EMERGENCY OF PRECISE FIRING SEQUENCES DRIVEN BY TEMPORALLY STRUCTURED STIMULI **IN LARGE SCALE NEURAL NETWORKS**

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Neural Network Model

• Connectivity: the initial network is created by distributing 8.000 excitatory and 2.000 inhibitory units following Sobol quasi random distribution an a 100x100 lattice. Connections between cells are Grouping Algorithm [Tetko, Villa 2001]. Example of a detected patestablished following a 2D Gaussian probability density with different tern, (a) - raster fragments, (b) – times of the pattern occurrences: parameters for excitatory and inhibitory units.

Precise Firing Patterns

• Spike train of the units active by the end of simulation were scanned for occurrences of firing patterns by means of the Pattern

• STDP rule: synapses are characterized by 4 activation levels. Each post- or presynaptic spike modifies a real valued function: postsynaptic spike coming shortly after the postsynaptic one increments the function, spiking in the opposite order decrements the function. Then • Characteristics of detected patterns: the function crosses a boundary the synapse change the activation level. As soon as the activation falls down to the lower level the synapse is definitively excluded from the network. Examples of STDP modifications, (a) – the level stabilized, (b,c) – the level falls down because of the spiking order (c), because of absence of activity:



• Early developmental phase: If during first 800 seconds of simulation the firing rate exceeds the threshold the unit is eliminated from the network with some probability. Evaluation of number of units:



Results

	stimulation		coupled
	OFF	ON	networks
active cells	5352	4240	4860
total patterns	197	147	241
triplets/quadruplets	59/138	61/86	107/134
multi-unit patterns	6	5	8

Number of patterns per stimulation:





• Stimulation: The duration of each stimulus is 100 ms, its rate is 0.5 Hz. 800 excitatory units are selected arbitrary and divided into two groups, A and B. Each group is subdivided into 10 subgroups of 40 units and receives a depolarization each ms of the stimulus in the following order:

$$AB: \begin{bmatrix} A_1, A_2, \dots A_{10}, B_1, B_2, \dots B_{10} \end{bmatrix}; \qquad BA: \begin{bmatrix} B_1, B_2, \dots B_{10}, A_1, A_2, \dots A_{10} \\ 5times & 5times \end{bmatrix}; \qquad ba: \begin{bmatrix} B_1, B_2, \dots B_{10}, A_1, A_2, \dots A_{10} \\ 5times & 5times \end{bmatrix}$$

AB and BA orders are random and equiprobable.

Simulations

- Stimulation **ON**: keeping the same rules and the same parameters the simulation was repeated 30 times with different random generator seeds.
- Stimulation **OFF**: the seeds were reused to reproduce 30 simulations in absence of stimulation.



 Intra pattern intervals, distribution of the first (a,c,e) and the second (b,d,f) intervals of triplets:





 Coupled Networks: spike trains of the excitatory units of a similar network active by the end of simulation were used as input for simulations generated by the same 30 seeds.





– inhibitory units

 stimulated (input) units – units active by the end of the simulation (output units)

Cumulative histogram of pattern occurrences:





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