

Non-Self Rejection by Emergent Structures on Evolving Networks of the Spiking Neurons

Shinichi Nagai

Honda Research Institute Japan Co., Ltd.
8-1 Honcho, Wako-shi, Saitama, 351-0114, Japan
sinn@jp.honda-ri.com

Abstract. Generic networks of the spiking neurons provide enormous varieties of the spatio-temporal orders of the activity patterns that could represent valid information. Not to miss relevant neural codings beyond our current stereotypes, further empirical investigations on the generic networks are important. In this report, randomly generated sparse recurrent networks of the spiking neurons with activity dependent local synaptic re-wiring rule are computationally simulated. Emergence of non-trivial order during the re-wiring is indirectly confirmed by the rejection of the channels that carry only non-autonomous signals.

1 Introduction

Development of the methods for the physiological experiments have introduced fine description of the neuron. Finding the importance of spike timing provided novel informatic potentials of neuronal networks [1], [2]. Fortunately, development of the computational power coincide which made it possible to process enormous experimental data and to simulate computational models of the neuronal networks with respectable scale and complexity [2], [3]. However, and therefore, such data processing and model simulation began to demand greater costs to test entire possibilities further rapidly because of the newly acquired degree of freedom itself. Hence, arbitrary strong postulations are necessary to establish meaningful theory that are practically testable. To make sound postulations, many empirical investigation must precede. In this report, model for generic network of spiking neurons are computationally implemented to examine emergence of the non-trivial order as the candidate for the neuronal coding.

2 Network Model

2.1 Spiking Neuron

Spike Processing The network consists of conventional leaky-integrate-and-fire type spiking neurons (Fig. 1). Spikes that arrive at a neuron are temporally integrated at the post-synaptic nodes with respective synaptic weights. Responses of the post-synaptic nodes are summed up at the dendrite. The dendritic activity is multiplied by the gain and integrated at the neurosoma. Therefore, the

neurosoma is second order leaky integrator of the spikes. When the response of the neurosoma exceed certain threshold, a spike is released and the neurosoma is flushed. Even with less activation than the threshold, it fires stochastically in certain probability. The threshold consists of constant and variable components. The variable part is a leaky integrator of the releasing spikes. After the spike, the threshold rises and then gradually decays. Therefore, the neuron has relative refractory period. For the simplicity, time constants of these three kinds of leaky integrators are set same. The spike processing in the neuron is discretized into fixed time steps so that the time constants of leaky integrators are as long as around 100 time steps to be simulated.

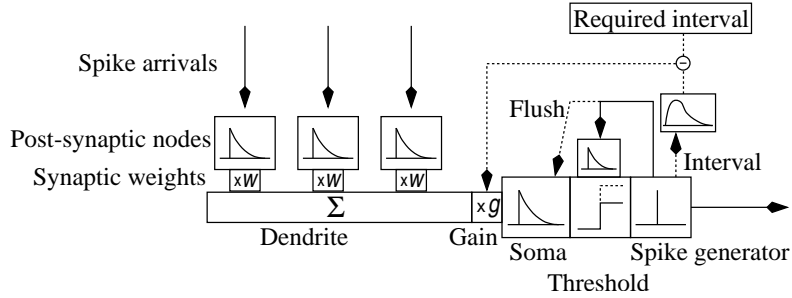


Fig. 1. Leaky-integrate-and-fire type model of the spiking neuron is implemented in conventional way. The model has refractoriness and mean frequency control. Spike reception, post-synaptic membrane response, dendritic integration, somatic accumulation, spike generation and adaptive threshold is calculated every time steps (*solid lines and stuck blocks*), while after-spike flush of somatic accumulation and mean frequency adaptation are driven by each spike release (*broken lines*).

Spike Frequency Control Every neuron has required mean firing rate toward which the firing rate of individual neurons are controlled locally. Log of the inter-spike intervals are accumulated by the second order leaky integrator and the difference from the required one is used to bias the dendritic gain of the neuron to compensate the difference gradually. This control process is driven only on every spike release.

2.2 Sparse Network

Simulations start from randomly generated sparse network of the neurons. Self-, multiple and reciprocal connections are prohibited. Typical number of neurons is 128 which are all excitatory and have restricted number of post-synaptic nodes at which spikes from other neurons arrive and unlimited number of output spike destinations. All synaptic weights on each neurons are the same and sum of them are set so that completely simultaneous spike arrivals to all post-synaptic nodes

provide critical impact to the neuron with which resting neuron just reaches the threshold. During the re-wiring, this condition is always kept.

2.3 Synaptic Contribution

Contributions of the post-synaptic nodes to the spike release are accumulated in every nodes. Employed empirical implementation is second order leaky integration of the post-synaptic response sampled at every spike release subtracted the leaky integration of the variable part of the threshold sampled at every spike arrival. For former term becomes large when spike is released immediately after the spike arrival at the node and latter term becomes large when spike arrives at the node immediately after the spike release, this implementation simulates temporally anti-symmetric Hebbian learning rule apart from the weight modification.

3 Simulation Results

3.1 General Settings

Dynamics 128 excitatory neurons are randomly interconnected and examined during the network reconfiguration. Time constants for signal processing of all neurons are set 100 time steps of the simulation. Required mean firing rate of all neurons are set toward $1/3$ [spikes/time constant]. Time constants for feed-back frequency control and synaptic contribution accumulation are set 16 [spikes] and 1000 [spikes] respectively. Because these two slow dynamics are driven only at each spike events, the speed changes depending on the firing rate.

Two classes of neurons 16 out of 128 neurons are randomly chosen as ‘source neurons’ which receive large amount of signals from outside the network. As the representative of the activity evoked by the external input, ‘source neurons’ are implemented to release spontaneous Poisson spikes whose rate is close to the required one. In contrast, residual 112 ‘medium neurons’ releases much fewer spontaneous spikes as many as only 10% of the requirement. Therefore, they need input spikes from other neurons in the network.

3.2 Pruning

During the simulation, every neurons are sequentially chosen to prune off the least contributing post-synaptic node. The random sequence is repeated in the same order till all individual neurons have only one post-synaptic node. Initial number of the post-synaptic node of a neuron is 13 and the pruning procedure is done in 10^7 time steps at regular interval. Two cases are examined; whether spontaneous spiking frequency of the ‘source neuron’ is equal to the required one or half (Fig. 2).

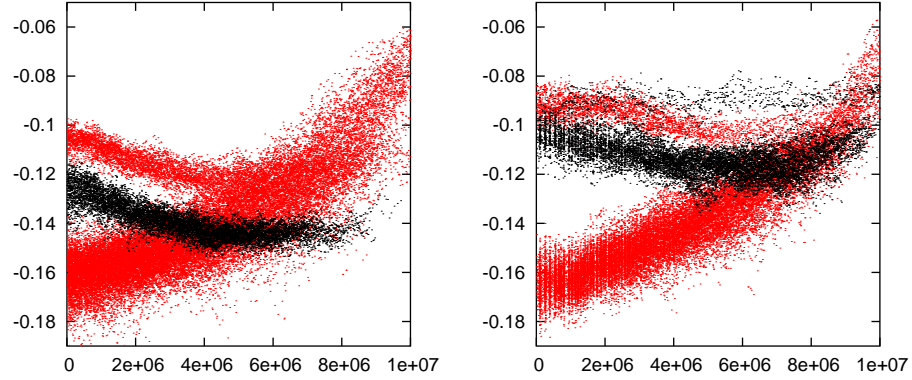


Fig. 2. Development of the synaptic contribution is recorded during the pruning. Abscissa is time and axis is synaptic contribution. Each black and red dot represent synaptic node whose spike source is at ‘source neuron’ and ‘medium neuron’ respectively. Spontaneous activities of the ‘source neurons’ are equal to the required mean firing rate (*left*) or half (*right*). Dots are evenly thinned out so that the density is visible.

Fate of the Pure Source Because initial autonomous network of ‘medium neurons’ apart from ‘source neurons’ has strong bistability on the population activity, mean firing rate control would never converge in moderate frequency. While both absence and saturation of the spikes hardly gain the synaptic contribution, ‘source neurons’ which constantly provide respectable number of spikes take the initiative. As the number of synapses decrease, such a bistability disappear and rather steady reverberation of moderate activity arises, when pure ‘source neurons’ whose spike timing has no relation to the reverberation lose advantages (see Fig. 2 *left*). Finally, they are rejected by all destinations.

Affected Source In contrast, ‘source neurons’ that are affected by the reverberation on the network since spontaneous activity is not sufficient for the required firing rate would not be detached.

3.3 Restricted Evolution

Evolving networks with constant number of the post-synaptic nodes are examined. Settings are similar to the pruning examinations above, but initial number of the post synaptic nodes for every neuron is preserved adding a new synapse from a randomly chosen neuron. Consistently to the result of the pruning, pure ‘source neurons’ get less contributing, while affected ones become dominant (Fig. 3).

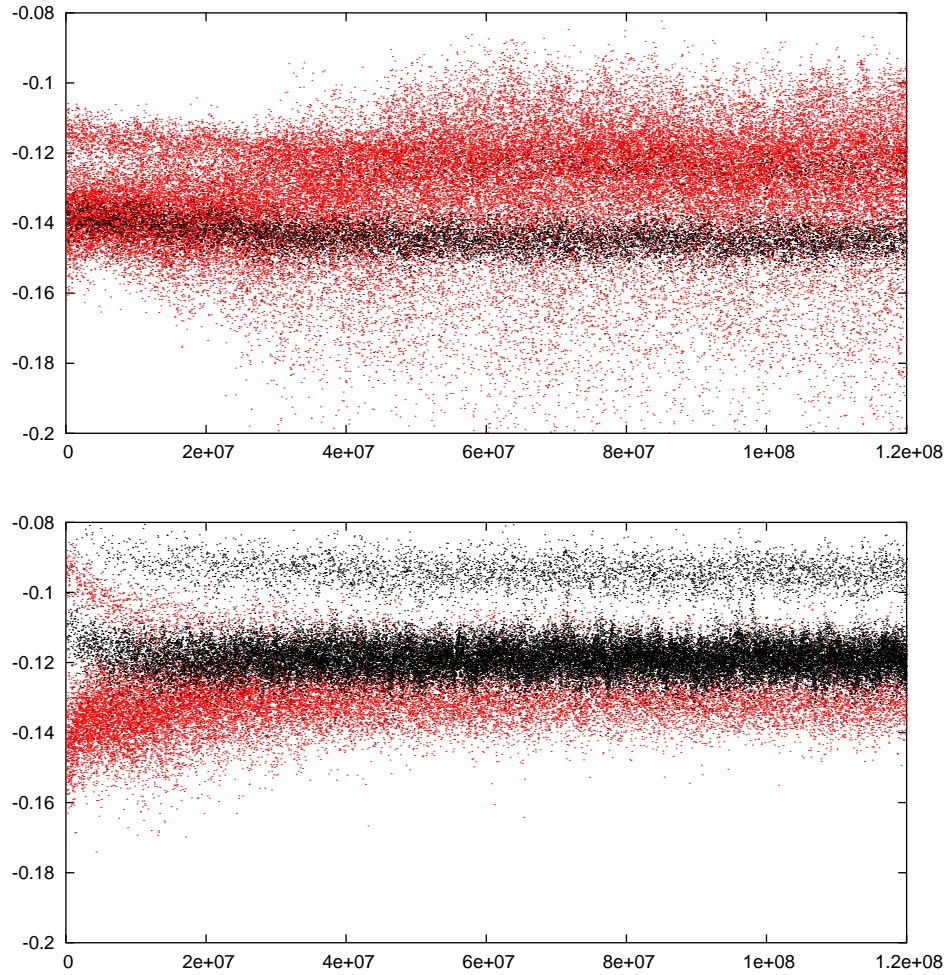


Fig. 3. Development of the synaptic contribution is recorded during the restricted evolution. Number of the post-synaptic nodes of a neuron (7) is preserved. As ‘medium neurons’ form specific reverberation network, synapses from pure ‘source neurons’ got less contributing (*top*), while affected ‘source neurons’ provide more outputs with greater contributions (*bottom*).

4 Discussion

Though the results are far from optimization of the information preservation during the reverberation, significant order on the spatio-temporal activity pattern is obtained by means of distributed pruning process. The examined emergence of the order is indicated so indirectly that it is necessary to suspend the re-wiring process to mine and specify emerged coding. Bistability of the population activity, which must be avoided for temporal coding, is very common problem of recurrent networks. Typical solutions have given the network specific topologies such as near planar [4] or layered [3] configurations. In this report such topology was not given but may have emerged. Graph-theoretic assay of the configuration seems interesting. Many parameters, such as synaptic weights, being left homogeneous could be subject to the neural net approaches for further tuning.

In comparison with the other part of the brain, neocortex easily disintegrate into incoherent fragments of functionalities. Therefore, rather than the other monolithic models, fragile one in this report is plausible to simulate neocortex. Also, different fates of affected and pure ‘source neuron’ shown in Fig. 3 are analogous to that of layer 4 neurons of primary and higher associate sensory cortices respectively.

Unless all of potential varieties of orders are argued, further interesting investigation on this network is to look for the persistence as the representative of the coding, let the evolution going on. Such an investigation should be the first step to the evolving identity of individuals during ontogenesis.

References

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