Emergence of filters from natural scenes in a sparse spike coding scheme

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Abstract

To explore new coding strategies in the visual system, we defined a general framework of overcomplete representation with spike coding by defining lateral interactions [Perrinet et al., 2002]. This algorithm uses arbitrary dictionaries and a greedy matching pursuit to describe the image by spike events so that images are described by a sparse spike list. We investigated a learning scheme to find adaptively optimal filters using a reinforcement scheme. This learning algorithm adapts the filters toward the image patches that generated the spike and leads to the emergence of V1-like filters in a similar fashion to [Olshausen and Field, 1998]. It's originality resides in the biological plausibility, its simplicity and the improved convergence to an optimal representation.

1 Dynamical models of neural coding

Based on the results of psycho-physiological experiments which showed the rapidity of categorization in primates [Thorpe et al., 1996], we studied with the team of Simon Thorpe in Toulouse (France) new paradigms of coding in the nervous system. In particular, we analyzed the performance of an artificial neural network which neurons fired only once and where the information

is using the relative latency of spikes. This model proved to be very efficient for pattern recognition, since it is highly parallel and exhibits intrinsic properties (invariance to contrast changes, equalization of the input).
A spiking neuron model was applied to a model of information transmission in the optic nerve. This retinal model used a wavelet-like transform and used the relative regularity of the ranked coefficients to transmit the coefficient values by their rank [Van Rullen and Thorpe, 2001]. However, the constraints on the filters present limits (orthogonality of the filters, sensibility of the representation to small perturbations) which are incompatible to realistic models. We answered to these drawbacks by exploring over-complete representations, i.e. where the dictionary of filters is much larger than the dimension of the input space. In particular, I linked this theory with the Matching Pursuit algorithm (MP) [Mallat and Zhang, 1993] to present an efficient neuromimetic coding scheme. This strategy corresponds to a "greedy" pursuit —the best match is recursively chosen and its projection is subtracted to the residual image— so that it forms a sparse spike code of the image [Perrinet et al., 2002]. In particular, this algorithm was extended to a multi-layer spiking neurons network, and we applied this representation in the primary visual cortex to various image processing tasks (pattern recognition, edge detection).

2 Emergence of spatial filters

We explored strategies linking this algorithm with the algorithms of emergence of V1-like filters [Olshausen and Field, 1998]. We used the same protocol as this experience (initial random filters, whitened filters) but its architecture is different since the algorithm is linked with a reinforcement of the filters to the patch from the image that elicited the firing. It is therefore parallel (patches may be chosen in the whole image) and, for instance, filters which are similar by a small translation would be unstable and diverge to different solutions. We observe similar results as in [Olshausen and Field, 1998] yielding to a set of filters similar to simple cells in the primary visual area (see Fig. 1).
An extension of this model was to introduce lateral connectivity in this learning scheme. This therefore introduced topological relations between neurons which associated neighboring spatial responses to neighboring neurons. This strategy leaded to a better convergence and to the emergence of a "pin-wheel"

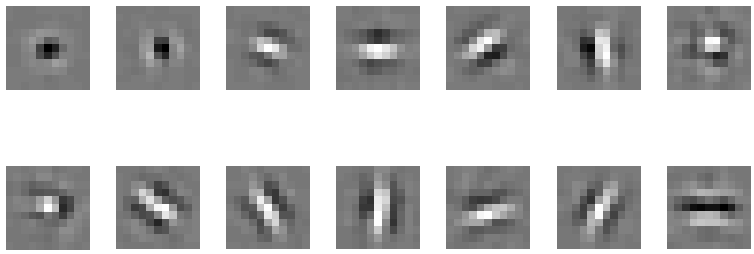

Figure 1: **Emergence of filters using an adaptive scheme**. We simulated the propagation of the visual information through the retina and then through a second layer which filters are initially randomly set. By reinforcing the receptive fields of neurons toward the patch that elicited the firing of a neuron, we progressively extract primitives of the image which compete through the MP algorithm. Using the same protocol as Olshausen and Field [1998], V1-like orientation selective emerge, but the parallel propagation avoids doubles.

by associating the learning for neighboring neurons (see Fig. 2).

Conclusion : toward a model of neural representation

Extending the sparse spike coding algorithm, this strategy builds an efficient dictionary of spatial filters which are particularly adapted to the processing of images. It leads to the emergence of independant filters for this size of the dictionnary which are direction selective filters, as is observed in the primary visual cortex (V1). This strategy was also improved by introducing topological constraints and further investigations leads to the fomation of spatio-temporal filters in the visual flow which may be fitting the response of neurons in V1.

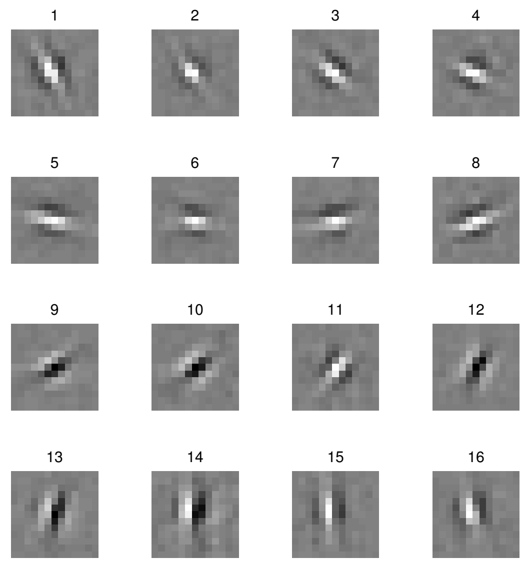

Figure 2: **Emergence of a topological set of orientation selective.** As presented above, we simulated the emergence of filters in the primary visual area but introduced lateral connections between filters so that neighboring spiking, thus learning, was enhanced. This lead to the emergence of topological relations between neighboring filters (cyclically numbered from 1 to 16) similar to the neurophysiologically observed *pinwheels*.

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