

1. Overview

Goal:

- A computational model to learn the feature bases (receptive fields) of simple and complex cells in the primary visual cortex.
- Address the translation invariance developed from c cells via natural image sequences.

Approach:

- Reconstruct an input via a linear combination of feature bases in simple cells.
- Modulate the simple cell representation via multiplicative interactions from complex cells.
- Enforce a sparseness prior for the latent representation of simple cells and complex cells.
- Enforce a slowness prior and a trace-like rule for the representation of complex cells.

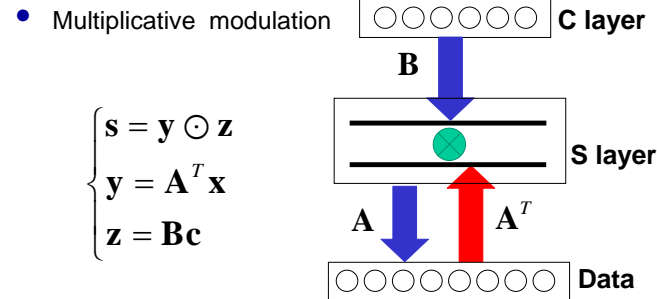
Advantages:

- Provided a factorized approach via the product of two-order tensor weight parameters and only one latent variable for invariant representation, more efficient than bilinear models that contain three-order tensor weight parameters and two latent variables.
- Demonstrated general simple cell feature maps and complex cell invariant receptive fields simultaneously.

2. Generative model

- Minimizing the sum of squared errors over images from s cells

$$\min E_0 : E_0 = \frac{1}{2} \|\mathbf{x}(t) - \mathbf{A}\mathbf{s}(t)\|_2^2$$



3. Sparseness prior

Sparse constraint of both S and C layers.

$$\min E_{sp} : E_{sp} = \lambda_c \sum_k |c_k(t)| + \lambda_y \sum_m |y_m(t)|$$

4. Slowness prior

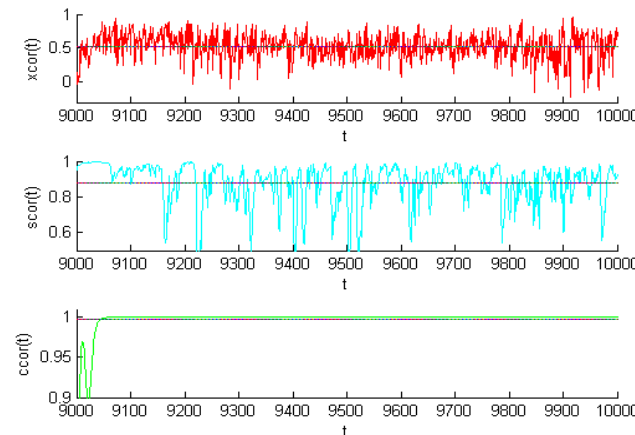
Boost temporal autocorrelation for C cells

$$\min E_{cr} : E_{cr} = \frac{\alpha}{2} \|\mathbf{c}(t) - \mathbf{c}(t-1)\|_2^2$$

5. Learn feature bases

Total energy function

$$\min E : E = E_0 + E_{sp} + E_{cr} \Rightarrow \begin{cases} \frac{d\mathbf{c}(t)}{dt} = -\eta_c \frac{\partial E}{\partial \mathbf{c}(t)} \\ \frac{d\mathbf{A}}{dt} = -\eta_A \frac{\partial E}{\partial \mathbf{A}} \\ \frac{d\mathbf{B}}{dt} = -\eta_B \frac{\partial E}{\partial \mathbf{B}} \end{cases}$$



6. Experimental results

Natural image sequences

