioned cognitive mechanisms were achieved by developing adequate functional hierarchy by utilizing the constraint of the multiple timescale property and the topological connectivity imposed on the network configuration.**

***Index Terms*— Dynamic neural network model, Compositional semantics, Functional hierarchy, Higher-order cognition, Self-organization, Socially intelligent robot.**

I. Introduction

Recently, research on socially intelligent robots have drawn significant attention in both academia and industries [1-3]. Investigating theories and methods for developing robots that can perform human-level interactions with other agents is the major interest of the aforementioned research [1]. Those research on socially intelligent robots have been conducted with the design philosophy that processes of thinking, acting, and communicating are one inseparable process [1, 2].

Especially, researchers in the field referred to as developmental robotics [4, 5], have tried to apply various psychological aspects evidenced in human infant development, in building cognitive models of socially intelligent robots. Concurrently, to understand the underlying mechanism or principles for the development of social cognitive functions, in robotic experiments, they have reconstructed cognitive functions by utilizing psychologically and neurobiologically plausible models [4, 5]. However, in most cases, those reconstructed functions have been limited to relatively simple ones as compared to those in even three-year-old human infants, because such studies in developmental robotics are still in an early stage.

In the aforementioned research context, the current research aims for reconstruction of higher cognitive mechanisms via sensory-motor learning in a neurobiologically plausible manner. The communicative tasks, in this research, were designed to address the issue of systematicity. Systematicity is considered to be one of the indispensable competencies of the higher cognitive systems such as language systems [6, 7]. Here, systematicity in language processing refers to the cognitive capability of humans to infer the meaning of unknown sentences from known sentences, by extracting compositional semantic rules from them. In the adopted tasks, we utilize human gestures characterized by systematicity as a communicative mean. (It has been shown that human natural gesture recognition capability is also endowed by systematicity [8, 9].) More specifically, a humanoid robot is trained to generate specific compositional motor primitive patterns as corresponding to imperative gestures demonstrated by the human subject. It is noted that the imperative gestures demonstrated by the human subject consists of various combinatorial sequences of movement patterns by the predefined compositional semantic rules. Details of the tasks will be explained in Section III.

The achievement of the complex communicative interactions between human and robot is considered to encounter with the following technical challenges. Solely from learning of lower level perceptual flows, without utilizing explicit cues for extracting task rules or segmenting phase, the robot should achieve following goals: (1) acquisition of compositional semantics with generalization for performing higher cognitive communicative tasks characterized by systematicity, (2) development of a further higher-order cognitive mechanism for controlling the turn-taking process, as well as controlling the contextual flow as situated to on-going task processes. These technical challenges of targeting development of higher-order

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cognitive competency out of lower level perceptual experiences could contribute significantly to the realization of truly human-like socially intelligent robots.

For the purpose of accomplishing the discussed challenges, the current study takes an approach based on the paradigm of dynamical systems and self-organization in modeling the development of the objective cognitive-behavioral processes. Because this is considered as a promising approach to account for the essence of the embodied cognition [10-12]. Especially, the current research follows the results from the study conducted by Yamashita and Tani [13], as they showed that functional hierarchy for generating complex behaviors can be developed through iterative learning of sensory-motor experiences by utilizing the reported multiple timescales recurrent neural network (MTRNN) model. Also, the current study is related to a robotics study on the associative learning between proto-language and behaviors conducted by Sugita and Tani [14] which utilized the recurrent neural network with parametric bias (RNNPB). This study investigated how the compositional semantic rules can be extracted with generalization from the iterated tutoring experience by learning.

The novelty of this study is twofold. First point is that intentional states to generate an adequate robot corresponding response to a human gesture was developed in the context units activity while perceiving a continuous human movement flow without using the error regression scheme shown in the previous studies [13, 14]. This scheme is advantageous because the experimenter does not need to (1) segment responses and gestures in the continuous flows, (2) tune additional parameters such as time window length. The second point is that this study showed that the network can develop another level of the higher cognitive capability to control both turn-taking process and contextual flow of an on-going task without introducing additional experimenter-designed modules or mechanisms. The network developed this competency just learning through experience of continuous task sessions. Details of these claims are described throughout the paper.

We conducted a set of neurorobotic experiments by following the aforementioned frameworks. Both quantitative and qualitative analysis on the results of the experiment clarify how the higher cognitive competency necessary for achieving human-like communicative skills can be developed in the course of self-organizing adequate dynamic structures in the adopted dynamic neural network model. Next section will describe details of the adopted network model.

II. Dynamic Neural Network Model

A. Overview

The MTRNN model adopted in this study is characterized by multiple timescales dynamics and hierarchical structure of multiple subnetworks [13]. In the current study, the intention for generation of a specific motor response is not set by the experimenter. The intention is expected to be developed in the internal (context) dynamics while perceiving continuous flow of the human gesture patterns starting from initial neutral value. After demonstration of a human gesture, the corresponding motor response is expected to be autonomously generated as reflected with the top-down intention developed in the internal dynamics so far. It is highly speculated that such mechanism of turn taking from observation of the gesture to generation of its action can be developed in the dynamical structure of the network model if the network is trained with sufficient amount of tutoring for pairing observation of the gesture and generation of its own corresponding motor response. Next subsections describe further details of the adopted network model.

B. Model Architecture

We modified the MTRNN model [13] which is composed of multiple levels of subnetworks characterized by different timescale dynamics. The typical architecture of MTRNN adopted in the current experiments is shown in Fig. 1. The network architecture consists of four context dynamics subnetworks. Input and output units are connected to the fast context dynamics subnetwork, the lowest-level subnetwork. As shown in Fig. 1, contexts in higher-level subnetworks have larger time constants than the ones in the lower-level. The numbers of the context units from lowest to highest subnetworks are 30, 30, 20, and 20, respectively. The same network configuration is used throughout the experiments, except for the one that is designed for examining importance of characteristics of the MTRNN: the multiple time scales dynamics and topological connectivity.

The input is sent from the motion tracker (4 dimensional position data measured for left hand and right hand of the human subject as denoted by $x_{V,t}$) and from the NAO robot guided by the experimenter (the encoder reading of 4 DOF joints as denoted by $x_{P,t}$). To sparsely encode the inputs, softmax transformation is independently applied to each dime-

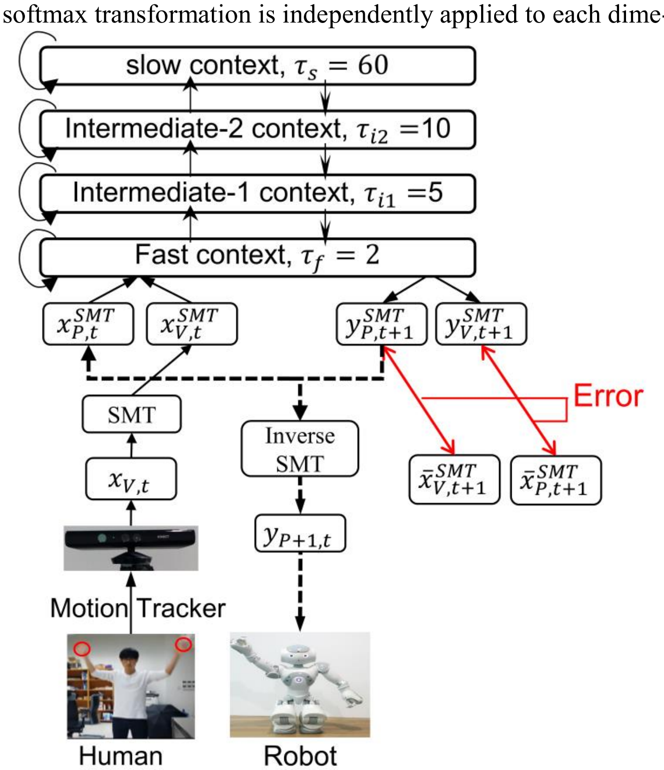

Fig 1. The whole system architecture for the performing the communicative tasks with MTRNN. SMT denotes softmax transformation. $x^{SMT}_{V,t}$ and $x^{SMT}_{P,t}$ are the vision and proprioception inputs at time step t, respectively. $x^{SMT}_{V,t+1}$ and $x^{SMT}_{P,t+1}$ are vision and proprioception prediction outputs, $\bar{x}^{SMT}_{V,t+1}$ and $\bar{x}^{SMT}_{P,t+1}$ are their targets. τ is the time constant of the context unit.

nsion of the inputs. These transformed data were used as the input and target-output of the network.

C. Forward Dynamics

For given connectivity weights, the forward dynamics of all neural units including output units and context units in different timescale subnetworks are computed by following (1~3).

$$u_{i,t+1} = \begin{cases} (1-\frac{1}{\tau_i})u_{i,t} + \frac{1}{\tau_i}\left(\sum_{j\in I} w_{ij}x_{j,t} + \sum_{l\in C} w_{il}c_{l,t} + b_i\right)(i\in C), \\ \sum_{l\in C} w_{il}c_{l,t+1} + b_i \qquad (i\in O), \end{cases} \tag{1}$$

$$c_{i,t+1} = f(u_{i,t+1}), \tag{2}$$

$$y_{ij,t+1} = \frac{\exp(u_{ij,t+1})}{\sum_k \exp(u_{ij,t+1})} \quad (\ i\in V, P \wedge j, k = 1, 2, ..., l(i)\ ), \tag{3}$$

where x_t, u_t, and c_t represent the input, internal state, and context activation value at time t, respectively, τ is the time constant of the context unit, C, I and O are the neuron indices of the context, input and output layers, w_{ij} is the ith unit to jth unit connectivity. V and P are sets of indices corresponding to vision and proprioception, $l(i)$ is the length of the ith dimension's reference vector, and $f()$ is hyperbolic tangent. We used 9 as $l(i)$ for all i. The output $y_{ij,t+1}$ is computed by using the softmax function. This softmax output activation function is used to help learning by making the output activate sparsely. The forward dynamics generate a sequence of one-step prediction for the output vector. In the current study, the initial internal state of each context unit is set by a neutral value of 0.0.

D. Training

A learning scheme referred to as back-propagation through time (BPTT) algorithm [15] is utilized for training of the network. The network was trained to optimize its learnable parameters (θ) to minimize Kullbak-Leibler divergence (KLD) between target and prediction outputs as described in the following (4).

$$E = \sum_t \sum_i \bar{x}_{i,t+1} \log\left(\bar{x}_{i,t+1} \big/ y_{i,t+1} \right) \quad (\ i\in O\ ), \tag{4}$$

where $y_{i,t+1}$ and $\bar{x}_{i,t+1}$ are prediction and target outputs. The learnable parameters that consist of connectivity and bias are updated in a direction of minimizing prediction error, *i.e.* opposite direction to that of the gradient as described in (5).

$$\theta(n+1) = \theta(n) - \alpha \, \partial E / \partial\theta, \tag{5}$$

where α is learning rate. Detail equations for calculating delta parameters are described in the following [16].

As can be seen in Fig. 1, the MTRNN is a type of deep neural network, which has a deep hierarchical structure of multiple subnetworks and each of them has different timescale dynamics with a different time constant. Therefore, the network would learn multiple timescale correlations and self-organize into a functional hierarchy between multiple subnetworks by utilizing its hierarchical structure and multiple timescale dynamics. As a result of the learning by means of prediction error minimization, the network becomes able to represent the states of both the environment and itself, and makes links between them at the level of the slow dynamics subnetwork. This permits the network to develop adequate higher-level cognition for communicating with others in the outer world.

The initial learnable parameters, weights and biases, are randomly set with a Gaussian distribution. The range of the Gaussian distributions for the weights and biases were [-0.1, 0.1] and [-1, 1] for the biases. The initial learning rate was set as $0.1/T_{total} \times d$, where T_{total} is summation of the time step over all training sequences, and d is dimensionality of the output.

In order to accelerate the learning speed as well as to achieve better generalization capability, a scheme of adaptive learning rate was employed. Details of the adaptive learning rate algorithm is given in Appendix A. Furthermore, because the learning error often fluctuates as the training proceeds, we employed a scheme of selecting the best learning parameters obtained in the course of the entire training process, whose exact scheme is described in Appendix-B.

III. General Task Design

Tasks in this paper were designed to investigate how robots employing the MTRNN model develop higher order communicative competency from sensory-motor learning. We designed the following communicative tasks for addressing the technical challenges aforementioned in Section I: (1) acquisition of compositional semantic rules from partial training exemplar, (2) further higher-order cognitive capability for adaptive control of the contextual memory.

Communicative tasks in the current study consist of sequentially-combined imperative gestures demonstrated by a human and corresponding responses generated by a robot. Example pairs of imperative human gestures and robot response in the communicative tasks are shown in Fig. 2. As it can be seen in Fig. 2, an imperative is a sequential combination of human movement patterns: human movement primitives (HMPs), order commands, and speed commands. Three different HMPs determine corresponding robot motor

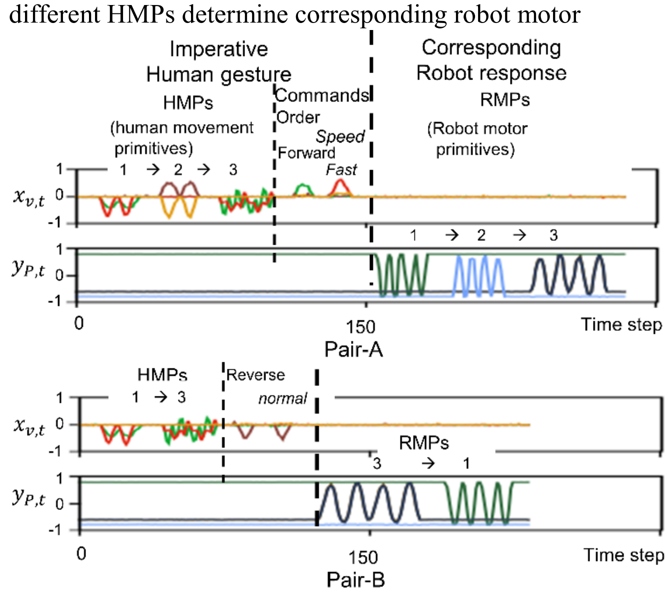

Fig. 2. Examples of pairs in the communicative task. A human demonstrates an imperative gesture pattern, and after some delay, a robot generates the corresponding response. An imperative gesture consists of the movement primitives, order and speed commands.

primitives (RMPs). Two order commands are verb-like commands indicating either forward or reverse order in generation of motor primitive sequences. Three speed commands are adverb-like commands indicating generation speed of robot motor primitive, *i.e.* either fast, normal or slow.

These communicative tasks have the following complexities. First, both imperative human gestures and the corresponding robot responses are a combination of movement patterns. Second, the same movement patterns could have different meanings depending on their previous pattern's type. For example, in Pair-B in Fig. 2 although two succeeding reverse order command and the normal speed command are in the same shape, their types are different. Third, in Experiment 1 case, the imperative gesture is generated by the more complex compositional semantic rule; a human subject can demonstrate one to three movement primitives before demonstrating commands. The proposed network has to develop higher-order cognitive function to segment patterns and phases. Moreover the network has to extract the underlying meanings of each of segmented and combination of patterns, and acquire rules among those segments by entirely via iterative learning of the continuous sensory-motor flows.

IV. Experimental Result and Analysis

A series of experiments on human-robot communicative skills based on learning was conducted for the purpose of examining a set of essential problems described previously.
The success rate was measured by counting the number of the sessions (consisting of a pair of human gesture part and robot response generation part) that the network successfully performed. If the mean KLD between motor target and prediction outputs was lower than 0.01 during the session, the session was considered as successful.

A. Experiment 1: Achievement of Systematicity.

In this experiment, the higher level generalization capability of the network in the higher cognitive level, extracting compositional semantic rules from gesture-response pairs, is examined. All possible 234 gesture-response pairs combined with the compositional rule are used. The network was trained using 156 pairs (including 12 validation pairs) and tested using remaining 78 pairs. The network was trained 3 times with different initial learnable parameters. The network configuration, which is explained in sub-section II-B were used. The average test result showed success rate of 87.0%. The network showed relatively good generalization result. The learning curve for the training and test pairs during training process is shown in Fig 3. As shown in Fig 3, both training and test errors gradually decreased as the training proceeded. Although test KLD curves fluctuated during learning, the fluctuation showed correlation with the training one. Therefore, by applying learning parameter selection scheme as described in Appendix B, it was possible to select the proper learning parameters that showed high success rate for test pairs.
Fig. 4 shows how the slow context dynamics developed along with the perception of the human gesture patterns and generation of the motor response, respectively. As it can be seen in Fig. 4, the slow context unit activities in these two trials were the same before the demonstration of the third movement

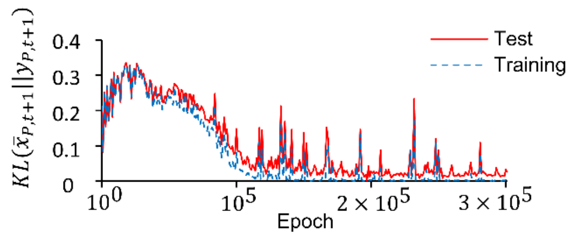

Fig. 3. Evolution of mean KLD between motor target and prediction outputs for the training pairs (blue dotted line) and test ones (solid red line) during training.

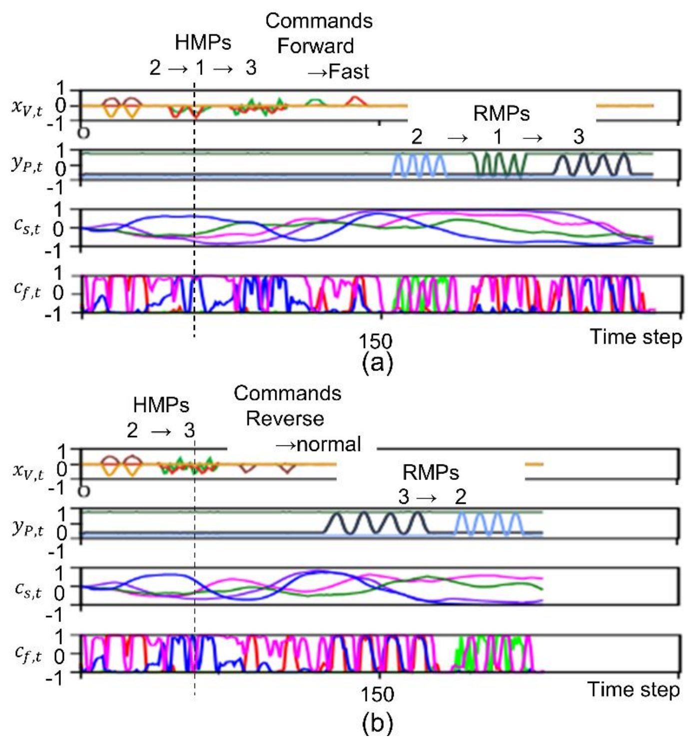

Fig. 4. Two examples of test trial results in (a) and (b), plotted with the slow context units activity. $x_{V,t}$, $y_{P,t}$, $c_{s,t}$ and $c_{f,t}$ indicate the vision (Kinect) inputs, the motor (proprioception) output, and the slow and fast context units activities.

primitive, and differentiated after that. This implies that the slow context activities were developed to represents the current context by integrating the gesture sequence patterns perceived in the past. Also, the differently developed activities trigger generation of the corresponding motor primitive sequences. In profiles of fast context unit activity, on the contrary, we observed one to one mapping between patterns and profiles. In conclusion, it can be said that the slow dynamics subnetwork is successful in extracting longer time correlated structures such as semantic rules from observed perceptual sequences. The fast dynamics subnetwork, on the other hand, involves with processing detail features of on-going perceptual or motor primitive patterns. The current experiment results show that the adopted MTRNN model successfully achieve the goal. Table I shows success rates of the networks trained under same training condition 1 but different network configurations. This results imply that both topological connectivity among subnetworks and multiple timescales property are essential in achievement of the goal by developing adequate functional hierarchy.

TABLE I.

	1st subnet	2nd subnet	3rd subnet	4th subnet	Success rate (%)
τ	2	5	10	60	87.0
N_c[a]	30	30	20	20	
τ	2	5	10	100	84.3
N_c	30	30	20	20	

(a) Multiple subnetworks & Multiple time constants

	1st subnet	2nd subnet	3rd subnet	4th subnet	Success rate (%)
τ	2	2	2	2	0.6
N_c	30	30	20	20	
τ	20	20	20	20	44.9
N_c	30	30	20	20	
τ	60	60	60	60	32.0
N_c	30	30	20	20	

(b) Multiple subnetworks & Single time constant

	1st subnet				Success rate (%)
τ	2	5	10	60	58.0
N_c	30	30	20	20	
τ	2	5	10	100	69.5
N_c	30	30	20	20	

(c) Single subnetwork & Multiple time constants

	1st subnet	Success rate (%)
τ	2	1.0
N_c	100	
τ	20	3.1
N_c	100	
τ	60	45.8
N_c	100	

(d) Single subnetwork & Single time constant

[a]N_c = Number of context unit

COMPARISON OF SUCCESS RATES

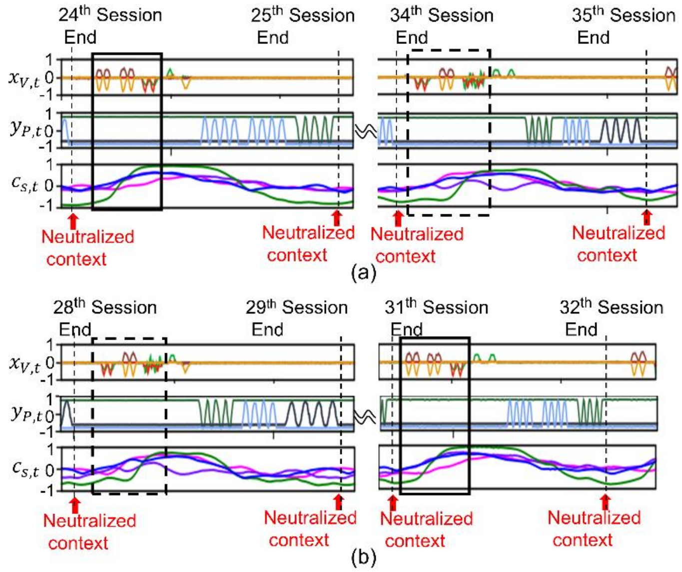

Fig. 5. Two examples of test trial results during iterative cycles of sessions plotted with slow context activities. $x_{V,t}$, $y_{P,t}$ and $c_{S,t}$ indicate vision input, proprioception output and fast context. Two solid line rectangles and two dashed line rectangles indicate portions of the same imperative gestures. At each end of session, the context activity becomes similar as pointed by red arrows of "neutralized context".

B. Experiment 2: Development of Further Higher Cognition

In this experiment, we investigated how the network can acquire a certain high-order cognitive mechanism for controlling the contextual memory for both preserving and resetting it as situated to the on-going task process. Different from the previous experiment, this experiment was conducted in more natural task settings; multiple session iterates continuously without termination. This settings brings another technical challenge which is how the robot can segment task sequence into each session without receiving explicit cues of indicating onset or end of the session. Same as Experiment 1, the network has to keep the activity of context units to develop while receiving the sequences of gesture movement primitives. When the gesture demonstration is finished, the network should be able to trigger the turn taking for generating its own motor response. Furthermore, in iterated session case, when the motor response is finished, the context states should be reset for preparing for next session to be started. This sort of task process requires aforementioned cognitive mechanism.

How can the network acquire such a sophisticated mechanism involving with a sort of "meta-level" control of the contextual memory? Our hypothesis was that such contextual control skills could be acquired if the network is trained for longer iterations of the sessions. We tested the hypothesis by conducting learning experiment in which the network was trained with 26 trials each of which consists of 9 sessions with simplified form of gesture-response pairs to focus on the current technical challenge. In this experiment, imperative gesture consisted of 3 concatenated movement primitives (12 different primitive sequences were arbitrarily selected), followed by a forward order command and 3 different speed commands. All of the possible 36 gesture sequences were included in the training.

After training the network under the aforementioned conditions, the performance of the robot was examined by iterating 36 sessions in which the gesture sequence was randomly selected from 36 possible gesture sequences at each session. The test results showed that the robot performed with the success rate of 84.4%. This result is much better than the one where the network was trained with the single session condition and tested with the same condition, less than 10%.

Fig. 5 shows examples of two different test trials for concatenated sessions. The same categories of imperative gestures showed similar slow context activities regardless of the task content in the previous session. Furthermore, the slow context activities seemed to be reset to a neutral value immediately before the onset of every new session, as seen in Fig. 5 denoted by red arrows of "neutralized context". To investigate developed mechanisms more quantitatively, for all different sessions, variances of the internal states of the slow context units at the end of the sessions were computed for the cases of training with a single and 9 concatenated sessions. Surprisingly, the variances were obtained as 0.42 for the training with single session case and 0.0645 for the training with 9 concatenated session case.

These results indicate that the mechanism for autonomous resetting of the context states at the end of each session can be developed provided that the network is trained with relatively long iterative cycles of sessions.

V. CONCLUSION

In this study, we showed that the adopted MTRNN can achieve higher-order cognitive competency out of lower level perceptual experiences. In Experiment 1, the MTRNN recognized and generated not only learned compositional actions but also unlearned ones by extracting and applying complex semantic compositional rules hidden in sensory-motor flows. Moreover, we showed multiple timescales dynamics and deep hierarchical structure were essential for the achievement. Furthermore, in Experiment 2, the MTRNN developed further higher cognitive skill that is controlling the contextual memory when adapting to the task processes in terms of remembering and forgetting. It should be noted that the network developed the abilities entirely via sensory-motor learning without being provided with any cues, such as symbols explicitly indicating the meaning of movement patterns or task phases.

However, there are still rooms for further studies. In the current study, the network learned whole sequences at the same time, regardless of a complexity of them. It will be more natural to begin learning from a simple task: generation of the corresponding RMP after perceiving a single HMP, forward do and normal speed commands. And then, proceed further for more complex tasks. Studies on such staged developmental learning may crucial for both more deep understanding of development of human cognition and improving the competency of the model. Moreover, future study should focus on realization of truly open-ended human-robot social interactions. Also, investigation of learning methods should be done to remedy the shortcomings of current model and learning scheme: expensive computational time and hyper parameter tuning by trial and errors.

APPENDIX

A. Adaptive Learning Rate Algorithm

In each epoch, the learning rate was updated by using the following algorithm [17].

(1) Calculate the delta errors using randomly selected λ percent of the training sequences.
(2) Calculate the rate (r) of the KL-divergences before and after updating parameters using whole training and validation sequences.
(3) If $r > r_{th}$, then update α to $\alpha\alpha_{dec}$ and go back to (2).
(4) If $r < 1$, then update α to $\alpha\alpha_{inc}$ and go to the next epoch.

In this study, we set r_{th} to 1.1, α_{dec} to 0.7, and α_{inc} to 1.2 based on the parameter setting used by Namikawa [17]. To improve generalization capability by reducing overfitting to the training data, we also considered error on validation data in updating the learning rate [18]. Validation sequences in this study were composed of the inexperienced human gestures and robot responses. Therefore, utilizing validation error in updating the learning rate has important meaning in general rule learning, because it can prevent the network to extract particular rules only be applicable to the training sequences.

B. Criteria of Best Training Epoch

The best iteration was selected after 300,000 epoch. The epoch that minimizes the following error function (B.1) was treated as the best epoch.

$$E = E_{tr} + \frac{N_{tr}}{N_{val}} E_{val}, \tag{B.1}$$

where, E_{tr} and E_{val} are the training and validation errors, and N_{tr} and N_{val} are the numbers of training and validation data, respectively.

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