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Learning visual stimuli in neuromorphic VLSI

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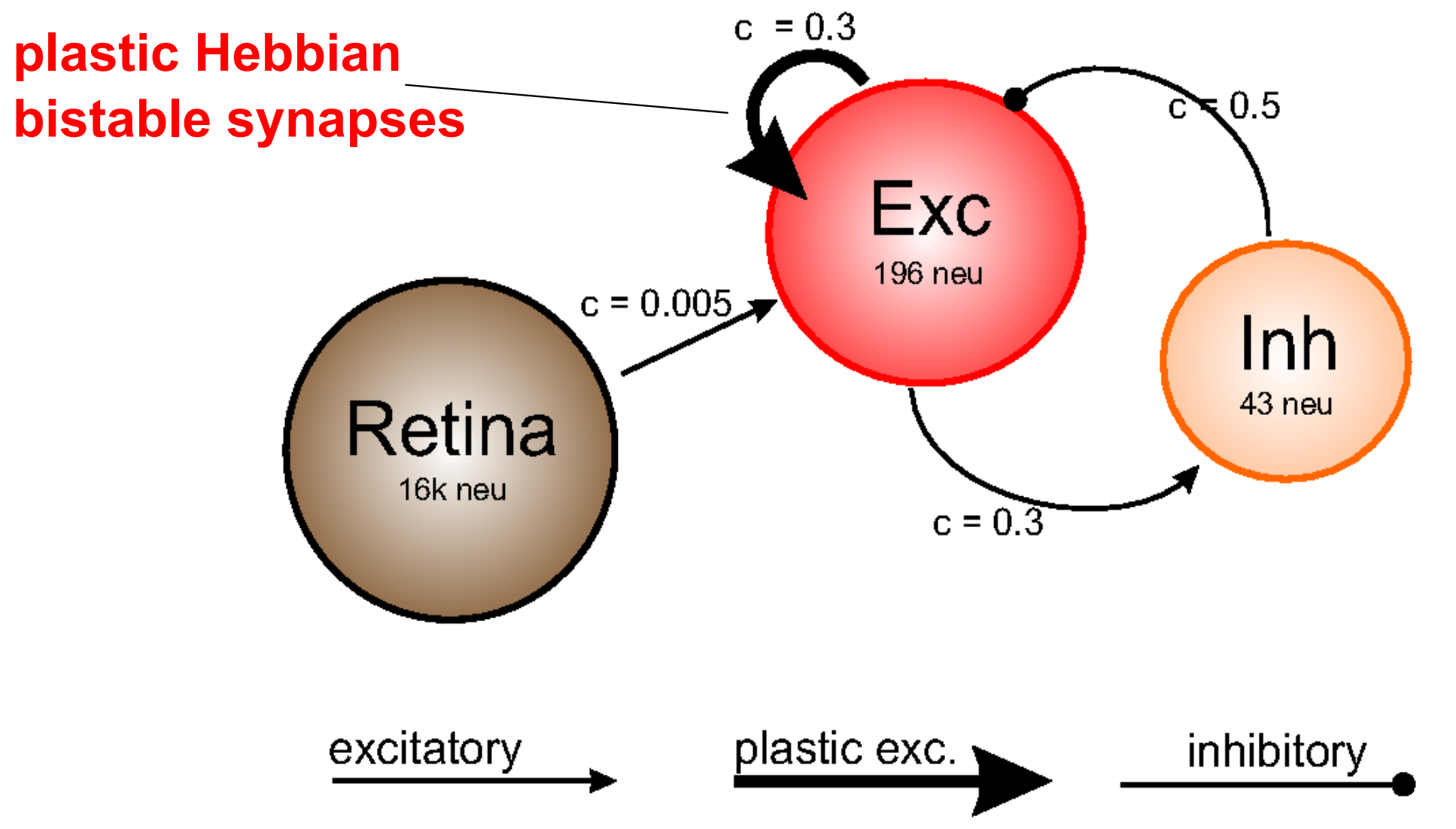
Abstract

We demonstrate a recurrent attractor neural network of spiking neurons and plastic Hebbian synapses, distributed over two neuromorphic chips, which autonomously learns in real time to classify simple visual stimuli acquired through a silicon retina connected with the chips. Unsupervised synaptic changes induced by the stimuli generate associated attractor representations which we checked to be robust to corruption of the stimuli (error correction) and to intervening distractors.

1 Recurrent Attractor network

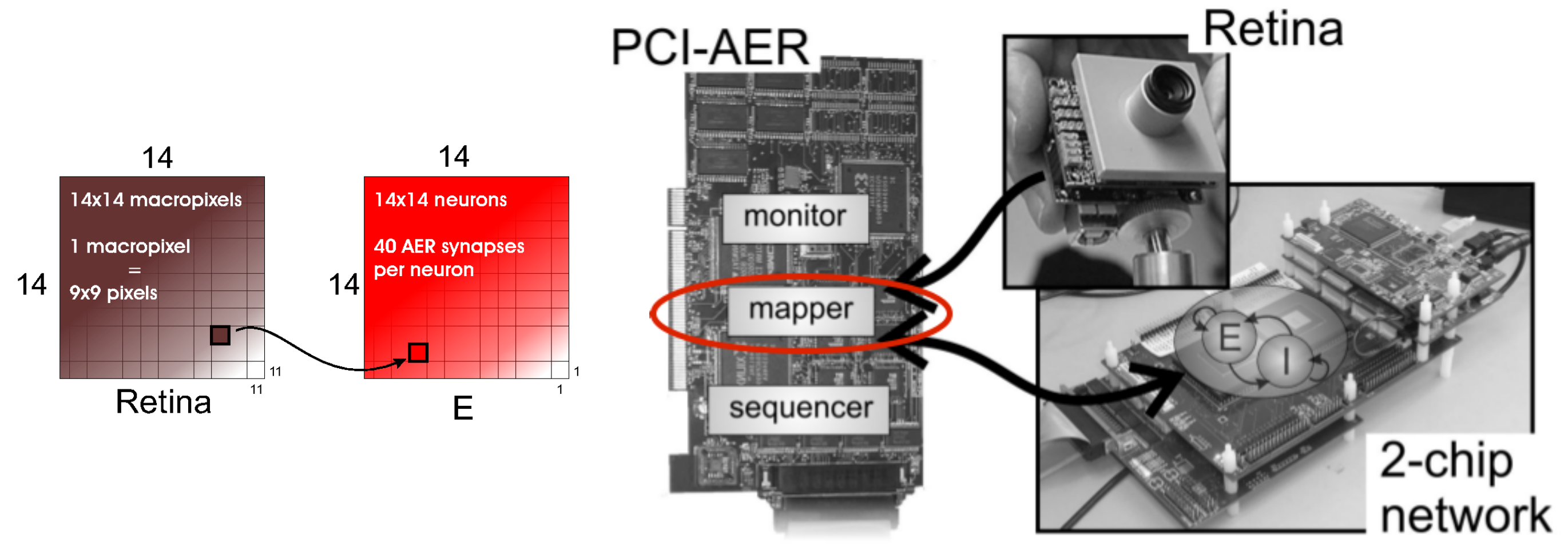
Network topology and parameters implemented have been suggested by mean-field analysis. The **network model is based on bistability of recurrent attractor dynamics**.



The networks consists of three populations of neurons: Retina, Excitatory and Inhibitory. The populations counts respectively 16384 neurons, 196 neurons and 43 neurons.

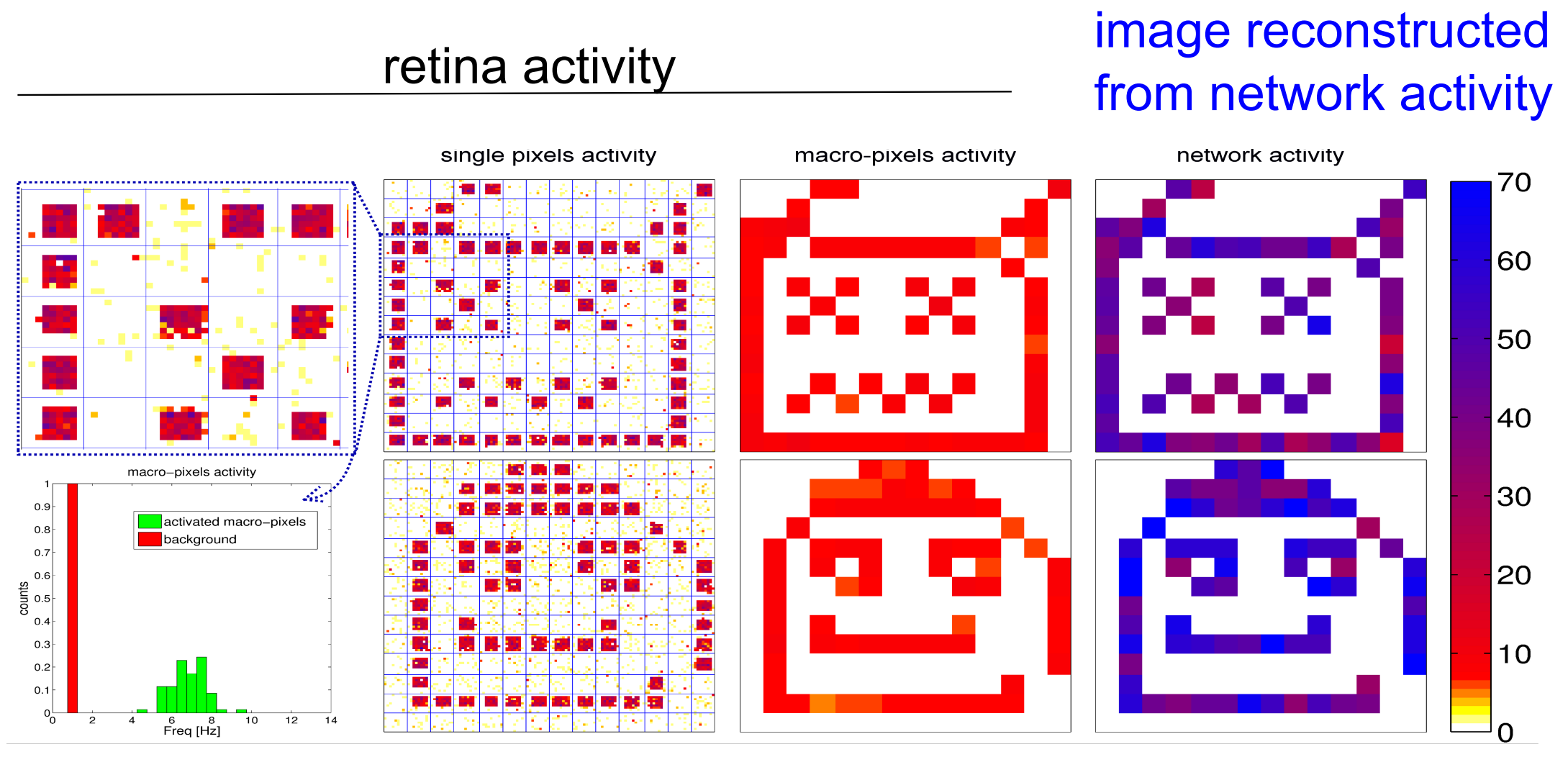
After learning the network exhibits **self-sustaining states of elevated reverberant activity** and those **can be predicted** in the mean field approximation by the **effective transfer function** [1] (see Box 3).

2 Neuromorphic setup



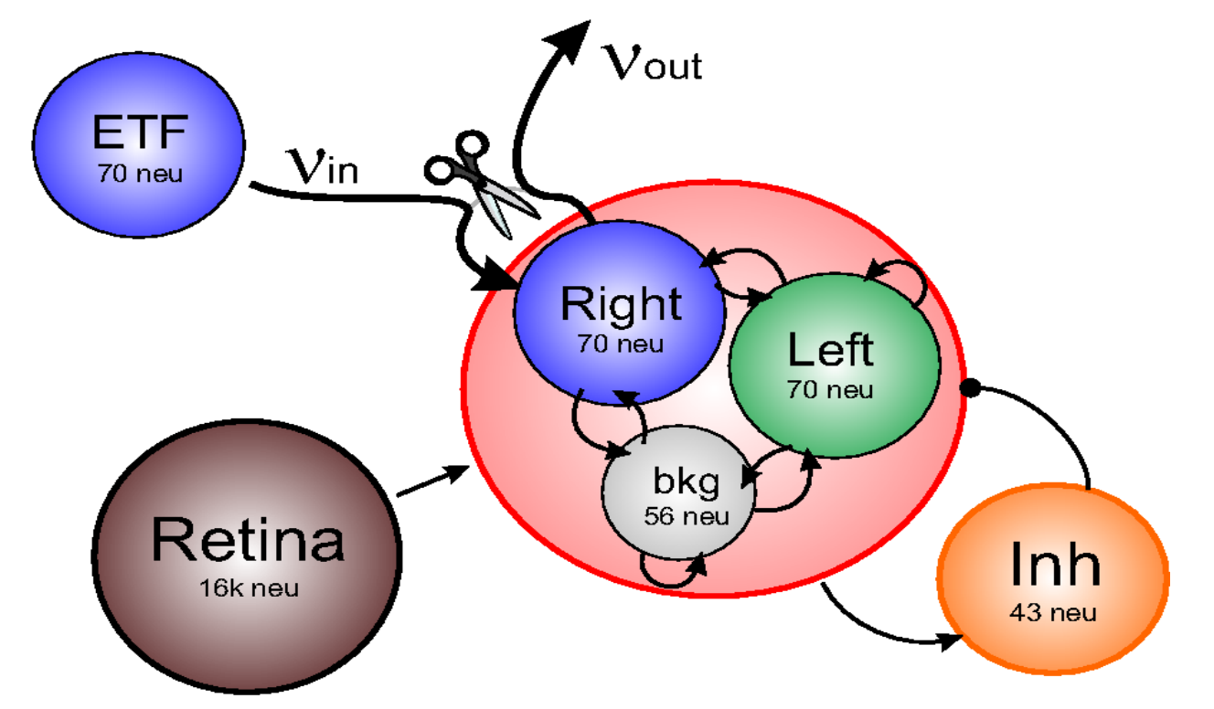
The setup consists of a distributed attractor network on two aVLSI spiking neuron chips. The input to the network is provided through silicon retina (DVS) [2]. The silicon retina is fixed in front of a screen thought which visual stimuli are presented. They are square maro-pixels which contains noise pixels that stochastically update their state (black or white) at a fixed mean frequency.

The figure on the left depicts the mapping from the 16k pixels of the retina to the 196 neurons in the recurrent network on chip. While the figure below shows the propagation of the signal in the multi-chip architecture.



3 Predictability of stable memories

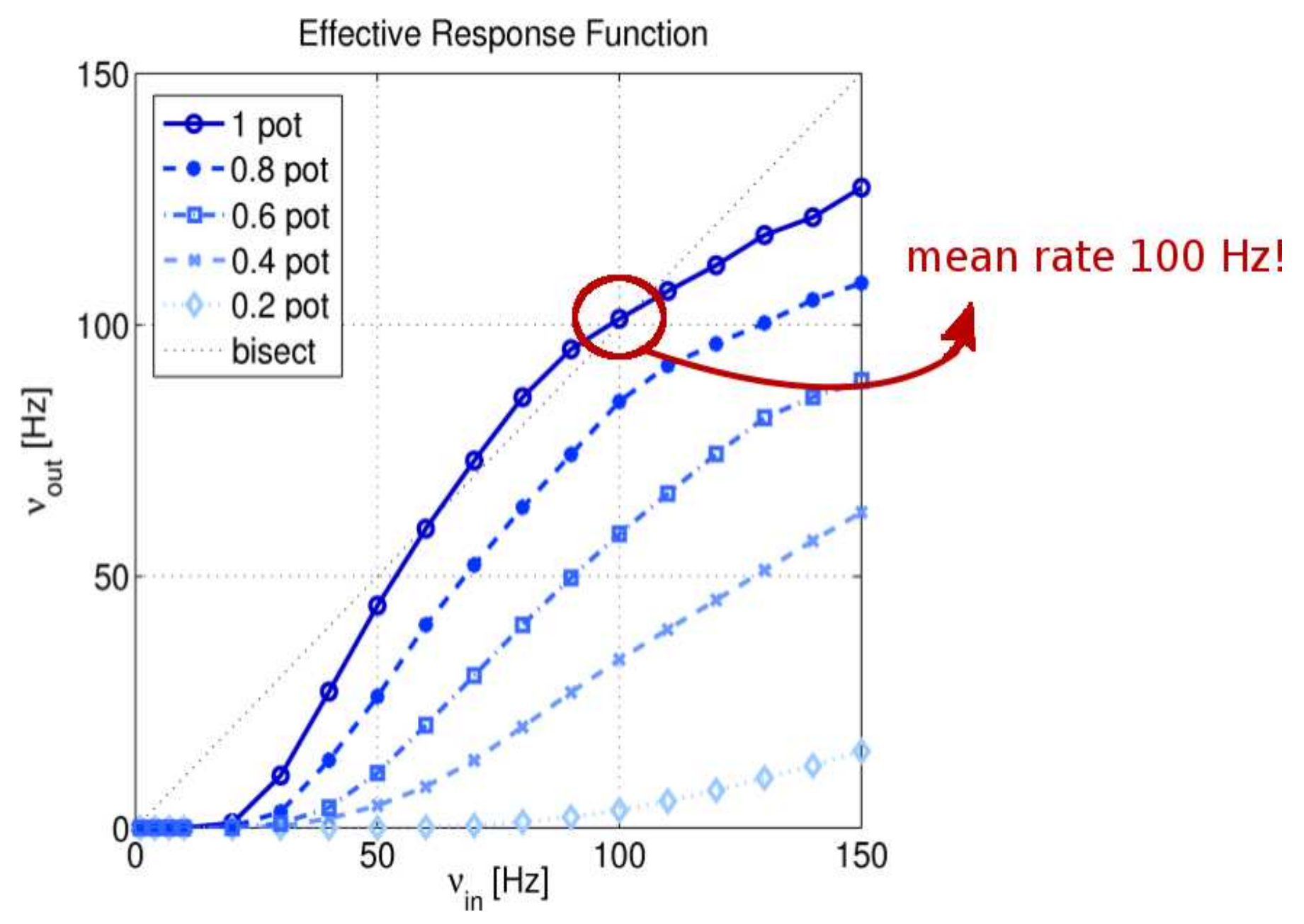
We fine tuned network paramenter by measuring the **effective transfer function** for pool of neurons that encode for memories.
As the synaptic modification takes place in between recurrent connections the transfer function starts to **exhibit meta-stable fixed points of the network dynamics**.



Synaptic potentiation creates a structure in the recurrent connectivity thus partitioning the excitatory population in sub-populations selective to input stimuli.

The necessary synaptic potentiation levels and the population mean-firing rate after stimulus removal are both in quantitative agreement with the effective transfer function prediction.

With 90% potentiated synapses the effective transfer function correctly predicts selective attractor states at about 100Hz.



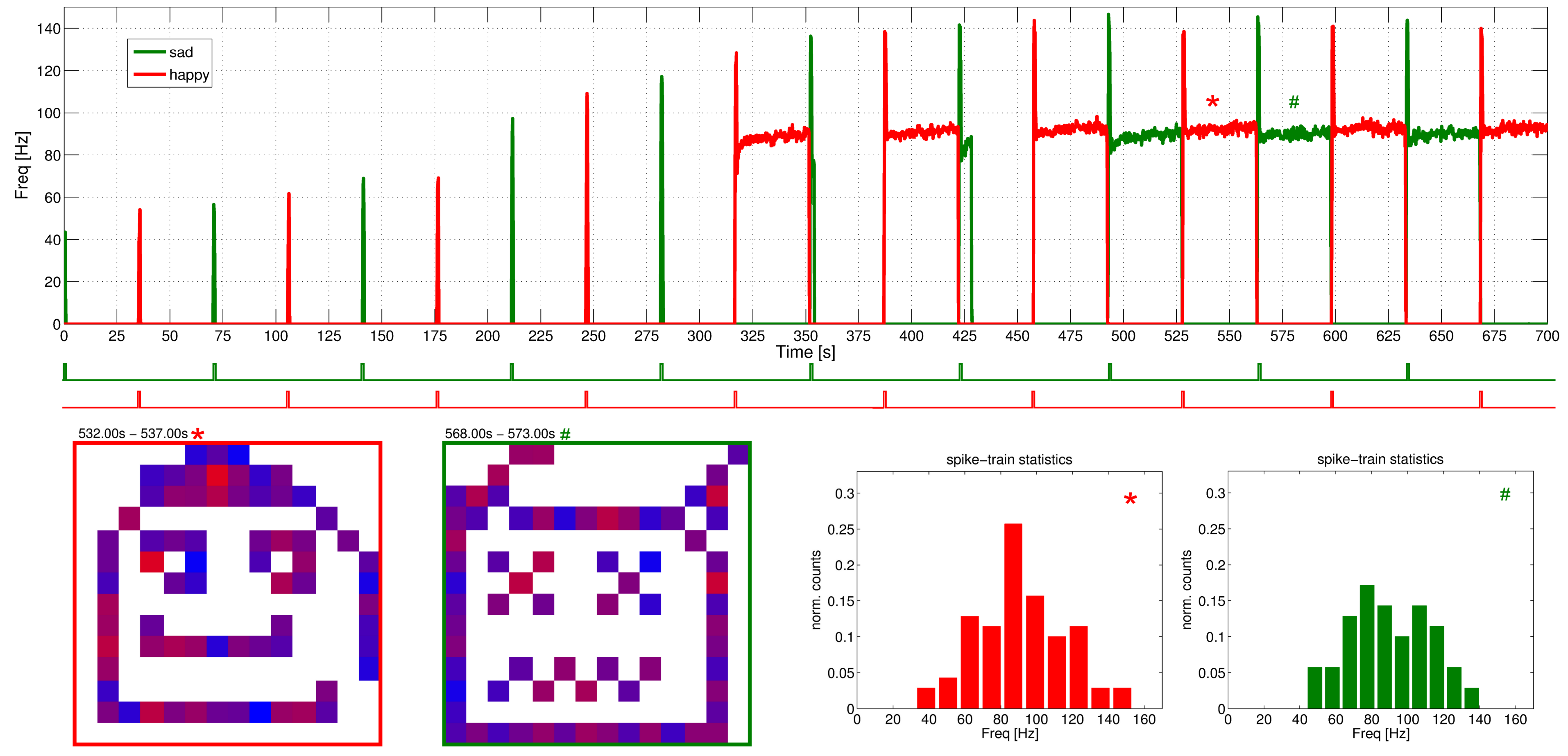
4 UNSUPERVISED LEARNING: establishing attractor states

Visual stimulation induces unsupervised modifications of the on chip synaptic weight matrix up to the point in which the selective reverberation states of activity are supported in the absense of stimulus.

The silicon retina continuosly measures at every pixel location the temporal contrast of the scene and encodes the contrast level into the output firing rate of the neurons corresponding to the pixel. The visual stimuli are provided via an LCD monitor in front of the retina.

Learning is supported by on chip plastic **Hebbian-like bistable synapses**. The learning protocol consists in repeatedly presenting the visual cue stimuli. In the plot below we show a case in which the repetition of two different visual stimuli is alternated over time.

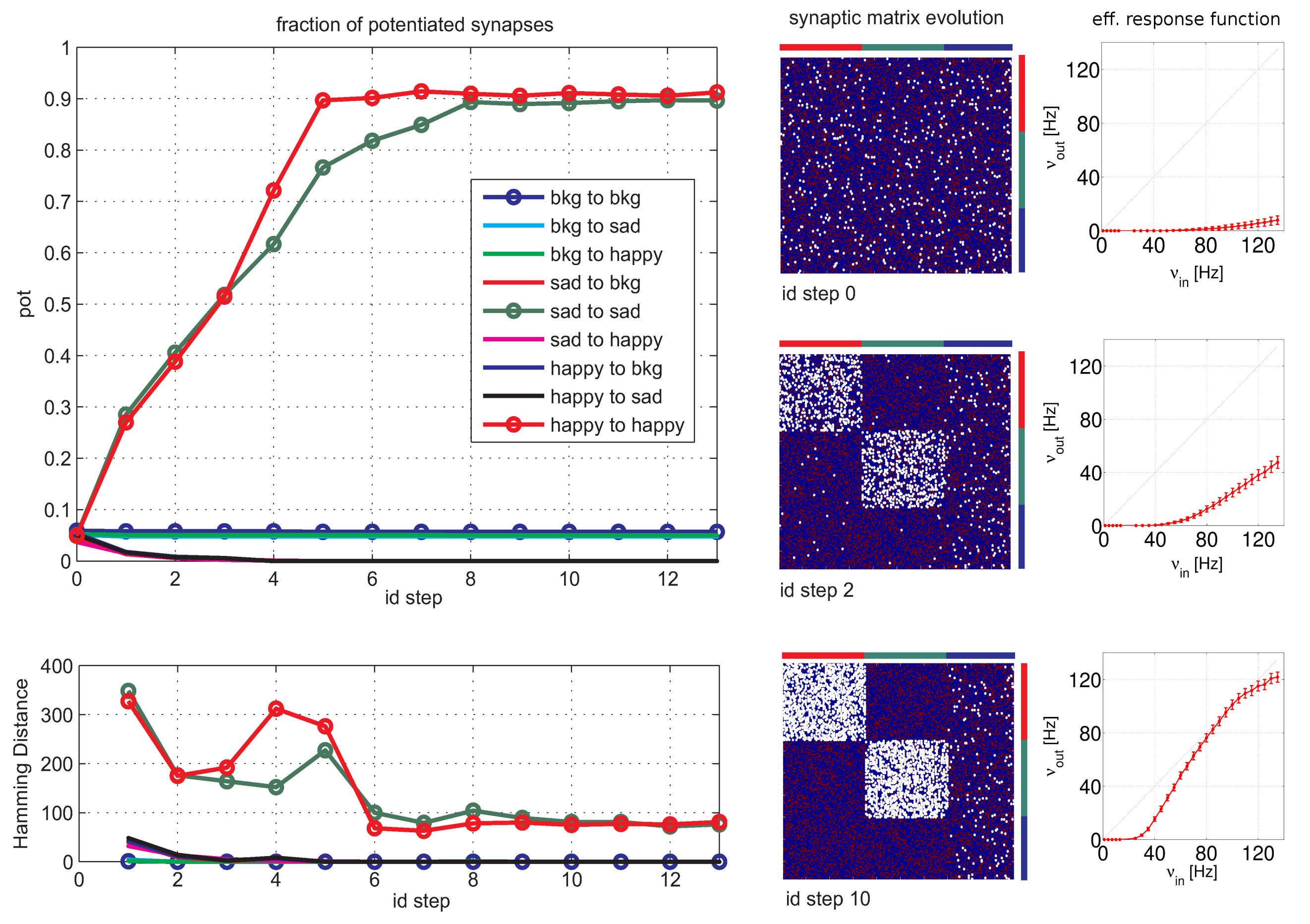
After presenting the stimulus few times there is an increase in the activity of the network that is due to synaptic potentiation. The mature network is able, after the removal of the stimulus, to sustain the pattern.



From a microscopic point of view, subset of synapses upgrade their synaptic efficacy to their high level. This increases self excitation in a subset of neurons in the network. On the right the distribution of the firing rate of the neurons in each of the two sub-populations is reported.

5 Synaptic matrix evolution

We report here the fraction of the potentiated synapses connecting the excitatory neurons throughout learning.
In the second column the state of the synapses (white = potentiated) is reported at three learning steps.
Learning creates a structure in the initially homogeneous connectivity.



6 Robust associative memory

After learning we obtain a robust associative memory. When the network is in a memory state (attractor state), the ongoing dynamics makes it stable against distractors (see t = 16s in the figure)

Upon presentation of degraded visual stimuli the network is able to retrieve the activity patterns corresponding to the complete stimuli thus expressing pattern completion capabilities (see t = 23s in the figure).

Acknowledgements

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