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Sparse codes of V1 simple-cells and the emergence of globular receptive fields - a comparative study

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Summary

Abstract

- multiple cause models with sparse priors
- linear or non-linear superposition of basis functions
- maximization of the data likelihood on image patches
- likelihood maximization using a novel form of variational EM (ET)
- same parameter set and training method for both models
- comparative analysis of the obtained basis functions

Results

- Gabor-like basis functions are obtained in both cases
- more elongated basis functions when using the non-linear model
- higher fraction of globular basis functions for the non-linear model

Linear vs. non-linear component extraction

$p(\vec{s}\,|\,\Theta) = \prod_h \pi^{s_h}(1-\pi)^{1-s_h}$ (Bernoulli prior)

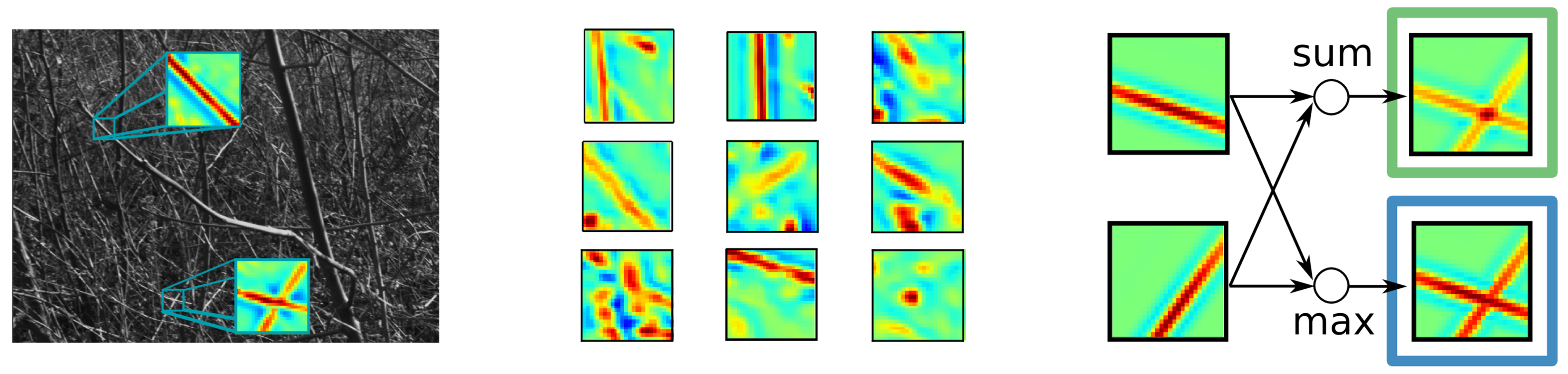
$p(\vec{y}\,|\,\vec{s},\Theta) = \mathcal{N}(\vec{y};\ \sum_h s_h \vec{W}_h, \sigma^2)$ (BSC; linear superposition)

$p(\vec{y}\,|\,\vec{s},\Theta) = \mathcal{N}(\vec{y};\ \max_h\{s_h \vec{W}_h\}, \sigma^2)$ (MCA; non-linear superposition)

$\vec{y} \in \mathbb{R}^D$ observed variables
$\vec{s} \in \{0,1\}^H$ hidden variables
$W \in \mathbb{R}^{D\times H}$ basis functions
π prior parameter
σ observation noise level

We study two generative models: Binary Sparse Coding (BSC; [1]) and Maximal Causes Analysis (MCA; [2, 3]). As in standard approaches such as Sparse Coding [4] or Independent Component Analysis, both BSC and MCA assume a sparse prior with independent hidden variables. In the place where standard approaches and BSC use the sum to combine basis functions, MCA uses a (pixel-wise) maximum operation. To derive tractable approximations for parameter estimation we, for both models, apply Expectation Truncation (ET; [5]) - a variational EM approach. The resulting learning algorithms are applicable to large-scale problems with hundreds of observed and hidden variables. Furthermore, ET allows one to infer all model parameters including observation noise, σ, and the degree of sparseness, π.

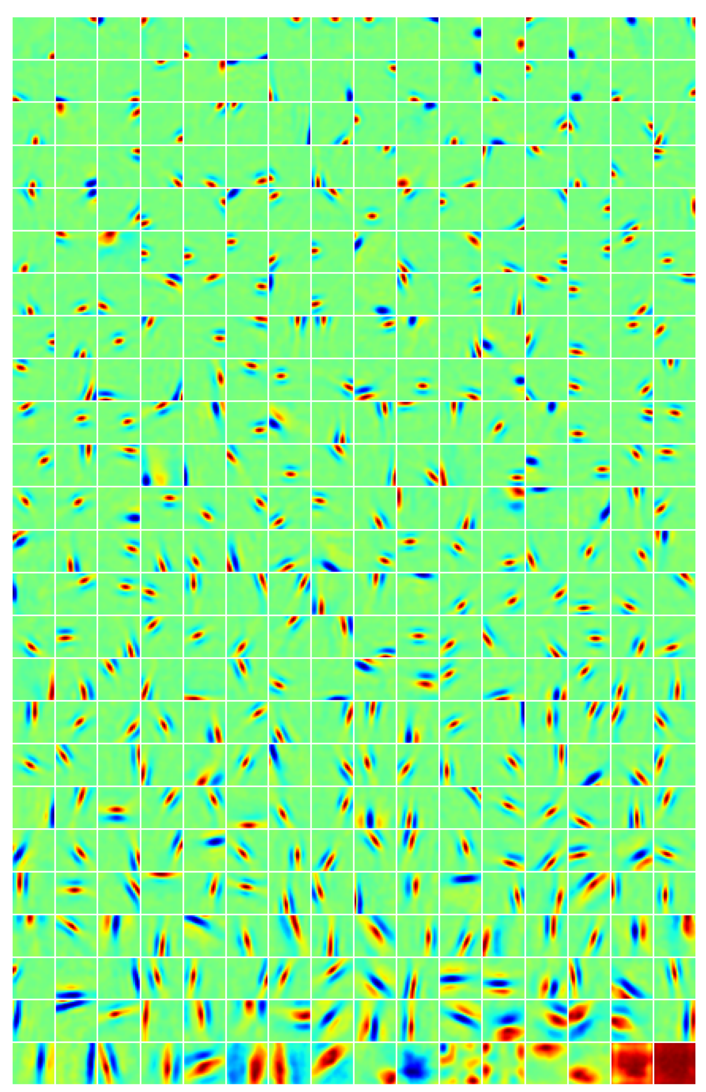
Application to natural image patches

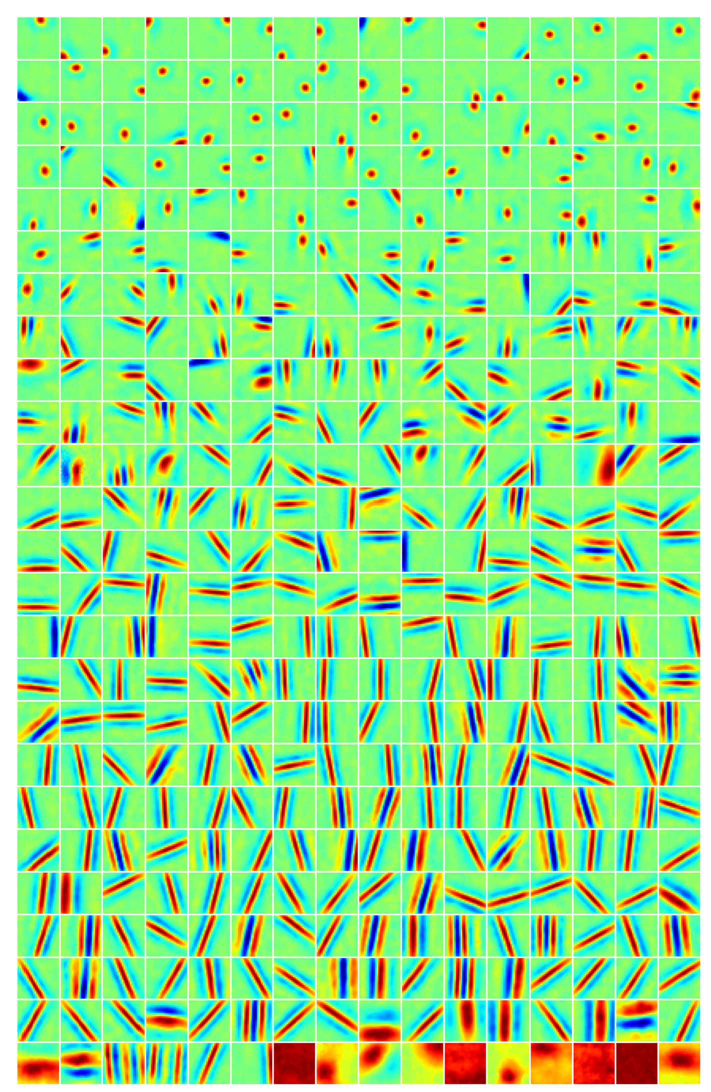


The strong non-linearity of the MCA generative model may represent a more plausible assumption for the superposition of components in preprocessed image patches.

To study the implications of the linear vs. non-linear superposition for visual data, both algorithms were applied to $N = 200\,000$ image patches extracted from the van Hateren image database (26×26 pixels; preprocessed using a DoG filter and channel splitting to ensure non-negativity). Parameters of both models were inferred for the same set of patches using the same training scheme with the same parameter initialization.

Inferred basis functions (H=400):

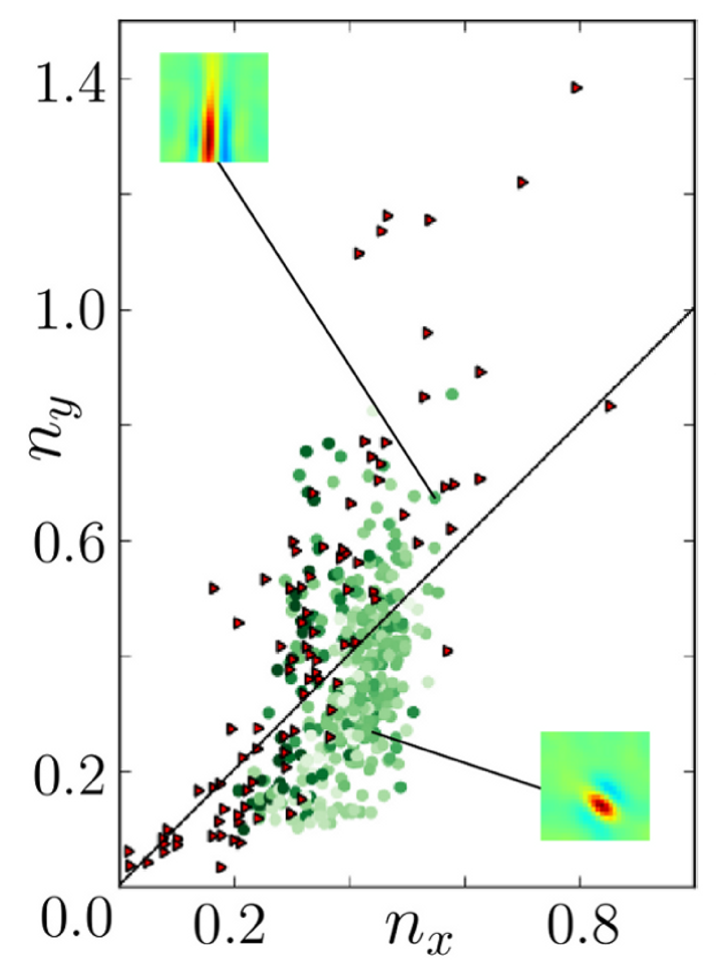

Basis functions inferred by BSC


Basis functions inferred by MCA

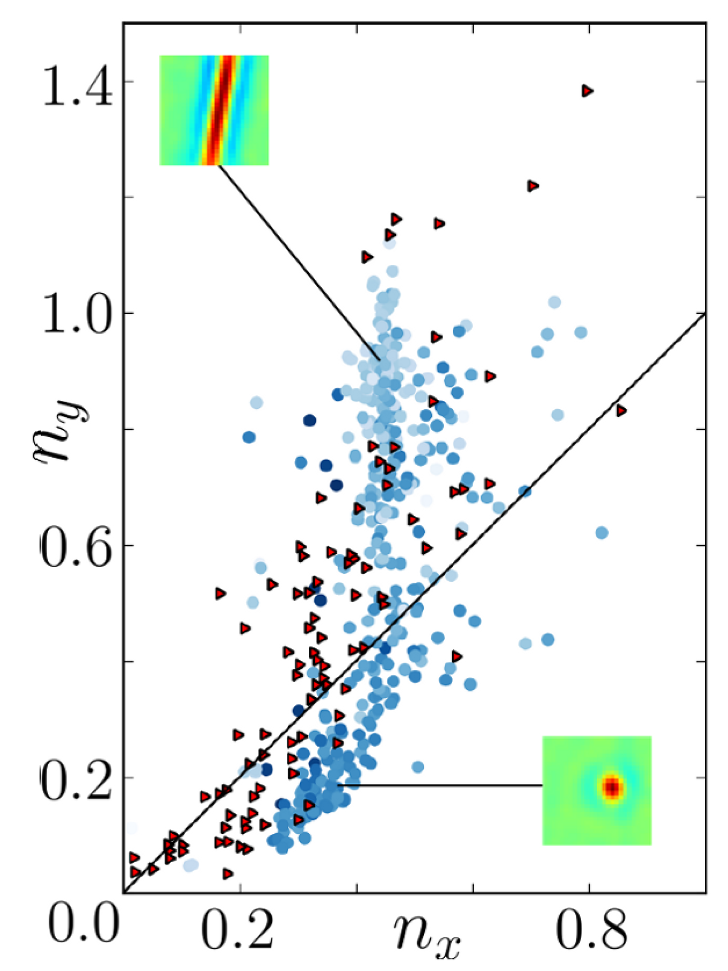
Analysis of obtained basis functions

To analyze the receptive fields associated with the inferred basis functions, we convoluted (reverse-correlated) the basis functions and matched them with Gabor wavelets and with difference of gaussian kernels.

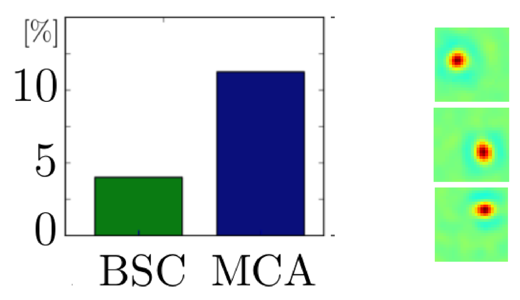
Shape of the gaussian envelope; shown simultaneously with data measured *in vivo* [6] (red triangles).



n_x/n_y distribution for BSC



n_x/n_y distribution for MCA



Fraction of globular fields; fields that are better matched by DoG kernels than by Gabor wavelet functions. The receptive fields extracted by MCA have a significantly higher fraction of globular shaped fields.

Conclusions

- in both models Gabor-like basis functions are inferred
- linear and non-linear models result in very different RF distributions
- MCA infers a much higher fraction of globular RFs
- continuous linear models can represent globular structures by superimposing gabors

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