Study on Modular Reservoir Network with Spike-Timing Dependent Synaptic Plasticity for Pattern Recognition

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修士学位論文要約（令和２年９月）

スパイクタイミング依存シナプス可塑性を実装したパターン認識向けモジュール型リザーバネットワークに関する研究

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Study on Modular Reservoir Network with Spike-Timing Dependent Synaptic Plasticity for Pattern Recognition

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Liquid state machine (LSM) is a type of recurrent spiking neural network with low computational cost and fast convergence. In fields including pattern recognition and neurophysiology, the LSM has achieved success. The use of spiking neurons in LSM also reduce the power consumption and enhance the long-term memory of sequences. However, the application of LSMs are still limited, because the simulation of spiking neurons is more expensive than that of artificial neurons and lacks general algorithms to update the weight of synapses simultaneously. In this work, in order to ease the simulation of large-scale spiking networks, the modular network topology was explored, which enable the network to be simulated separately. Also, to find an efficient method to optimize the weights of LSM, the Hough Transform based static wiring method and spike-timing dependent plasticity (STDP) learning is also applied to the modular LSM network. The experiments are performed on MATLAB using the MNIST dataset as inputs. The robustness and classification accuracy of networks with different topology are also evaluated. The results show that the modular LSM has great potential on both reducing the simulation cost and improving the network functionality.

1. Introduction

The LSM is one practical paradigm of spiking recurrent neuron network (RNN) proposed by Maass [1] in 2002. Compared with the typical RNNs whose weights are updated by backpropagation through time (BPTT), the recurrent synapses of LSMs are kept to be constants while the states of neurons are learned by a simple readout function. In this way the number of parameters and the power consumption is reduced as shown in [2]. However, the parallelization of simulation of spiking neurons is not as convenient as artificial neurons, which limits the scale and functionality of LSM.

Besides, the topology of LSM recurrent connection also influence the network property significantly. In this work, the random, small-world (SW), metric, and modular topologies with the same size are implemented to compare the performance on pattern recognition tasks.

The purpose of the work is to scale up the size of LSM with the least possible increase in computation load and find efficient topology and method to boost the network performance. The static wiring method based on Hough Transform (HT) is given in chapter 3, and the dynamic learning method is shown in chapter 5 using STDP.

2. Theory of Liquid State Machine

A typical LSM is constituted by input neurons, reservoir network and readout function three parts. The reservoir network contains multiple neurons which are connected recurrently. Specifically, in LSM, the reservoir neurons are always spiking neurons instead of artificial neurons. In the architecture of LSM, the spike trains are firstly received by input neurons, which feed the signals into the reservoir network through input synapses. The input synapses could be set randomly or optimized by certain local learning rules such as STDP.

In our methodology, the input signal is MNIST images, which are converted into spike trains via Poisson coding. The reservoir network is formed by different topological architectures, which are (1) random, generated according to Erdös-Renyi algorithm, (2) SW, constructed by Watts & Strogatz's method, (3) metric, proposed by Maass, and (4) modular topology, modules of which are connected in directed acyclic graph to reduce the simulation cost as shown in chapter 4. Finally, a support vector machine

(SVM) is used as the readout function, which shows lower variance compared to a linear map readout.

3. Input Synapse Optimization

Inspired from previous works in neuroscience [3], the HT, which is a common method in image processing, is implemented by pre-defined input synapses. The effectiveness of HT on LSM is evaluated by comparing the classification performance with another LSM with random input synapses and the same size. As shown in Fig. 1, the classification accuracy of modular LSM with HT is improve by 3% compared with the modular LSM with random input synapses. SW and metric LSMs with random input synapses are also simulated as references, which yield lower accuracy than the modular network. Also, all reservoirs achieve better performance than the SVM-only case, which indicates the effectiveness of the LSM learning.

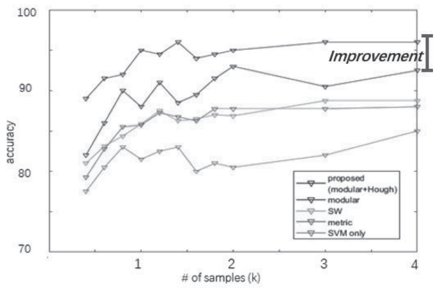

Fig.1 learning curves of different LSMs. The application of Hough Transform based rewiring improve the accuracy of modular LSM [4].

4. Effect of Reservoir Topology on Computational Efficiency and Robustness

In order to reduce the simulation cost of large-scale LSMs, in this chapter, the computational cost of LSMs with different network topology is evaluated by calculating the FLOPS, which is the number of float operations per iteration. In the experiments, because of the application of divide-and-conquer algorithm, the computation cost for the modular LSM is two times lower than other LSMs. Moreover, since the noise in modular network can hardly cause global influence, the modular LSM casts higher robustness and suffer less accuracy loss over the system noise, which is generated by randomly disabling synapses in the network.

5. Unsupervised Learning of LSM

In this chapter, the effect and application of STDP algorithm on LSMs are studied. Referenced from previous studies on STDP-based spiking network, here the modular LSM is adopted, where the STDP mechanism is only applied on inter-modular synapses while the recurrent connections inside each module are unchanged in order to keep the regularity and track the learning progress. After the learning with STDP, the weight matrices of each LSM neurons converge to mask different symbols. Moreover, the weight distribution of the synapses also converges to binary values, which indicates that the STDP could serve as one efficient method to prune insignificant edges in the network. According to the experimental results, the application of STDP improves the accuracy of LSM from 60% to 70% compared with the LSM with random weights initialized by Gaussian distribution. Besides, the results and mechanisms of STDP-based synapses optimization method are compared with HT-based static synapses rewiring method in this chapter.

6. Conclusions

In this work, the input synapses optimization method on reservoir networks is studied. In chapter 3, it is shown that the HT-based rewiring method on input synapses of modular LSMs yields significant improvement on accuracy over the random synapses. The application of acyclic-directed-graph based modular structure in chapter 4 not only reduces the computation cost by half through divide-and-conquer and parallelization, but also improves the robustness over the system noise. The effect and mechanism of STDP based synapses optimization method are studied in chapter 5. From the experiments, the STDP could both increase the learning accuracy and enhance the visualization of feature extraction by the weight matrices of LSM neurons.

Reference

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