

Chapter 11

Computational Models Relevant for Visual Cortex

In this chapter, some ANN models, which are potentially relevant for modeling cortical visual processing in the holonomic context, will be briefly presented. They either produce ICA-like processing or collective oscillatory dynamics with phase-processing. Activity of modules like these could shape the image-bearing wavelets. These models are presented, because they are extraordinarily computationally efficient and because they have some relevant common features in-between as well as with some physiological reports — and such a non-trivial compatibility is remarkable if found in autonomous models.

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ANN WITH INHIBITORY FEEDBACK- LOOP GIVING INFOMAX OUTPUTS

The Harpur & Prager (1996) model is illustrated in Figure 1(a). It performs *infomax* by a unique ICA-like process without any explicit phase-processing. It anyway achieves statistical independence by recurrent opposite-weighted connections and by the resulting competition between “neurons”. *Output weight-vectors represent Gabor-like wavelets.*

The input vector is $\vec{x} = (x_1, \dots, x_m)$; the output vector is $\vec{a} = (a_1, \dots, a_n)$; feed-forward (*j-to-i*) connection-weights are elements in the vector ($\vec{w}_i = w_{i1}, \dots, w_{im}$); their feedback (*i-to-j*) parallels are their negatives: $-w_{ij}$.

The ANN “algorithm”, which (iteratively) processes images by minimizing the discrepancy $|\vec{x}'|^2$, is as follows:

$$\begin{aligned}\vec{x}' &= \vec{x} - \sum_{i=1}^n a_i \vec{w}_i \quad (\text{index } i \text{ belongs to the output “neuron(s)”}); \\ \Delta a_i &= \mu \vec{x}' \cdot \vec{w}_i, \quad 0 < \mu \leq 1 \quad (\mu \text{ is adjustable learning rate}); \\ \Delta \vec{w}_i &= \eta a_i \vec{x}' \quad (\eta \text{ is learning rate}).\end{aligned}$$

Comparing the model’s connectivity with an experimental report on the rat visual cortex¹, one can see similarities which suggest to relate $\vec{x}'$ with V1 and $\vec{a}$ with the extrastriate cortex. Namely, it is reported that feedback connections from the extrastriate cortex “provide input directly to [V1’s pyramidal] neurons which make the reciprocal forward connection, and that feedback-recipient forward-projecting neurons are strongly interconnected”. However, Harpur & Prager (1996) neglect the *direct* intra-layer connections, so there is just indirect (although essential) mutual influence between “neurons” of the “V1”-layer. *The Baird (1990) model of networks of oscillators* incorporates the reported extrastriate-to-striate “top-down” modulatory connectivity and the reported interconnections of forward-projecting excitatory neurons of V1, possibly.

NETWORK OF UNITS WITH COUPLED OSCILLATORY ACTIVITIES, EMBEDDED IN NEUROPIL

By comparing subfigures of Figure 1, one sees that the Baird (1990) oscillatory ANN model has a loop-structure similar to the Olshausen & Field (1997) net and to the Harpur & Prager (1996) net, and fits the experimentally found striate–extrastriate loop. However, Baird considers the sources of inhibitory feedback as *interneurons* without (significant) connections other than with their excitatory partner in the main

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