

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

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Abstract

Generic network of the spiking neurons provides an enormous variety of spatio-temporal orders of activity patterns that could represent valid information. Not to miss relevant neural coding, further empirical investigation on generic network that are free from our stereotypes is important. As models for the neocortex, randomly generated sparse recurrent networks of spiking neurons with spike time dependent local synaptic rewiring process are computationally simulated. The emergence of nontrivial spatio-temporal orders during the rewiring is indirectly observed by selective rejection of the newly introduced channels.

Key words: Spike time coding, Rewiring network, Self-organization, STDP

1 Introduction

Though many details of the neuron have been revealed, little is known about the processing scheme of the brain. The potential of spike time coding is interesting finding [2,4,5], however, too many possibilities are left for us to make arbitrary postulations. Systematic knowledge about the typical phenomena on the network of such neurons is lacking, hence empirical computer simulation of biologically plausible models is important. To explore a coding scheme in the neocortex, following characteristics seem essential. 1) Enormous number of neurons, 2) Structural homogeneity, 3) Sparse synaptic connections and local processing, 4) Spike timing sensitivity, 5) Radical reconfiguration. The last one plays an essential role, although it is not very clear whether mature neocortex reconfigures synaptic connections. It seems plausible since radical synaptic reconfiguration is observed during prenatal and infant development and regeneration, and signal dependent radical functional re-mapping is found even in adult.

To examine self-organization of the non-stereotyped order, networks of the

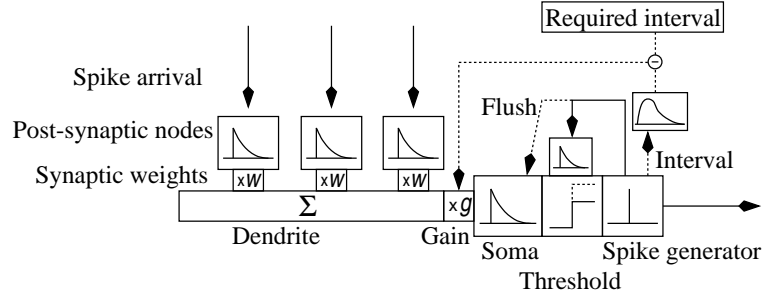


Fig. 1. Integrate-and-fire type model of the spiking neuron is implemented in conventional way. Spike reception, post-synaptic membrane response, dendritic integration, somatic membrane potential, spike generation and variable threshold are calculated every time steps (*solid lines and stuck blocks*), while after-spike flush of somatic membrane potential and mean firing rate control are driven by each spike release (*broken lines*).

spiking neurons are computationally simulated. Due to the limitation on the computational power, the first item of the essential characteristics listed above was omitted.

2 Network Model

The model network consists of conventional integrate-and-fire type spiking neurons (Fig. 1). For the potential of analog timing coding, after-spike partial reset of the membrane potential and relative refractoriness are employed.

Since it is difficult to predict emergent properties of the population dynamics on the recurrent network, autonomous feed-back control of the mean firing rate is empirically implemented to each neurons. Inter-spike intervals are watched and the difference from the required one is used to bias the dendritic gain of the neuron to compensate the difference gradually.

Simulations start from randomly generated sparse network of the neurons. Self-, multiple and reciprocal connections are prohibited. All neurons are excitatory. Neurons have restricted number of post-synaptic nodes at which spikes from other neurons arrive and unlimited number of output spike destinations. During the rewiring, this condition is always maintained.

Contributions of the synaptic nodes to the spike propagation are accumulated in every nodes. Spike event driven accumulation of the contingent temporal relationship between pre- and post-synaptic spike events is employed to measure the contribution. The implementation simulates temporally anti-symmetric spike time dependent plasticity rule apart from the weight modification. More details are described in the appendix.

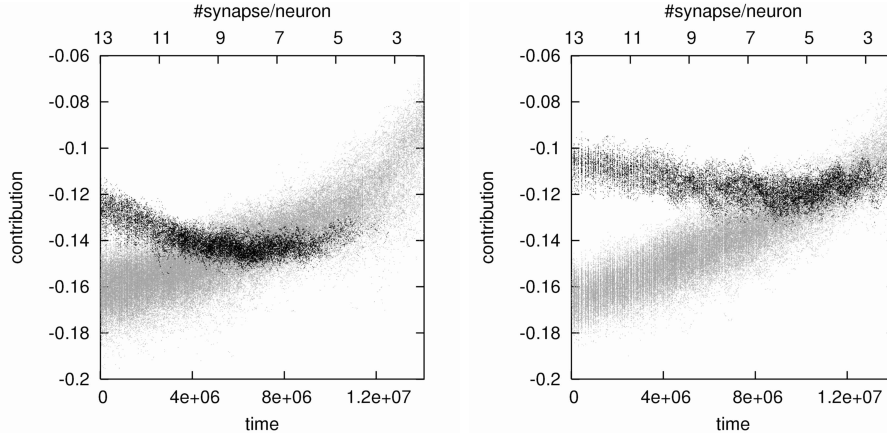


Fig. 2. Development of the synaptic contributions are recorded during the pruning. Horizontal and vertical axes represent the time and the synaptic contribution respectively. Each black or grey dot represents the contribution of a synaptic node whose spike source is ‘source neuron’ or ‘medium neuron’ 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. Not a few grey dots may be invisible beneath the black dots.

3 Simulation Results

128 excitatory neurons are randomly interconnected and examined during the network reconfiguration. To represent the activity evoked by external events, 16 out of 128 neurons are randomly chosen as ‘source neurons’ which provide major non-autonomous signals into the network. The ‘source neurons’ are implemented to release spontaneous Poisson spikes in the rate close to the target rate. In contrast, residual 112 ‘medium neurons’ release much fewer spontaneous spikes as many as only 10% of the requirement. Therefore, they need inputs from other neurons within the network to fire with the required rate.

During the simulation, every neurons are sequentially chosen to prune off the least contributing post-synaptic node. A random sequence is repeated in the same order till all individual neurons have only two 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 firing rate of the ‘source neuron’ is equal to the target rate or only half (Fig. 2).

On the initial recurrent network of ‘medium neurons’ apart from ‘source neurons’ which has strong bistability on the population activity, mean firing rate control would never converge in a moderate rate. While both absence and saturation of the spikes hardly gain spike time conscious synaptic contribution, ‘source neurons’ which constantly provide respectable number of spikes take

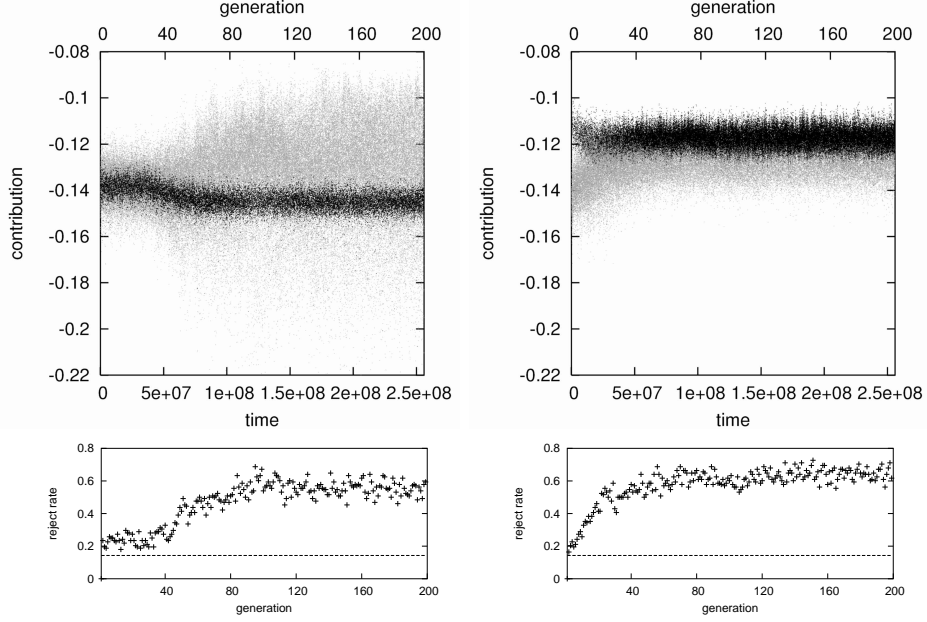


Fig. 3. Development of the distribution of the synaptic contribution (*top*) and the reject rate of new synapses (*bottom*) during the reconfiguration. Results with pure source neurons (*left*) and 50% affected source neurons (*right*) are shown. Horizontal broken lines represent the chance rate.

the initiative on the spike propagation. As the number of synapses decreases, such a bistability disappears and rather steady reverberation of moderate activity arises, when pure ‘source neurons’ whose spike timing has no relation to the reverberation lose advantages (Fig. 2 *left*). Finally, pure ‘source neurons’ are rejected by all destinations. 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 (Fig. 2 *right*).

Also, evolving networks with constant number of the post-synaptic nodes are examined. Parameters are set similar to the pruning examinations above, but initial number of the post synaptic nodes for every neuron is preserved by attaching a new synapse from a randomly chosen neuron. In a given random order, every neurons are repeatedly chosen at the constant interval of 2×10^6 time steps to replace the least contributing synapse to the new one. In both cases, emergence of non-trivial orders is observed with significantly high rejection rate of random new connections. Consistently to the result of the pruning, pure ‘source neurons’ get less contributing, while affected ones become dominant (Fig. 3).

4 Discussion

Non-trivial orders on the spatio-temporal activity pattern are obtained by means of spike time dependent distributed reconfiguration process. The examined emergence of the orders is indicated so indirectly that further intensive inspection with suspended rewiring process is necessary to specify the coding.

Bistability of the population activity, which must be avoided for spike time coding, is a common problem of recurrent networks. Typical solutions have given the network certain specific configurations such as near planar [3] or layered [1] ones. In this report such a configuration was not given but certain one may have emerged. Graph-theoretic assay of the configuration would be interesting. Many parameters, such as synaptic weights, kept homogeneous could be subject to the neural net approaches for further tuning.

Different fates of affected and pure ‘source neurons’ shown in Fig. 3 could explain the difference between import neurons of primary sensory cortex where input information is dominant and higher associate cortex where rather internal one is important.

In comparison with the other parts of the brain, neocortex easily disintegrates into incoherent fragments of functionalities. Therefore, rather than other monolithic models, fragile one in this report would become plausible model when the scale become so large that monolithity can hardly be maintained. Unless all of potential varieties of orders are argued out, further interesting investigation on this network is to look for the persistence as the representative of the coding, let the evolution going on, as a first step to the evolving identity of individuals during ontogenesis.

A Details on the model

Following equations are implemented with variables ϑ_j : variable part of the threshold of j -th neuron, w_{ji} : synaptic weight on j -th neuron from i -th neuron, v_{ji} : post synaptic membrane potential, g_j : input gain, u_j : membrane potential on soma, x_j : output spike, Δt_j : recent spike interval, s_j : index of the averaged spike interval and z_{ji} : synaptic contribution.

$$\begin{aligned}
& \tau \dot{\vartheta}_j + \vartheta_j = 0 \\
& \tau \dot{v}_{ji} + v_{ji} = x_i(t) \\
& \tau \dot{u}_j + u_j = g_j \sum_{i=1}^n w_{ji} v_{ji}, \text{ where } \sum_{i=1}^n w_{ji} = e\tau \\
& \text{when } u_j > 1 + \vartheta_j \text{ or stochastic in the probability } p_j \\
& \quad x_j \leftarrow \delta(0), \quad u_j \leftarrow 0, \quad \vartheta_j \leftarrow 1 \\
& \quad \tau_s^2 \ddot{s}_j + 2\tau_s \dot{s}_j + s_j = \log(\Delta t_j) \\
& \quad g_j \leftarrow [1 + \gamma(s_j - \log T_\infty)] g_j \\
& \quad \tau_z \dot{z}_{ji} + z_{ji} = x_j v_{ji} \\
& \quad \tau_z \dot{z}_{ij} + z_{ij} = -x_j \vartheta_i \\
& \text{else} \\
& \quad x_j \leftarrow 0
\end{aligned}$$

Constants are set as $\tau = 100$ [time step], spontaneous firing probability $p_j = 1/300$ (pure source), $1/600$ (affected source) or $1/3000$ (medium), target firing interval $T_\infty = 300$ [time step], $\tau_s = 16$ [spike], $\gamma = 0.003$ and $\tau_z = 1000$ [spike].

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