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Computational capability of liquid state machines with spike-timing-dependent plasticity ☆

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ABSTRACT

Liquid state machine (LSM) is a recently developed computational model with a reservoir of recurrent spiking neural network (RSNN). This model has shown to be beneficial for performing computational tasks. In this paper, we present a novel type of LSM with self-organized RSNN instead of the traditional RSNN with random structure. Here, the spike-timing-dependent plasticity (STDP) which has been broadly observed in neurophysiological experiments is employed for the learning update of RSNN. Our computational results show that this model can carry out a class of biologically relevant real-time computational tasks with high accuracy. By evaluating the average mean squared error (MSE), we find that LSM with STDP learning is able to lead to a better performance than LSM with random reservoir, especially for the case of partial synaptic connections.

1. Introduction

Liquid state machine (LSM) is a recently developed neural network model that has gained increasing attention during the past decade [1–3]. Proposed by Maass et al. [1], LSM is a new form of computational model which is capable of conducting universal computations [2,3]. This model has three main parts, an input component (IC), a liquid component (LC), and a readout component (RC) [1]. LC acts as a medium through which the input can be expressed in a higher dimensional form called liquid state. For different tasks, the liquid states can be transformed into different forms through RC [4]. Typically, neural microcircuits are taken as implementations of LC, which receives one or several input spike trains and facilitate the projection of input into a higher dimensional space. Instead of online updating all of the synaptic conductivities in most of the traditional recurrent neural networks (RNN), synaptic weights of recurrent connections in LC are usually chosen randomly and fixed during the training process; while only the weights from neurons in LC to neurons in RC are trained by learning algorithm according to specific tasks [1,3]. This kind of RNN design, including the Echo State Networks proposed by Herbert Jaeger [5], is often referred as Reservoir Computing. Many studies have shown that this kind of neural network model is capable of performing various computational tasks with high accuracy and low computational cost [1,3,5].

Since neural network is the essential part in the implementation of LC, synaptic connections or network structure is closely related to the performance of the computational capability of LSM. Considering the modeling of neural networks, various topologies have been investigated, such as globally coupled networks [6], small-world networks [7,8], and scale-free networks [9]. Contrast to these predefined networks, self-organized neural networks [10–13] are more reasonable to be considered. The self-organization is usually managed through spike-timing dependent plasticity (STDP), which is a form of long-term synaptic plasticity both experimentally observed [14] and theoretically studied [15,16]. It has been broadly found in many neocortical layers and brain regions [17–19]. In [20], bidirectional and unidirectional connections developed from STDP learning can reflect different neural codes. Actually, the STDP explores the possible casual relationship between each pair of pre- and post-synaptic neurons [21].

Recently, LSM with STDP learning has been studied. In [22], STDP is used to train readout neurons so that a single neuron can recognize the state of LC according to the input signal. Computational capability can also be improved by combining STDP and Intrinsic Plasticity (IP) for reshaping of the network structure [23]. Besides, Hebbian Learning and STDP can be applied in LC to improve the separation property when LSM is used to deal with real-world speech data [24]. However, in these studies they did not

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consider the relationship between the intrinsic neural dynamics and synaptic plasticity of neural network. Thus the updated network with STDP learning rule is somewhat determined by initial conditions, and cannot fully take advantage of the internal dynamical states of neuronal population.

In papers [21,25] the authors proposed a novel neural network with active-neuron-dominant structure, which is self-organized via the STDP learning rule. In this model, strong connections are mainly distributed to the outward links of a few highly active neurons. Besides, a recent experimental study [26] found that a small population of highly active neurons may dominate the firing in neocortical networks, suggesting the existence of active-neuron-dominant connectivity in the neocortex. Such synapse distribution has shown to be beneficial for enhancing information transmission of neural circuits [21,25].

Based on these previous studies, here we apply this novel active-neuron-dominant structure presented in [25,21] to the neural network of LC and investigate its computational capability. In this model, neurons in LC are equally divided into four groups. Synaptic connections in each group are active-neuron-dominant, which are developed from the STDP rule before the training of readout weights for computational tasks. The computational capability of LSM with different settings of LC structure has been examined and evaluated by applying the average MSE. Our results show that LSM with STDP has a better performance than LSM with random LC for these computational tasks, which indicates the significant influence of STDP learning on the computational capability of LSM. In our model, the internal dynamics of neurons with different degrees of excitability are clearly extracted into an active-neuron-dominant topology after the STDP process, which contributes to the synchronous spiking behavior of LC network. It is the highly synchronous network activity in LC that contributes to the improvement of the computational performance of LSM system.

2. Network description

2.1. Network architecture

In our model, 400 Izhikevich neurons of LC are divided into four independent groups equally (see Fig. 1). Before computations of specific tasks, synapses between neurons in each group are firstly updated by the STDP learning rule in order to obtain the active-neuron-dominant network structure as described below. IC includes four independent input streams, each consists of eight spike trains generated by the Poisson process with randomly varying rates $r_i(t),\ i=1,\ldots,4$ (more details are given in Section 3). Four input streams are connected to four groups in LC separately (more connection types are discussed in Section 5). For each specific computational task, there is a readout neuron which is fully connected to all neurons in LC. With the same/fixed LC which has the active-neuron-dominant structure updated by STDP, readout neurons could be trained to deal with different computational tasks simultaneously. Note that during the computations, connections in LC always keep unchanged and only readouts are trained by linear regression for different tasks.

2.2. Neuron model

In this paper, regular spiking neurons are modeled by the two-variable integrate-and-fire (I&F) model of Izhikevich [27], which has shown to be both biologically plausible and computationally efficient. It is described by

$$\dot{v_i} = 0.04v_i^2 + 5v_i + 140 - u_i + I + I_i^{syn}$$
$$\dot{u_i} = a(bv_i - u_i) + D\xi_i \tag{1}$$

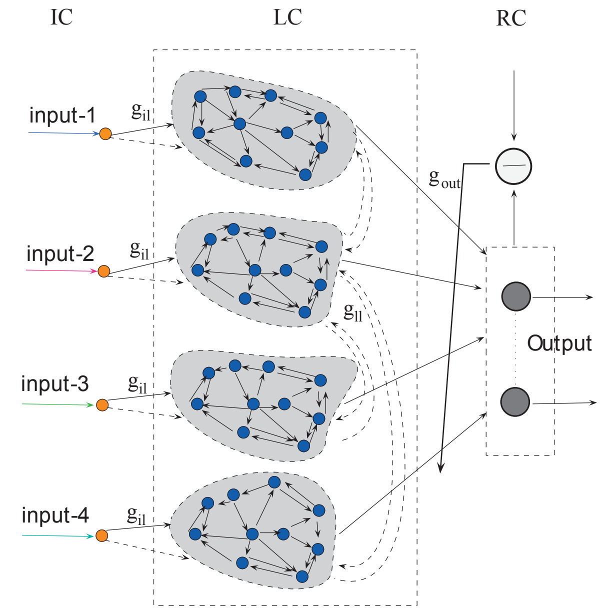

Fig. 1. Network structure. In this model, 400 Izhikevich neurons in LC are equally divided into four groups where each group receives one input stream independently. For each group, inputs in IC are fully or partially connected to neurons in LC. When fully connected, inputs are fully applied to all of the neurons in the corresponding LC group; when partially connected, inputs are partially applied to 5% selected randomly neurons from the population of each LC group. g_{il} is the synaptic weight. In LC, synaptic weights with the maximum value of g_{ll} in each group are generated by updating the STDP learning rule. For RC, every readout neuron is connected to all of the neurons in LC with synaptic weights g_{out}, which are trained by linear regression for different tasks.

$$\text{if } v_i > 30\text{ mV} \quad \text{then} \begin{cases} v_i \leftarrow c \\ u_i \leftarrow u_i + d \end{cases} \tag{2}$$

where $i = 1, 2, \ldots, N$, v_i represents the membrane potential and u_i is the membrane recovery variable. The parameters a, b, c, d are dimensionless. The variable ξ_i is the independent Gaussian noise with zero mean and intensity D that represents the noisy background. I stands for the externally applied current and I_i^{syn} is the total synaptic current through neuron i and is governed by the dynamics of the synaptic variable s_j:

$$I_i^{syn} = -\sum_{1(j\neq i)}^{N} g_{ji}s_j(v_i - v_{syn})$$
$$\dot{s_j} = \alpha(v_j)(1 - s_j) - s_j/\tau$$
$$\alpha(v_j) = \alpha_0/(1 + e^{-v_j/v_{shp}}) \tag{3}$$

here the synaptic recovery function $\alpha(v_j)$ can be taken as the Heaviside function. When the presynaptic cell is in the silent state $v_j < 0$, s_j can be reduced to $\dot{s_j} = -s_j/\tau$; otherwise, s_j jumps quickly to 1 and acts on the post-synaptic cells. The synaptic conductance g_{ji} from the jth neuron to the ith neuron will be updated through the STDP learning rule. Here, the excitatory synaptic reversal potential v_{syn} is set to be 0. The degree of neurons excitability is governed by the parameter b [27]. Neurons with larger b are prone to exhibit larger excitability and fire with a higher frequency than others. In order to establish a heterogenous network, the parameter value b_i of ith neuron is uniformly distributed in $[0.12, 0.2]$.

2.3. Self-organization of recurrent neural network

In our simulation synapses between mutually connected neurons are updated by the STDP modification function F, which selectively strengthens the pre-to-post synapses with relatively shorter latencies or stronger mutual correlations, while weakens the remaining synapses [10]. The synaptic conductance