Spike Neural Network of Motor Cortex Model for Arm Reaching Controlling

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***Abstract*—Motor Cortex modeling is significant to understand movement planning and execution, and inter-connected recurrent neural network has successful described the dynamics of neurons. However, most of existing methods take continues signal based neural networks to simulate the MC activities, which do not reflect the biological spike neural signal. To address this limitation, we proposed a spike neural network based modeling approach to model the Motor Cortex activity in arm reaching task. Specifically, we built a model of motor cortex based on integrate-and-fire spiking neurons with conductance-based synapses. Second, we carefully design the interconnections of neurons with two different time scale and assigned them into two layers. Besides, prior knowledge based parameter initialization is also proposed to ensure the spikes communication and the training performance. Experiments show the effectiveness of proposed the method that high similar with real spike at single cell and population level.**

I. Introduction

Motor cortex (MC) is fundamental for the generation of voluntary movement. Approaches to understand how the MC controls movement involves recording neuronal activity while animals perform tasks. Traditionally, many of these experiments focus on the representations that relate single-neuron activity to specific movement parameters (such as movement direction [1], effector position and velocity[2]). However, the representative perspective fails to explain the phenomenons that some neurons do not relate to any movement parameter and some neurons simultaneously relate to multiple movement parameters.

There has been a shift in the studies of MC from representations at the single-neuron level to the dynamics that generates MC population activity. Recent studies have emphasized that MC is a dynamical system, where movement preparation sets the initial condition for the movement onset, and neuronal activity evolve as a result of internal dynamics within MC and inputs from other areas during movement execution [3], [4]. Rotational dynamics was observed after dimensionality reduction of MC population activity during arm reaching, revealing the basic pattern of complex single-neuron responses [5]. Recurrent neural network (RNN) that can approximate any dynamical system, is a widely used modeling tool to interpret how observed motor cortical patterns may emerge. Sussillo et al.[6] trained RNN to generate muscle activity, using preparatory activity as initial conditions. Network with simple dynamics displayed surprising similarity to recorded

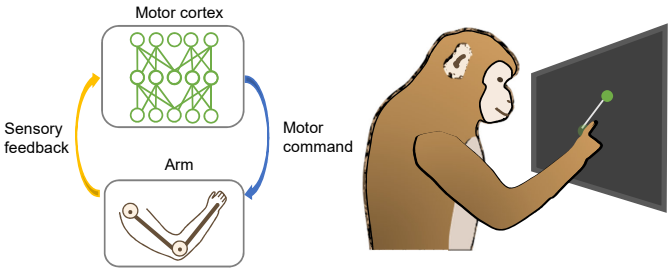

Fig. 1. Understanding motor cortical control via neural network model. Monkey reaches his hand to the target on the screen. His brain receives instructions of the task, and generates motor command to the arm for movement. The sensory feedback was sent to the brain during reaching. The motor control system can be modeled as a closed-loop system. Motor cortex is simulated by artificial neural network, such as RNN and the arm is replaced by a musculoskeletal model.

MC data at both the single-neuron and population levels. Kao et al.[7] from the view of pattern-generating network, optimized the initial conditions for the desired movement, bolstered the dynamical system perspective that initial conditions seed the subsequent movement. Moreover, inputs from other brain areas are essential for cortical pattern generation. Kalidindi et al.[8] constructed an RNN model to control an arm model and simultaneously received sensory feedback from the arm, highlighting the sensory feedback in the motor cortical dynamics. However, most of contemporary MC models are firing-rate-based network which abstract away from individual spikes to firing rates[9], and neurons (often called nodes) in the models do not mimic the actual neural computations. Interpretation from simplified computational representations of neural activity may not capture the whole picture of motor cortical dynamics.

Alternatively, spiking neural networks (SNN) [10], [11], [12] are based on biologically plausible neurons and mimic the way neurons communicate through discrete spikes, enabling more accurate representation of temporal patterns and neural population dynamics. Dewolf et al.[13] presented a SNN model of the MC and cerebellum to control a three-link arm model for center-our reach task; their model can adapt to unknown perturbations and accounts for experimental data. Hennequin et al.[14] proposed a model with fine-tuned recurrent synapses and control different activity states for

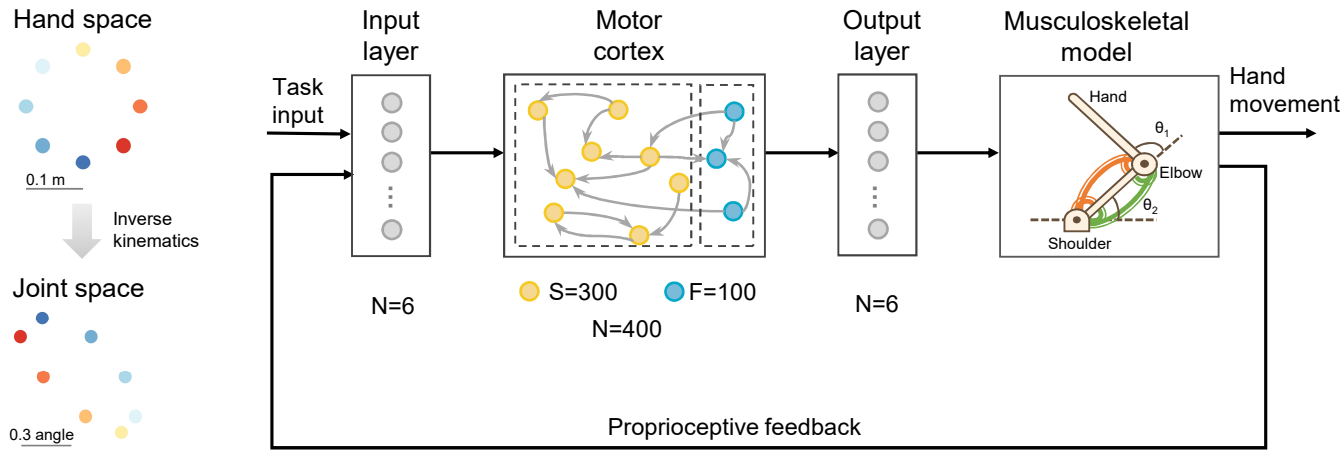

Fig. 2. The structure of proposed Recurrent Spike Neural Networks. The task signal and feedback information are sent into input layer, a group of inter-connected spike neurons process and generate spike stream to driven the muscle to actuate the two link of arm.

multidimensional movement patterns. The network displayed simultaneous firing rate and spiking variability. DePasquale et al.[9] proposed a training method for SNN by leveraging lower-dimensional factors extracted from either data or firing-rate-based networks. They trained the network to generate muscle activity recorded in the reach task, and spiking-neuron responses resembled to the real MC data. However, these models models either rely entirely on external input or recurrent synapses, or ignore sensory feedback during movement execution, could only partially capture the MC activity.

Here, we propose a recurrent spiking neural networks (RSNN) of MC that are trained to control an arm model to perform reaching task as the monkey did (Figure 1A). Inspired by the multiple timescale model[15], our network are composed of two assembles of neurons, each with different temporal properties. The first assemble is composed of the "slow" neurons with large time constant, while the second is composed of "fast" neurons with small time constant. Multiple timescales can result in functional hierarchy in motor control system, where basic elements are flexibly integrated into various patterns[15]. Moreover, the task input as well as proprioceptive feedback from the virtual arm went into the "slow" assemble, which interacts with "fast" assemble. Then the activity of "fast" assemble was readout into muscle activity that actuated arm model (Figure 1B, C). Despite not being fit to real MC data, our network reproduced neural population activity at both single-neuron and population-level, qualitatively and quantitatively. Thus our model suggest the possibility that multiple timescales may be essential in motor cortical control.

II. Modeling Framework for Reach Generation

To simulate the process that monkey performs the reaching task, we elaborated a technique framework where an MC network controlled a musculoskeletal arm model (Figure 1). In this section, we describe the model architecture optimization. We first describe the MC network architecture, and introduce the single neuron and corresponding synaptic transmission model, and then illustrate how to transfer the neural activity to the hand movement. Besides, the definition of loss function and the training method are explained. Finally, we also described analyzing population dynamics of model and real MC data. All the simulations were performed on the BrainPy [16].

A. The inputs to the network

The external inputs include the task input that represents target position, and sensory feedback. First, the target position in hand space was transformed into the desired joint angles (Figure 2). Second, we only used the proprioceptive feedback as the sensory feedback because human rely almost entirely on the proprioceptive feedback to estimate hand motion[17], and multisensory integration display subadditive[18]. The proprioceptive feedback $\boldsymbol{u_p}$ consisted of joint angles and velocities. The input layer integrate all the input to

$$\boldsymbol{I^{in}} = \boldsymbol{W^{in}}\boldsymbol{u} \tag{1}$$

where $\boldsymbol{u} = (\boldsymbol{u_t}, \boldsymbol{u_p})$.

B. Motor Cortex Network Model

1) Single-Neuron Model: Single neuron was modeled as leaky integrate-and-fire (LIF) neuron[19], according to:

$$\tau \frac{d\boldsymbol{V}}{dt} = -(\boldsymbol{V} - V_{\text{rest}}) + \boldsymbol{I(t)} \tag{2}$$

where $\tau = 8$, and $\tau = 40$ for "fast" and "slow" neuron, respectively. V is the membrane potential and $V_{\text{rest}} = 0$ is the resting membrane potential. When $\boldsymbol{V}$ reaches the threshold of 1 mV, the neuron emitted a spike. The membrane potential was then reset to -0.2 mV and holds for an absolute refractory period of 2 ms. $\boldsymbol{I(t)}$ is the time-variant synaptic inputs.

2) Exponential Synapse Model: We assume that the release, diffusion, receptor binding of neurotransmitters and channel opening all occur instantaneously. The postsynaptic receptor conductance $\boldsymbol{g}$ was defined as:

$$\boldsymbol{g}_i(t) = \boldsymbol{W}_{ij}^{rec} e^{-(t-t_0)/\tau} \tag{3}$$

$\tau = 10$ ms, t_0 is the time of the pre-synaptic spike, W_{ij}^{rec} reflected the conductance of neuron j to neuron i.

Most synaptic ion channels display an approximately linear current-voltage relationship when they open. Thus, the post-synaptic current is defined as:

$$I_i^{syn}(t) = g_i(t)(E - V_i(t)) \tag{4}$$

where $E = 0$ is the reversal potential, and V is the post-synaptic voltage.

3) Spike Network Structure: Neurons ($N = 400$) in the MC network are divided into the fast ($N_f = 100$) and the slow ($N_s = 300$). The first assemble composed of spiking neurons with small time constant ($\tau_f = 5$), resulting in rapid spiking, whereas the second assemble consisted of spiking neurons with large time constant ($\tau_s = 15$), leading to slow spiking. All the neurons have recurrent connections to each other at both within assemble and assemble to assemble. Moreover, we restricted that only half of the presynaptic neurons projected to postsynaptic neurons for sparse connection. Only the "fast" assemble was connected to the input layer and output layer. The network readout into muscle activity $\boldsymbol{m(t)}$:

$$\tau_m \frac{d\boldsymbol{m}}{dt} = -(\boldsymbol{m}-) + \boldsymbol{W^{out}s} \tag{5}$$

where $\tau_m = 200$ for smooth, $\boldsymbol{s}$ is the spikes from the slow assemble, $\boldsymbol{W^{out}}$ is the output matrix.

C. Musculoskeletal Arm Model

To simulate arm reaching, we constructed a planar two-link arm model as detailed in the previous work [20], [21]. Briefly, the upper link and the lower link are connected at the elbow (Figure 1). The arm model is actuated by six muscle, whose activity is the output of the MC network. Then, the muscle activity is converted to muscle forces according to the length/velocity properties of muscle. The muscle forces are further converted to the joint torques $\boldsymbol{\tau(t)}$ that changes the arm state:

$$\ddot{\boldsymbol{\theta}} = \mathcal{M}(\boldsymbol{\theta})^{-1}\left(\boldsymbol{\tau(t)} - \mathcal{X}\left(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}\right) - \mathcal{B}\dot{\boldsymbol{\theta}}\right) \tag{6}$$

where the arm state θ includes the joint angles and velocities $\theta = (\theta_1, \theta_2, \dot{\theta}_1, \dot{\theta}_2)$. The non-linear function $\mathcal{M}$ and $\mathcal{X}$ is the matrix of inertia and the centripetal and Coriolis forces. The position of the end effector (hand) is:

$$\boldsymbol{y} = \begin{pmatrix} L_1 \cos\theta_1 + L_2 \cos(\theta_1 + \theta_2) \\ L_1 \sin\theta_1 + L_2 \sin(\theta_1 + \theta_2) \end{pmatrix} \tag{7}$$

D. Network Optimization

Network was optimized to control the arm model to hold on before go cue, and reach the target after that within in 600 ms. The loss function was the squared error between the predicted and the desired hand velocity:

$$L = \frac{1}{8T}\sum_{c=1}^{C}\sum_{i=1}^{M}\int_0^T \left(v_p red(c,t) - v_d es(c,t)\right)^2 dt + \alpha L_1 \tag{8}$$

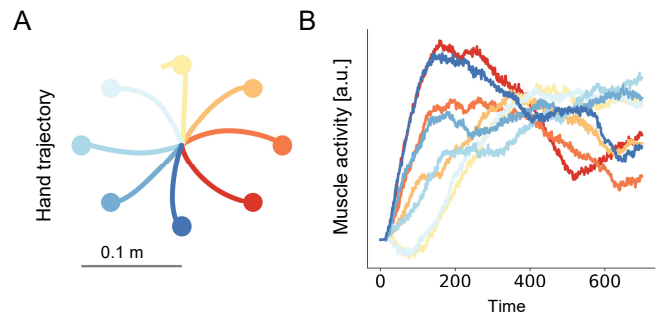

Fig. 3. Hand trajectory and muscle activity produced by the model

where $L_1 = \frac{1}{8T_p}\sum_{c=1}^{C}\sum_{i=1}^{M}\int_0^T (m(c,t))^2\, dt$ penalized the muscle activity before go cue with $\alpha = 10$, $T_p = 300$. The network weights were trained by back-propagation. We used Adam optimizer ($lr = 10^{-4}$) and iterated it 2000 times.

E. Statistical Analysis

1) Neuronal data analysis: We analyzed the recordings from a monkey's MC during reaching [5] and spikes data from our model. As for the monkey data, we extracted the activity of 202 neurons in eight straight reach conditions. We processed the spike trains by computing the firing rates and averaging them for each reach condition. Then we smoothed firing rates by a 30 ms Gaussian filter. All the firing rates were computed for the execution period, time-locked to the movement onset. The following analyses were based on firing rates.

2) jPCA: jPCA captures the rotational dynamics within firing rate responses[5]. First, data was reduced to $\boldsymbol{X_{red}} \in \boldsymbol{R}^{\mathrm{k}\times ct}$ by PCA, where $\mathrm{c} = 8$ is the number of reach conditions, and $\mathrm{t} = 600$ is the number of time points, $\mathrm{k} = 6$ is the number of principal components. Second, the reduced data was fitted into a linear dynamical system $\boldsymbol{X}_{\text{red}} = \boldsymbol{M}_{skew}\boldsymbol{X}_{\text{red}}$, where $\boldsymbol{M}_{\text{skew}}$ is a skew-symmetric matrix that has purely imaginary eigenvalues. The neural trajectory in the plane of the first two eigenvectors of the $\boldsymbol{M}_{skew}$ rotates most strongly.

III. Experiment and Discussion

A. The comparison of model and data

The optimized model can simulate the MC and had a good performance in the eight-direction center out reaching task(Fig. 3). Both fast and slow neurons in the RSNN displayd strong directional tuning in the raster plot and PSTH and temporal complexity(Fig. 4 A and B): the slow example neuron only spiked at the movement onset and the fast example neuron fired during the whole movement epoch with multiphase and heterogeneous firing pattern which was also observed in monkey's MC. At neural population level, we computed the low-dimensional patterns via jPCA. All the neural population responses displayed rotational dynamics(Fig. 4 C). Although the fast assemble with fewer number of neurons than the slow assemble, its rotational structure was more similar to the overall dynamics, suggesting than the neurons connected to the output layer contribute more to the neural population responses. Furthermore, the ratio of fitting to the constrained

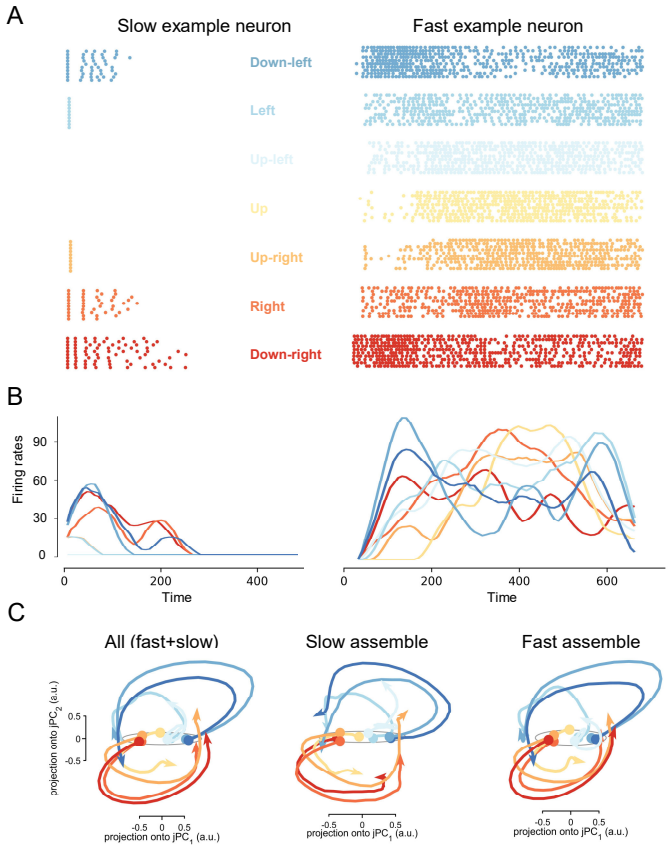

Fig. 4. Neural activity in the model.(A) Raster plot of spikes from a example neuron for 11 trials per direction. (B) Trial-averaged firing rates of the example neuron. (C) Neural population dynamics after jPCA.

and unconstrained dynamical system was 0.80, which indicates that the majority of the output layer's dynamics captured more rotational dynamics. Moreover, We observed rotational dynamics in the kinematic and feedback signals, except for muscle activity. This features are typical and agree with well-documented experimental results.

IV. Conclusion

In this paper, we proposed an recurrent spike neural network based modeling approach of motor cortex, which can relevantly reflect the cortex neural activities. Experiments show the spike fire rate pattern is high similar with the real record signal and driven the reaching task with high accuracy.

In the future research, we will optimize the network structure and training efficiency, increase the number of neurons, explore the mechanism of spike accumulations, and applied the recurrent spike neural network based approach into various neural activities modeling.

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