

Efficient Reward Learning Based on Body Representation in a Spiking Neural Network

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Abstract—Brain-body interactions guide the development of behavioral and cognitive functions. Sensory signals during behavior are relayed to the brain and evoke neural activity. This feedback is important for the organization of neural networks via neural plasticity, which in turn facilitates the generation of motor commands for new behaviors. In this study, we investigated how brain-body interactions develop and affect reward learning. We constructed a spiking neural network (SNN) model for the reward learning of canonical babbling, i.e., combination of a vowel and consonant. Motor commands to a vocal simulator were generated by SNN output and auditory signals representing the vocalized sound were fed back into the SNN. Synaptic weights in the SNN were updated using spike-timing-dependent plasticity (STDP). Connections from the SNN to the vocal simulator were modulated based on reward signals in terms of saliency of the vocalized sound. Our results showed that, under auditory feedback, STDP enabled the model to rapidly acquire babbling-like vocalization. We found that some neurons in the SNN were more highly activated during vocalization of a consonant than during other sounds. That is, neural dynamics in the SNN adapted to task-related articulator movements. Accordingly, body representation in the SNN facilitated brain-body interaction and accelerated the acquisition of babbling behavior.

Index Terms—brain-body interaction, canonical babbling, intrinsic plasticity, spiking neural network, spike-timing-dependent plasticity

I. INTRODUCTION

Brain-body interactions guide the development of behavioral and cognitive functions. Sensory signals arising from the body evoke neural activity that in turn alters the connectivity of neural networks through activity-dependent plasticity [1]. The activity of the organized neural networks then drives physical behavior by feeding sensory signals into neural networks. This form of interaction has attracted attention in developmental science [2] given the high plasticity and rapid growth of the infant brain [3], [4]. Yet, a computational mechanism permitting this interaction, especially if dynamics of the intrinsic neural spikes is different from the body movement in terms of their timescales, remains unclear. In addition to the scientific motivation for this study, reward-based skill learning in this context is also of interest for application to artificial systems.

Although the most existing studies in computational neuroscience have not considered embodiment, various studies have examined brain-body interactions. Yamada et al. [5] constructed a realistic fetal simulator consisting of a spiking neural network (SNN), skeletal muscles, and intrauterine environment, and found that body representation emerged

in the SNN if somatosensory signals were fed into a SNN with neural plasticity. Body representation was defined as an increase in the number of neurons exhibiting significantly higher activation during movement of a specific body part versus other body parts. Yet, the model did not investigate the effect of body representation on behavior because the organized SNN did not drive the body. In contrast, Warlaumont and Finnegan [6] proposed a model where output from a SNN supplied motor commands to a vocal simulator. Modulation of the synaptic weights of output neurons based on reward for vocalized sounds allowed the model to learn infant-like vocalization; however, this model did not include an auditory sensor or self-organization in the SNN. Recently, Park et al. [7] reported that behavior patterns can emerge as the result of an interaction between motor commands from a neural oscillator network and sensory signals from a musculoskeletal system, but this model did not consider neural plasticity or learning.

Our previous study showed that self-organization of the SNN in accordance with a spiking-timing-dependent plasticity (STDP) rule promoted the reward learning of vocalization [8]. This study emphasized the necessity of auditory feedback to the SNN for efficient reward learning. We speculated that STDP under auditory feedback enabled specific SNN activities to represent articulatory movements, which ultimately accelerated reward learning about weights between the SNN and a vocal simulator. Yet, our previous study did not inform the role of body representation in reward learning.

In the present study, we investigated the relationship between body representation in the SNN and reward learning performance. Self-vocalized sounds were fed into a SNN organized in accordance with STDP. The activities of some neurons in the SNN were converted to motor commands to drive a vocal simulator and output weights were modulated based on a reward for the vocalized sound. A key problem in this context is the difference between neural activity and bodily movements, especially in their timescales; neural spiking activity fluctuates quickly while speech articulator movements are relatively slow. If the SNN activates independently of movement, reward learning becomes difficult. Therefore, it is desirable that activity of the SNN is temporally related to movement. We hypothesized that STDP under auditory feedback would enable the SNN to represent task-related articulation and lead to efficient reward learning. We expected that auditory feedback would bias activity of the SNN towards

articulator movements because auditory signals should reflect the movements. This activity pattern derived from auditory feedback may be consolidated by STDP (see [9]). We examined this hypothesis by analyzing the learning performance and neural dynamics of the SNN in the babbling acquisition task. Existing studies have reported that reward based on sound saliency, i.e., the temporal variation in the frequency spectrum of the vocalized sounds, enables a learning model to acquire infant-like canonical babbling (a rhythmical series of consonants and vowels) [6], [8].

II. MODEL

A. Spiking neural network

Fig. 1 shows an overview of our model. The left large circle indicates the SNN consisting of 1000 Izhikevich-type spiking neurons [10]. The membrane potential v_i of the i th neuron is described as

$$\dot{v}_i = 0.04v_i^2 + 5v_i + 140 - u_i + I, \quad (1)$$

$$\dot{u}_i = a(bv_i - u_i) + D\xi_i, \quad (2)$$

$$\text{if } v_i \geq 30\text{mV, then } \begin{cases} v \leftarrow c, \\ u \leftarrow u + d, \end{cases} \quad (3)$$

where u_i denotes the membrane recovery variable, and a , b , c , and d are parameters. I denotes a total input current, e.g., synaptic current through other neurons and external input. In Eq. (2), ξ is the Gaussian noise with a mean of 0 and intensity D [11]. Eq. (3) describes the after-spiking resetting. Eight hundred neurons were excitatory and 200 are inhibitory (shown as red and blue circles in Fig. 1, respectively). Neuron parameters were in accordance with the existing model [11]. Each neuron had 100 randomly selected synaptic connections. Weight was initially sampled from the uniform distribution in the range of 0–6 and then modulated based on plasticity rules.

We employed two plasticity rules in this model: STDP [9] and intrinsic plasticity (IP) [11]. Synaptic weights of all excitatory neurons in the SNN were updated in accordance with STDP. This rule strengthens or weakens a connection between 2 neurons based on the time difference between their spikes. The amount of update of a synaptic weight Δw was calculated as

$$\Delta w = \begin{cases} A_+ e^{-\Delta t/\tau_+} & \text{if } \Delta t > 0, \\ -A_- e^{\Delta t/\tau_-} & \text{if } \Delta t \leq 0, \end{cases} \quad (4)$$

$$\Delta t = t_{\text{post}} - t_{\text{pre}}, \quad (5)$$

where A denotes the amplitude of the amount of update and τ denotes the decay constant. Δt represents the difference between spike timings of the pre- and post-synaptic neurons (t_{pre} and t_{post} , respectively). In Eq. (4), the cases of $t > 0$ and $t \leq 0$ indicate long-term potentiation and long-term depression, respectively. It is expected that this plasticity allows activity of the SNN to represent the temporal patterns of input signals [9].

The IP rule sustains the firing rate of a neuron at an adequate level. Standard SNN requires random inputs for sustained

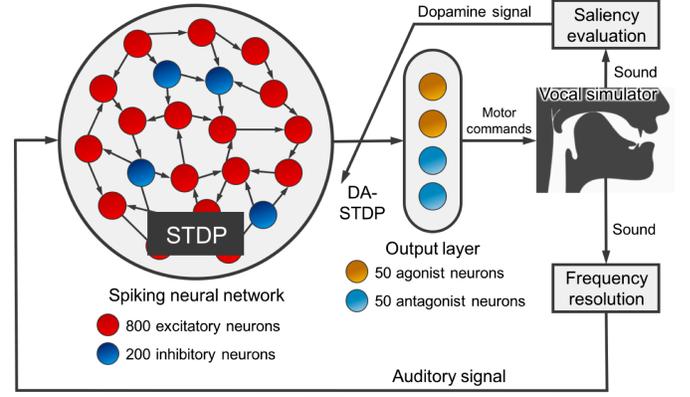


Fig. 1. An overview of the model of reward learning for babbling acquisition based on the self-organized spiking neural network (SNN). This model mainly consists of the SNN, an output layer, and a vocal simulator. The SNN and reward learning are models of the sensorimotor cortex and striatum, respectively (see [12]). Some neurons in the SNN connect to neurons in the output layer, and activity of the output layer yields motor commands for the vocal simulator. The vocalized sounds are converted into frequency information (auditory signals) and are fed into the SNN. Synaptic weights from the SNN to the output layer are modulated based on reward in accordance with sound saliency. Activity-dependent plasticity in the SNN is thought to enable activity of the SNN to represent the movements of articulators, leading to efficient reward learning. DA, dopamine-modulated; STDP, spike-timing-dependent plasticity.

activity as in our previous model [8]; however, random inputs can obscure sensory inputs and ultimately prevent the SNN from representing body movements. Therefore, we applied this homeostatic plasticity to all neurons in the SNN to assist their spontaneous activity without random inputs. This rule modulated the parameter b in Eq. (2), which is related to the sensitivity of action potential recovery if the inter-spike interval (ISI_i), i.e., the time difference between consecutive spikes of the i th neuron was outside the allowable range (T_{\min}, T_{\max}) [11]. The amount of update of the parameter Δb_i of the i th neurons is given as

$$\Delta b_i = \begin{cases} -\eta b_{\max} \exp\left(\frac{T_{\min} - ISI_i}{T_{\min}}\right) & \text{if } ISI_i < T_{\min}, \\ \eta b_{\max} \exp\left(\frac{T_{\max} - ISI_i}{T_{\max}}\right) & \text{if } ISI_i > T_{\max}, \\ 0 & \text{otherwise,} \end{cases} \quad (6)$$

$$ISI_i^k = t_i^{k+1} - t_i^k, \quad (7)$$

where η is a constant, b_{\max} is the maximum value of b , and Eq. (7) represents an ISI between the k th and $(k+1)$ th spikes of the i th neuron. The parameters for these plasticity rules were in accordance with the model described by [11].

B. Vocalization and reward learning

One hundred randomly selected excitatory neurons in the SNN were assumed to be output neurons, each of which connected to 40 neurons in the output layer. The output layer had 50 excitatory agonist neurons and 50 excitatory antagonist neurons (orange and light blue circles in Fig. 1, respectively).

The history of difference between firing of these agonist and antagonist neurons ($S_{\text{ago}}(t)$ and $S_{\text{ant}}(t)$, respectively) produced a motor command $m(t)$ at time t ms:

$$S_{\text{dif}}(t) = S_{\text{ago}}(t) - S_{\text{ant}}(t), \quad (8)$$

$$m(t) = \alpha \sum_{i=0}^{100} \left\{ S_{\text{dif}}(t-i) \left(1 - \exp\left(-\frac{i-100}{\tau_{\text{out}}}\right) \right) \right\}, \quad (9)$$

where $\alpha = 0.05$ and $\tau_{\text{out}} = 20$ ms denoting the motor gain and decay constant, respectively. This 1-dimensional motor command drove the masseter and orbicular oris muscles, which are related to the jaw closure and lip closure of the vocal simulator Praat [13].

The vocalized sound was converted to a frequency spectrum discretized into 100 frequency bands (1–20 Hz, 21–40 Hz, ..., 1981–2000Hz). The i th current input to the SNN I_i was proportionate to the frequency power of the i th band.

$$I_i = \beta E_i, \quad i = 1, 2, \dots, 100, \quad (10)$$

where input gain β was 13. Each I_i was fed into 2 randomly selected neurons in the SNN. This correspondence between frequency bands and neurons was fixed through learning, such that 200 neurons consistently receive auditory feedback. These processes were conducted every 1 ms.

Synaptic weights from the SNN to the output layer were updated by the dopamine-modulated STDP (DA-STDP) [14]. This applied STDP to the weights only in response to a reward. DA-STDP thereby enabled the output layer to produce firing patterns that satisfied the condition for a reward. A reward was given when saliency of the vocalized sound exceeded a threshold. Sound saliency was calculated as the averaged temporal variation of the time-series of the frequency spectrum [15]. Vocalized sounds including consonants and vowels in canonical babbling have high saliency. Our model evaluated saliency every 1,000 ms. Vocalized sound for the first 250 ms was discarded to account for the preparation of lung pressure. Thus, saliency evaluation was performed on sound produced in the latter 750 ms. An initial threshold was set to 4.5 and increased by 0.1 when saliency exceeded the threshold in 3 of 10 preceding trials or decreased by 0.1 when none of the preceding 10 trials exceeded the threshold.

III. EXPERIMENTAL SETTINGS

A. Model conditions

We designed 3 feedback conditions to investigate the effect of auditory feedback:

- (a) Auditory feedback: Auditory signals representing self-vocalized sound were fed back into the SNN as described above.
- (b) Surrogate feedback: Auditory signals produced in another trial were provided as feedback into the SNN. This feedback was not consistent with the motor commands.
- (c) Without feedback: No auditory signals were fed into the SNN.

We furthermore simulated a model that did not apply STDP in order to elucidate the effect of the STDP. Therefore, we

tested 6 conditions, i.e., 3 feedback conditions with and without STDP. The simulation time for each trial was 2000 s, and the results from each model condition were averaged from 10 runs.

B. Network analysis

Model were run for 200 s after each trial of 2000 s in order to analyze network structure and dynamics. Synaptic weights and neural parameters were fixed in this additional simulation. The first 100 s was discarded due to a transient state, such that the analysis was conducted on the latter 100 s.

We evaluated the complexity of neural dynamics in the SNN using a principle component analysis (PCA). The PCA reduced the dimensions of the time-series of firing for 1000 neurons over 100 s (1000 dimensions). We counted the number of principle components with an accumulated contribution rate of 0.8 to assess the number of linear spaces required for the explanation of the original time-series. This value also suggested the degree of complexity of the neural dynamics.

We analyzed individual neural behaviors in terms of articulatory movements, i.e., motor commands $m(t)$, using statistical t tests. We counted the number of neurons that exhibited statistically higher firing rates during a specific movement versus other movements. This analysis is a standard approach for identifying body representation in neural activity (e.g., [5], [16]). The value of the motor commands was between 1 and -1 . Higher values represented pursing of the lips for the pronunciation of a consonant and lower values represented pronunciation of a vowel. We segmented simulation periods into 3 parts: consonant periods ($m(t) \geq 0.5$), vowel periods ($m(t) \leq -0.5$), and other periods ($-0.5 < m(t) < 0.5$). The neural representation was evaluated for each period.

Neural activity in the output layer is a main contributor to learning performance because it generates motor commands. We evaluated the averaged firing rates of agonist and antagonist neurons to explore their relationships with learning performance.

IV. RESULTS

A. Learning performance

Fig. 2 shows model learning over time with the value of sound saliency denoted on the vertical axis. The red, blue, and gray curves indicate cases with STDP while the green, yellow, and purple curves indicate cases without STDP. The auditory feedback with STDP condition (red curve) was associated with the most rapid learning, whereas saliency increased gradually in the surrogate feedback and without feedback conditions. In contrast, cases without STDP failed to exhibit learning. This result suggested that STDP was necessary for learning and that learning was accelerated by auditory feedback.

Figs. 3 (a) and (b) show example spectrograms of the vocalized sounds before and after learning in the auditory feedback plus STDP condition. Initially, the simulator only pronounced a flat sound, i.e., a vowel. After learning, temporal variations appeared in the sound frequency, indicating the pronunciation of consonants.

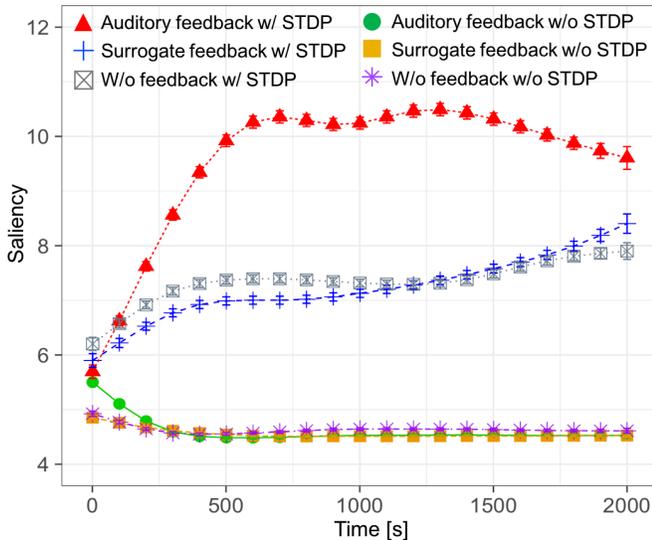


Fig. 2. Learning curves for the saliency of the vocalized sounds over time. The curves indicate generalized additive model fits and the error bars indicate 95% confidence intervals. STDP, spike-timing-dependent plasticity.

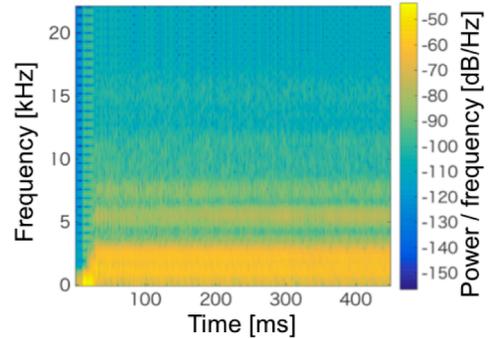
B. Weight distribution and complexity of neural activity

We analyzed synaptic weights and neural dynamics to identify how STDP enabled the model to learn babbling. Fig. 4 shows histograms of synaptic weights before and after STDP in the auditory feedback condition. Although the initial weights (gray histogram) had a uniform distribution, the weights after learning (red histogram) exhibited all-or-none extremes. STDP appeared to trim unnecessary connections and enhance connections between causally related neurons. This tendency was also observed in the surrogate feedback with STDP and without feedback with STDP conditions.

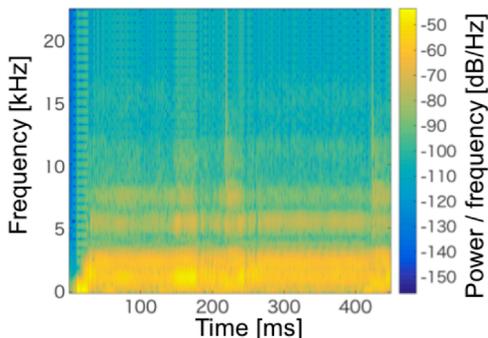
Fig. 5 shows the number of principle components in neural dynamics. The colors correspond to those in Fig. 2. Cases with STDP (red, blue, and gray bars) exhibited higher complexity than those without STDP (green, yellow, and purple bars). Therefore, STDP provided the SNN with more complex dynamics, possibly improving the learning ability of the SNN. Yet, complexity alone cannot explain the acceleration of reward learning in case of auditory feedback, as little difference was seen between the values of complexity in the auditory feedback and surrogate feedback conditions.

C. Articulatory representation

Fig. 6 shows the numbers of neurons that were more significantly activated during vocalization of a consonant, vowel, or others (yellow, blue, and gray bars, respectively) in cases with STDP. There were more neurons representing consonants in the auditory feedback condition compared to the surrogate and without feedback conditions. In contrast, the surrogate and without feedback conditions had more neurons representing vowels and others. Larger sound saliency requires more pronunciation of a consonant. Therefore, a higher num-



(a) Before learning



(b) After learning

Fig. 3. Spectrograms of vocalized sounds before learning (a) and after learning (b). The color indicates the frequency power.

ber of neurons representing consonants enabled the SNN to efficiently learn babbling.

D. Neural activity in the output layer

Fig. 7 shows the averaged firing rates of agonist and antagonist neurons in the output layer in cases with STDP. The firing rate was slightly smaller in the auditory feedback condition compared to the surrogate feedback and without feedback conditions. This suggested that the model exhibited high learning performance at lower activity cost in the output layer. Furthermore, the activity of agonist neurons was higher than that of antagonist neurons in the auditory feedback condition. The activity of agonist neurons produce lip-pursing behavior, i.e., pronunciation of a consonant. We hypothesize that reward learning based on the neural activity representing a consonant (Fig 6) enabled the model to produce consonants without the need for high activity in the output layer. In contrast, the SNNs in the surrogate feedback and without feedback conditions had complex dynamics representing vowels and others that were not related to the task. Therefore, it took a longer to extract task-related dynamics from all dynamics in the SNN.

V. DISCUSSION

In the present study, we proposed a reward learning model for canonical babbling based on a SNN that is fed audi-

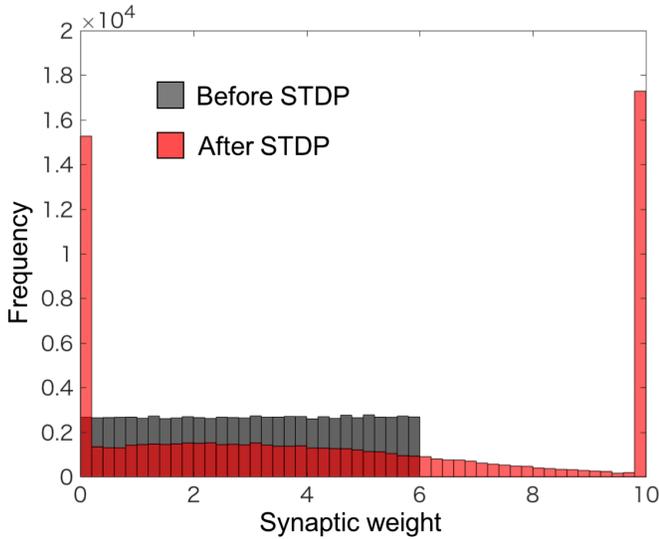


Fig. 4. Histograms of synaptic weights before and after spiking-timing-dependent plasticity (STDP) (gray and red bars, respectively).

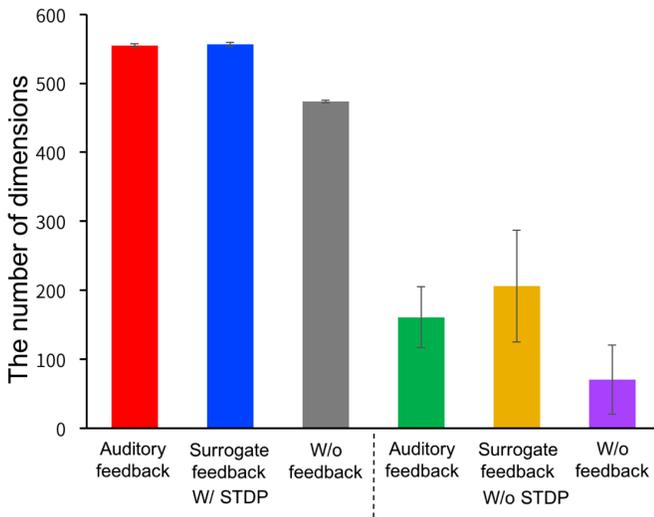


Fig. 5. Complexity of neural dynamics. Values indicate the number of principle components of neural dynamics with accumulated contributions of ≥ 0.8 . Bar colors correspond to those in Fig. 2. Error bars indicate the standard deviation.

tory feedback and organized with STDP and IP rules. Our experiment demonstrated that self-organization of the SNN through brain-body interaction promoted reward learning (see Fig. 2). We identified 2 important factors for the acceleration of learning: “complexity” and “representation”. Complexity is required for rapid adaptation to novel and diverse tasks or input while representation is utilized to respond to known tasks and inputs. STDP increases the complexity of neural dynamics (see Fig. 5) and makes the SNN sparser because it strengthens connections between related neurons and weakens unnecessary connections (see Fig. 4). The activity of sparse networks is

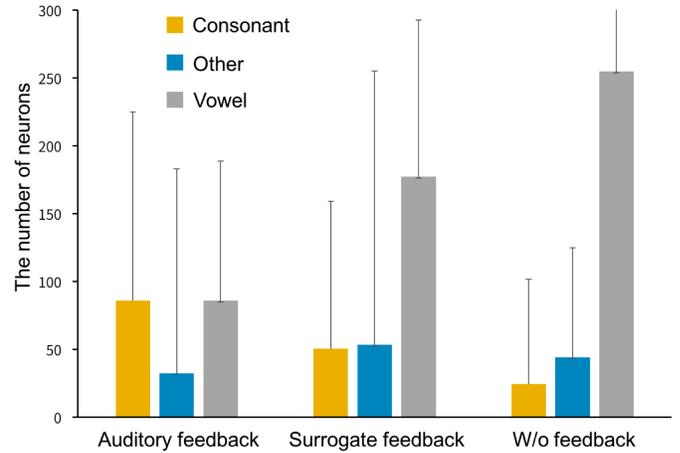


Fig. 6. The number of neurons showing a significantly higher degree of activation during vocalization of a consonant, vowel, or others. Error bars indicate the standard deviation.

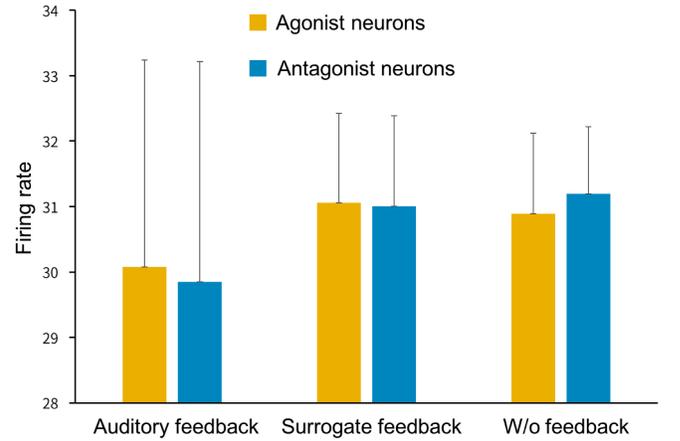


Fig. 7. Averaged firing rates of agonist and antagonist neurons as yellow and blue bars, respectively. Error bars indicate the standard deviation.

generally more complex than that of dense networks [17], [18]. Many studies have shown that STDP improves the learning performance of neural networks (e.g., [19], [20]). We suppose that our model learned to extract task-related dynamics, i.e., pronunciation of consonants, from complex neural dynamics that included diverse patterns. In contrast, Lazer et al. [21] reported that STDP reduced the complexity of activity in binary neural networks. Therefore, the relationship between complexity and STDP might be unique to the SNN.

The second factor, representation, relates to the acquisition of task-related dynamics in the SNN via STDP under auditory feedback (see Fig. 6). We observed an increase in the number of neurons that were highly activated during pronunciation of consonants in the auditory feedback condition. This finding suggests that neural dynamics in the SNN adapted to mimic patterns representing articulatory behavior. Park et al. [7] also showed that somatosensory feedback led to adaption of the

dynamics of a neural oscillator network to bodily movements. This adaptive brain-body interaction consequently produced diverse movement patterns [7]. Our study showed that utilizing such neural dynamics including body representation accelerates reward learning. Interestingly, body representation was not formed in the case of surrogate feedback when auditory signals were not consistent with motor commands. It can be speculated that activity generating motor commands and activity reflecting auditory signals enhanced the effect of STDP because they shared the same patterns of body movements. Furthermore, body representation enabled the model to learn babbling with lower neuronal activity in the output layer (see Fig. 7). High learning performance with less activity is advantageous in terms of metabolism and energy conservation.

Activity in the sensorimotor cortex of the adult brain represents the movements of speech-articulators and the vocalization of consonants and vowels [16]. Accordingly, some neurons are selectively activated during specific movements and vocalizations [16]. Our findings indicate that this body representation is acquired by the self-organization of cortical networks through brain-body interactions. If this interaction failed because of an auditory defect, e.g., in the without feedback condition, the acquisition of babbling behavior was delayed. In fact, the onset of canonical babbling is delayed in infants with hearing loss [22], [23].

VI. CONCLUSION

We investigated how a plastic brain network and body interacted and developed using a simple embodied SNN. SNN output actuated the muscles of a vocal simulator and the vocalized sounds were fed back into the SNN. Synaptic connections in the SNN were organized via STDP. The connections from the SNN to the vocal simulator were modulated via DA-STDP based on sound saliency, i.e., reward learning to produce canonical babbling. Our simulation showed that STDP under auditory feedback enabled SNN dynamics to represent articulatory movements. Such articulatory representation in the SNN produced motor commands with precise articulation and accordingly feedback represented the improved sound. Ultimately, this brain-body interaction accelerated reward learning for babbling acquisition. Additionally, we found that STDP yielded sparse SNN connectivity, which may have increased the complexity of its activity. These complex dynamics also seemed to contribute to reward learning. Therefore, the representation of bodily behaviors in complex dynamics of neural activity realized efficient behavioral reward learning. These results demonstrated the potential of the SNN as an artificial system that can promptly adapt to diverse tasks and environments. We plan to impose a novel task on our model after learning to investigate its adaptability.

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