Dynamic properties of large scale networks determined by synaptic pruning associated to Spike-Timing Dependent Plasticity.

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ABSTRACT

Massive synaptic pruning following over-growth is a general feature of mammalian brain maturation. Trigger signals able to induce synaptic pruning could be related to dynamic functions that depend on the timing of action potentials. We studied the emergence of structured connections in a simulated pruning after over-growth development experiment over a long period of time with a locally connected random network of 10,000 integrate-and-fire units (80% excitatory and 20% inhibitory) distributed on a 100x100 2D lattice according to a space-filling quasi-random Sobol distribution. Edge effects on the borders were limited by folding the network as a torus. Excitatory projections were dense in a local neighborhood, but low probability long-range excitatory projections were allowed. Sparse connections between the two populations of units were generated according to a two-dimensional Gaussian density function. Excitatory-excitatory synapses were modified according to a spike-timing-dependent synaptic plasticity (STDP) rule which implemented both long-term potentiation and long-term depression. The synaptic strengths were changed by discrete steps. Network activity was recorded as a multivariate time series akin of multi site multiple spike train recordings at a resolution of 1 ms. The firing pattern of each unit could be characterized by first- and second-order time domain analyses. Analyses are aimed at detecting synfire chains embedded in the large network. Synfire chains are diverging / converging chains of neurons discharging synchronously to sustain the propagation of the information through a feed-forward neural network. The rationale is that selected synaptic pruning may constitute the mechanism which let emerge synfire chains out of randomly connected networks.

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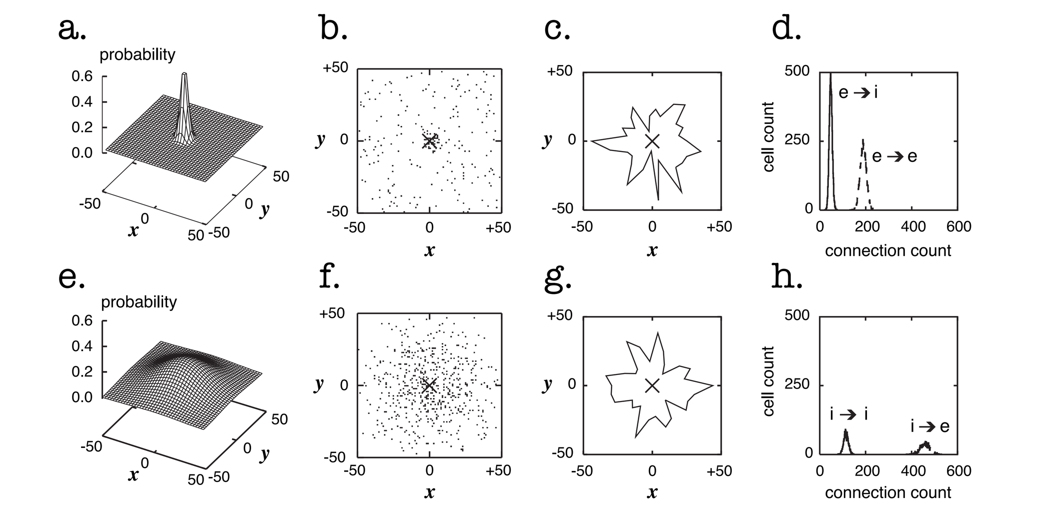
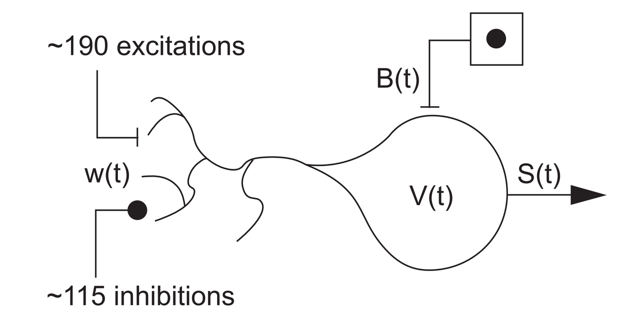


Figure 1. Geometrical features.
Main features of the connectivity for excitatory units (upper row) and inhibitory units (lowerrow). (a,e): Density function of the connectivity for a unit located at coordinates 0,0 on a 100×100 2D lattice; (b,f): Example of two projecting units, one for each class, located at the center of the 2D map. Each dot represents the location of a target unit connected by the projecting unit. (c,g): Orientation map of the projections of the same example units with polar coordinates smoothed with a bin equal to12. A circular line would represent a perfect pattern of isotropic connections. (d,h): Cumulative distributions of the connections.

All units of the network are simulated by a leaky integrate-and-fire neuromimes with a Poisson distribution of background activity intervals. Stimulations consist in 20 equally separated vertical bars moving from the left to the right of the 2D lattice for 100 ms, followed by a pause of 1900 ms, for the complete duration of the simulation. During simulation setup, 10% of the excitatory units were randomly chosen all over the surface of the network to receive the stimulation. Whenever a moving bar reached the column of an input unit, its membrane was depolarized by the addition of an amount, defined as the stimulation intensity, varying between 30 and 60mV (see Fig. 4).



V_{rest} = -78 [mV]
θ_i = -40 [mV]
k_{mem} = 7 [ms]
$t_{refract}$ = 1 [ms]
B_i = 10 [spikes/s]
EPSP = +0.84[mV]
IPSP = -1.60[mV]

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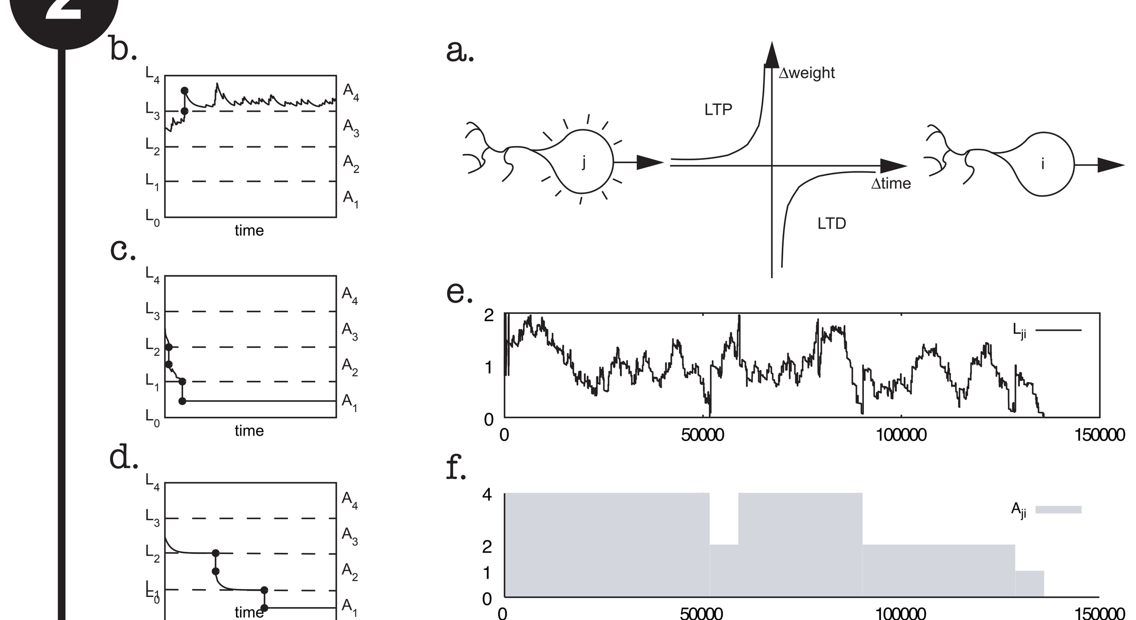

Figure 2. Pruning dynamics. The real-valued variable L_{ji} is increased or decreased according to the STDP rule schematized in (a). If the value L_{ji} reaches one of the boundaries a jump occurs in the integer-valued variable $[A_k]$. At the begin all exc-exc synapses have been set at activation level $[A_3]$. (b): Example of potentiation with an increase in synaptic strength that is stabilized on the long term. (c): Example of depression with a fast decrease in synaptic activation level down to its minimal level, $[A_1] = 0$ which provokes the elimination of the synapse. (d): Example of a synaptic link which neither affected by potentiation nor by depression, but its efficacy decays down to $[A_1] = 0$ according to a time constant. In this study, only excitatory-excitatory projections were subject to learning with $A_{ji}(t)$ in {0, 1, 2, 4}. Other connection types had $A_{ji}(t)$=1. (e): example of the evolution in time of the learning state variable L_{ji} of a sample projection; (f): activation level deduced from e. Note that discrete changes in activation level occur whenever $L_{ji}(t)$ reaches the lower or upper bounds until the projection is pruned out.

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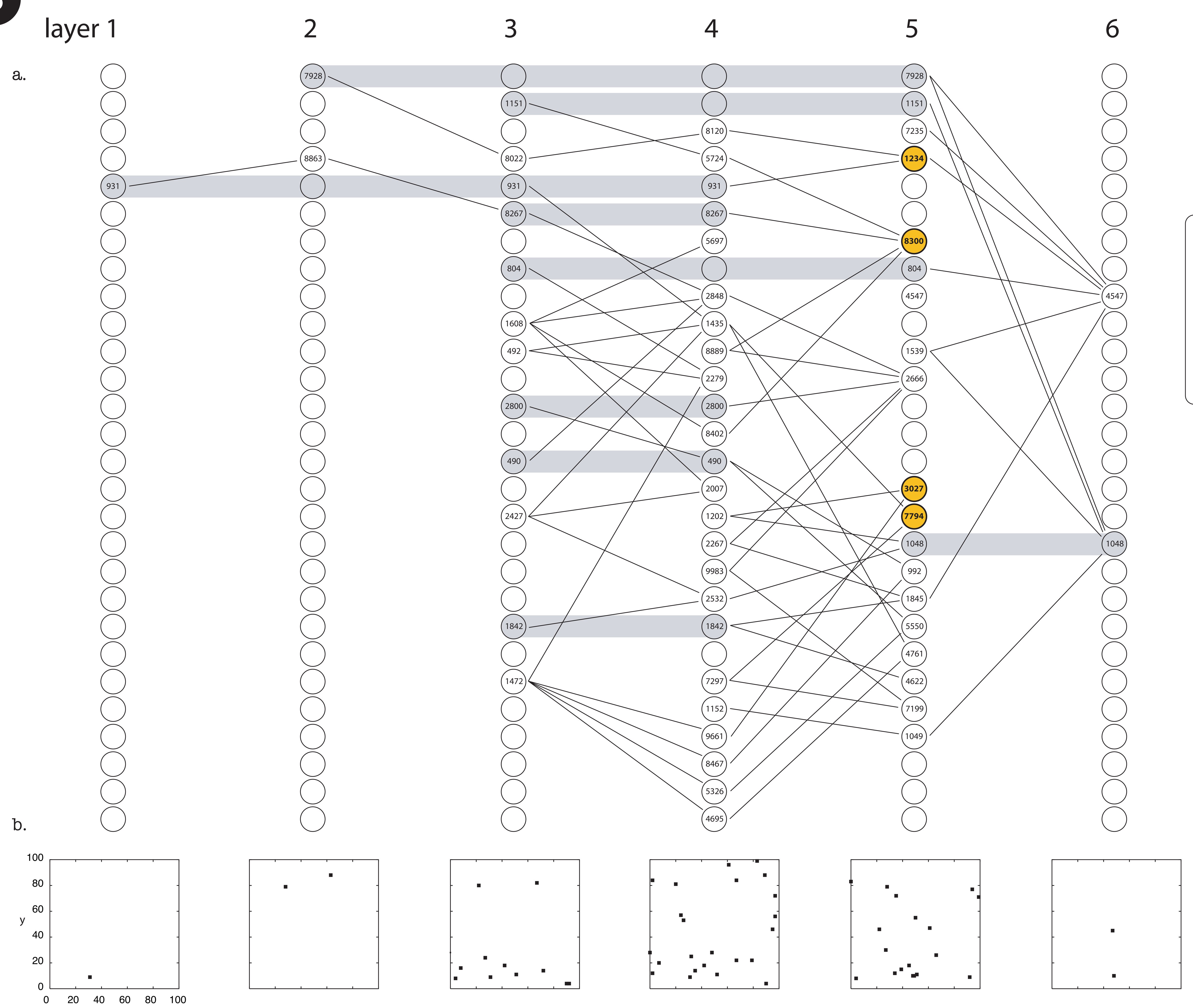

Figure 3. Reconstruction of a pool of diverging / converging units.
From all 8000 excitatory units, we extracted a pool of 49 interconnected units that were not directly stimulated during the simulation; (a): All connections within this pool are plotted, with units arranged in layers according to a best guess fit of their timing. Note that some units appear in more than one layer. They are highlighted in gray. (b): Each unit is represented as a dot at its position on the 2D torus wrapped lattice. Note that some units appear at several layers.

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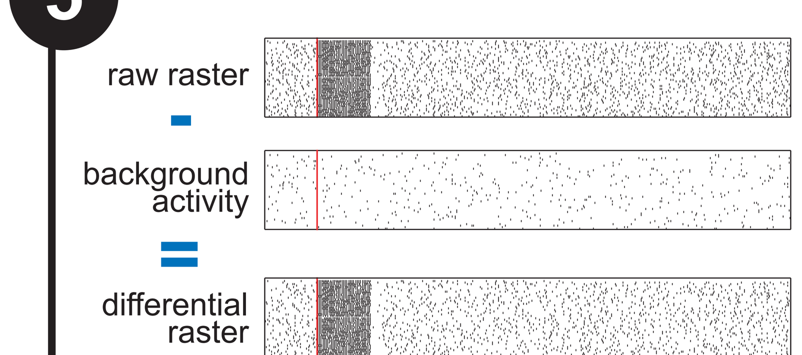

Figure 5. Construction of differential rasters. By substracting the Poisson background activity of a cell to its time serie, the activity produced by the connections of the network can be deduced.

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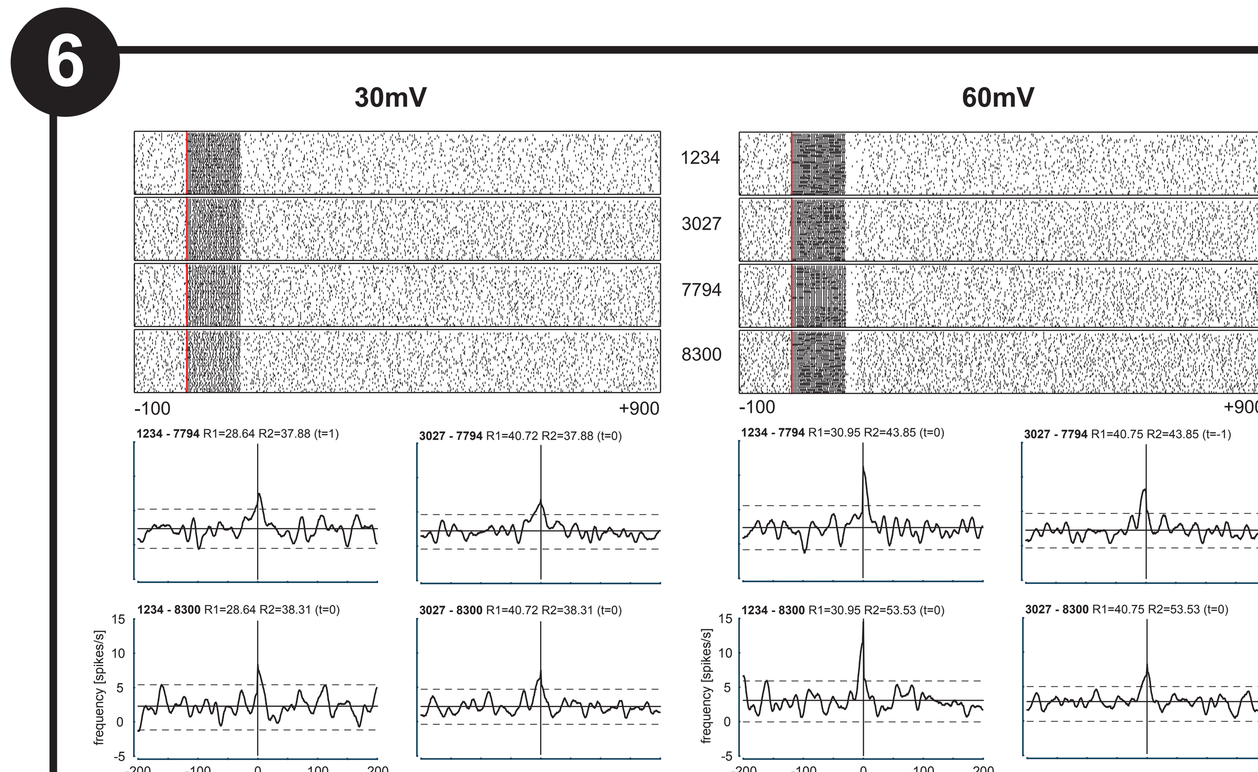

Figure 6. Firing patterns.
We studied the firing pattern of four units from layer 5, highlighted in orange in Fig. 3. after removing the Poisson distributed random background activity of the unit. (a,b): differential rasters for the selected units with 30 and 60mV stimulation (see Fig. 5); (c,d): differential crosscorrelograms between units. Note differences between stimulation intensities. Despite the fact that they don't share any direct common input from the pool, and that they all are on the same layer, some crosscorrelograms are significant, suggesting some kind of temporal relation.

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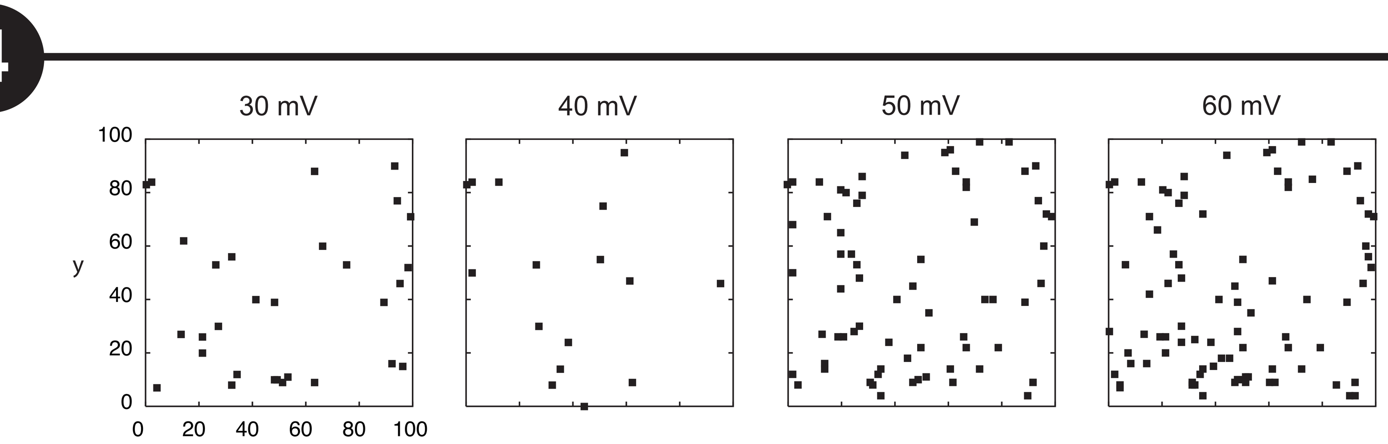

Figure 4. Position of the interconnected, not stimulated units as a function of the intensity of the stimulus. Some units take part to the pool with small stimulation intensities and are joined by an increasing number of units as the intensity of the stimulation is increased.

DISCUSSION

At the current state of our research, we have not yet found completely sustaining synfire chains emerging from synaptic pruning. Nevertheless, our results suggest that these structures may indeed appear in large networks as a consequence of unsupervised learning rules and specific stimuli.

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