

Effect of Stimulus-Driven Pruning on the Detection of Spatio-Temporal Pattern of Activity in Large Neural Networks

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Abstract

Massive synaptic pruning following over-growth is a general feature of mammalian brain maturation. Pruning starts near time of birth and is completed by time of sexual maturation. Trigger signals able to induce synaptic pruning could be related to dynamic functions that depend on the timing of action potentials. Spike-timing-dependent synaptic plasticity (STDP) is a change in the synaptic strength based on the ordering of pre- and post-synaptic spikes. The relation between synaptic efficacy and synaptic pruning [2, 6], suggests that the weak synapses may be modified and removed through competitive “learning” rules. We studied the emergence of cell assemblies out of a locally connected random network of integrate-and-fire units distributed on a 2D lattice [4]. The originality of our study stands on the size of the network, 10,000 units, the duration of the experiment, 10^6 time units (one time unit corresponding to the duration of a spike), and the application of an original bio-inspired STDP modification rule compatible with hardware implementation [3]. The synaptic modification rule was applied only to the excitatory–excitatory (*exc–exc*) connections. This plasticity rule might produce the strengthening of the connections among neurons that belong to cell assemblies characterized by recurrent patterns of firing. Conversely, those connections that are not recurrently activated might decrease in efficiency and eventually be eliminated. The main goal of our study is to determine whether or not, and under which conditions, such cell assemblies may emerge from a large neural network receiving background noise and content-related input organized in both temporal and spatial dimensions.

Each simulation was running for 10^6 discrete time steps (1 ms per time step), corresponding to about 16 minutes. After a stabilization period of 1,000 ms without any external input, a 100ms long stimulus was presented every 2,000 ms. Overall this corresponds to 500 presentations of the stimulus along one simulation run. Before the simulation started, two non-overlapping sets of 400 units were randomly selected from the 8,000 excitatory units of the network, labeled sets A and B . Each set was randomly divided into 10 ordered groups of 40 units, $A = \{A_1, A_2, \dots, A_{10}\}$ and $B = \{B_1, B_2, \dots, B_{10}\}$. At each time step during a stimulus presentation, the 40 units of one group received a large excitatory input on their membrane, leading to their synchronous firing. The 10 groups of a set were stimulated following an ordered sequence, thus defining a spatio-temporal stimulus composed by the repetition of 10ms long sequences. Thus, the overall stimulus duration corresponded to 100 ms. The following protocols were used: (1) no stimulus; (2) $10\times$ sequence A ; (3) $10\times$ sequence B ; (4) $5\times$ sequence A followed by $5\times$ sequence B ; (5) $5\times$ sequence B followed by $5\times$ sequence A ; (6) a random, equiprobable mix of protocols 3 and 4. All protocols were run a first time with the same initial conditions and random generator seed. The networks that emerged from the initial random connections through pruning under the different stimulus protocols were analyzed at time $t = 5 \cdot 10^5$. From the excitatory units that were not directly stimulated, we extracted those that had no input or output *exc–exc* connections in absence of stimulus (protocol 1), but maintained strong input and output *exc–exc* connections under every other protocol. From those units, we selected the 20 units that maintained the larger number of strong output connections.

After time $t = 5 \cdot 10^5$, the simulations were continued in two directions. In the first case the STDP-driven pruning was maintained as before and in the second case synaptic pruning was

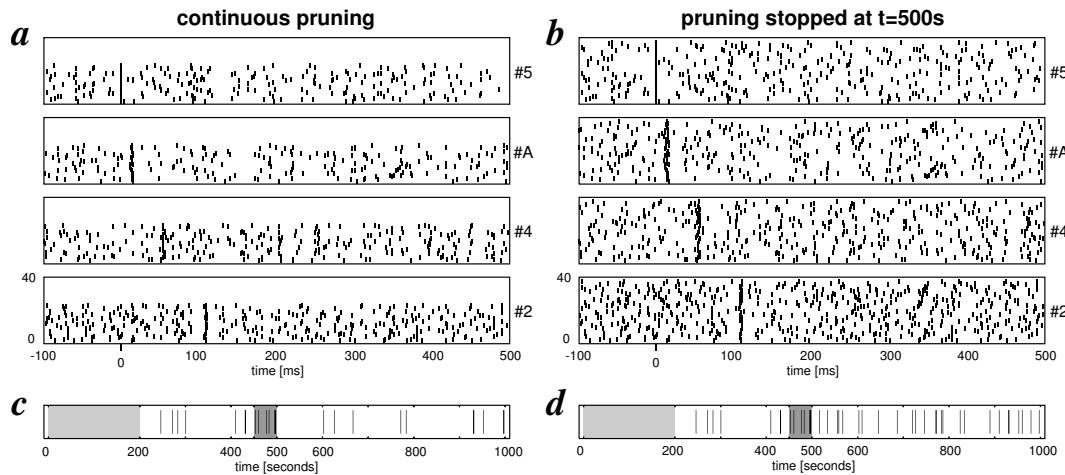


Figure 1: *Upper panels*: raster plots of the spatio-temporal pattern $\langle 5, A, 4, 2; 13, 53, 109 \rangle$ aligned on the first spike of the pattern. Full abscissa scale is 600 ms. *Lower panels*: strip representing 1000 seconds of simulated time, with ticks marking the timing of the first spike of the pattern. The pattern ($n = 6$ occurrences) was significantly detected in the interval 450 – 500 seconds (dark shaded area) and then searched throughout the simulation run starting from $t = 200$ seconds. 8 occurrences were observed in the interval 200 – 450 seconds. We observed 10 additional occurrences during continuous pruning (*a*, *c*); 26 additional occurrences if pruning stopped after 500 seconds (*b*, *d*).

discontinued (i.e. the pruning stopped after the first $5 \cdot 10^5$ time steps). The spike trains of the 20 selected units were recorded throughout the simulations. The recordings were chopped into 50 seconds chunks, subsequently analyzed for spatio-temporal pattern activity [7]. Figure 1 shows a sample pattern detected during both variants of the simulation, i.e. continuous vs. interrupted pruning.

The self-organization of spiking neurons into neuronal groups was recently described in a study featuring large simulated networks connected through STDP [5]. In absence of axonal conduction delays, we observed that the unsupervised pruning process, associated with short and stable stimulation patterns, tended to organize units in strongly interconnected feed-forward assemblies. The detection of complex spatio-temporal patterns in the simulated firing activity suggests that layered topologies may appear during the pruning process. Synfire chains [1] are diverging/converging chains of neurons discharging synchronously to sustain the propagation of the information through a feed-forward neural network. We currently investigate the possibility that the structures emerging from our simulations show such properties.

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