Région Provence-Alpes-Côte d'Azur

Efficient learning of sparse image representations using homeostatic regulation

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A*Midex Initiative d'excellence Aix-Marseille

Abstract

One core advantage of sparse representations is the efficient coding of complex signals using compact codes. For instance, it allows for the representation of any sample as a combination of few elements drawn from a large dictionary of basis functions. In the context of the efficient processing of natural images, we propose here that sparse coding can be optimised by designing a proper homeostatic rule regulating the competition between the elements of the dictionary. Indeed, a common design for unsupervised learning rules relies on a gradient descent over a cost measuring representation quality with respect to sparseness. The sparseness constraint introduces a competition which can be optimised by ensuring that each item in the dictionary is selected as often as others. We implemented this rule by introducing a gain normalisation similar to what is observed in biological neural networks. We validated this theoretical insight by challenging the matching pursuit sparse coding algorithm with the same learning rule but with or without homeostasis. Simulations show that for a given homeostasis rule, gradient descent performed similarly the learning of a dataset of image patches. While the coding accuracy did not vary much, including homeostasis changed qualitatively the learned features. In particular, homeostasis results in a more homogeneous set of orientation selective filters, which is closer to what is found in the visual cortex of mammals. To further validate these results, we will apply this algorithm to the optimisation of a visual system to be embedded in an aerial robot. In summary, this biologically-inspired learning rule demonstrates that principles observed in neural computations can help improve real-life machine learning algorithms.

Acknowledgment

This work was supported by the Doc2Amu project which received funding from a co-fund with the European Union's Horizon 2020 research and innovation programme and the region Provence Alpes Cote d'Azur. Correspondence and requests for materials should be addressed to LUP (email:laurent.perrinet@univ-amu.fr). Code and supplementary material available at `http://invibe.net/LaurentPerrinet/Publications/BoutinRuffierPerrinet17neurofrance`.

References

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1. Learning on natural images

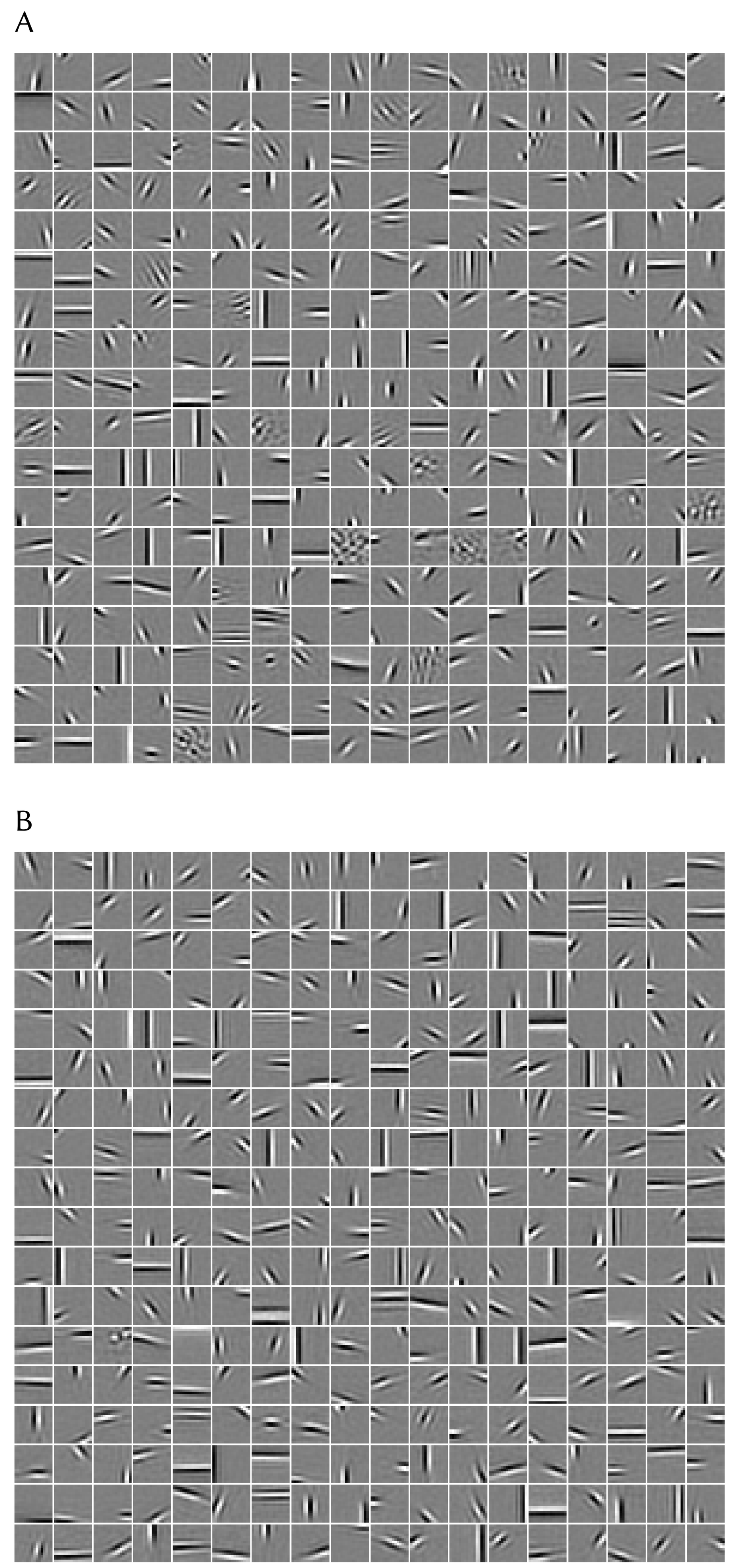

Figure 1: **Role of homeostasis in learning sparse representations**: We show the results of Sparse Hebbian Learning using two different homeostasis algorithms at convergence (20000 learning steps). 324 filters of the same size as the image patches (16×16) are presented in a matrix (separated by a white border). Note that their position in the matrix is arbitrary as in ICA. (A) When switching off the cooperative homeostasis during learning, the corresponding Sparse Hebbian Learning algorithm converges to a set of filters that contains some less localized filters and some high-frequency Gabor functions that correspond to more "textural" features. One may wonder if these filters are inefficient and capturing noise or if they rather correspond to independent features of natural images in the LGM model. (B) Results with the same coding and learning algorithm but by enabling homeostasis.

2. Simulating a perturbation

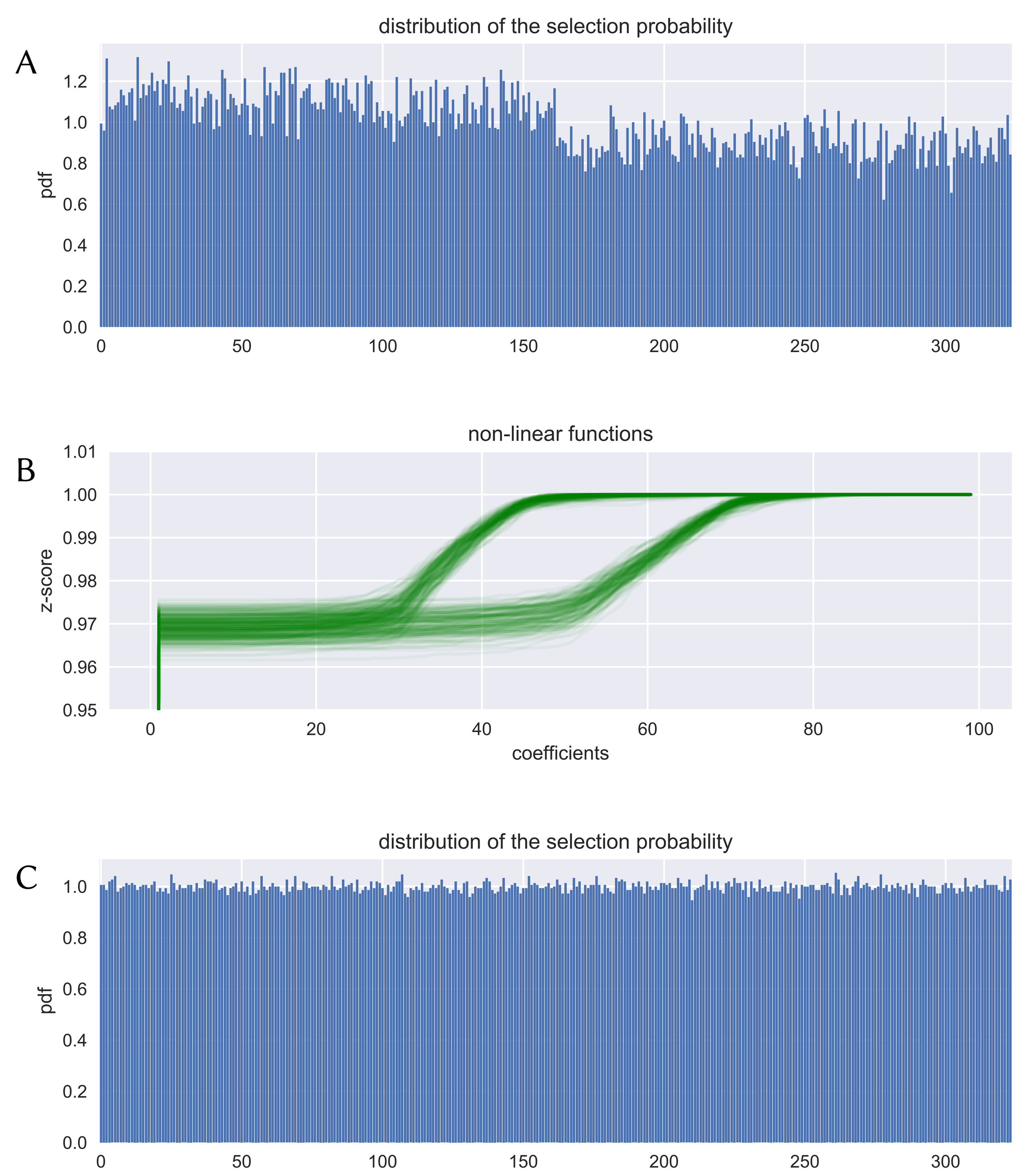

Figure 2: **Quantitative role of homeostasis in sparse coding**: We show the results of Sparse Coding using the two different homeostasis algorithms using surrogate data where each filter was equiprobable but for which we manipulated the first half of the coefficients to be artificially twice as big. (A) Such a situation replicates a situation arising during learning when a sub-group of filters is more active, e. g. because it learned more salient features. Here, we show the probability of the selection of the different filters (normalised to an average of 1) which shows a bias of the standard Matching Pursuit to select more often filters whose activity is higher. (B) Non-linear homeostatic functions learned using Hebbian learning. These functions were initialised as the cumulative distribution function of uniform random variables. Then they are used to modify choices in the Matching step of the Matching Pursuit algorithm. Progressively, the non-linear functions converge to the (hidden) cumulative distributions of the coefficients of the surrogate, clearly showing the group of filters with twice a big coefficients. (C) At convergence, the probability of choosing any filter is uniform. As a result, entropy is maximal, a property which is essential for the optimal representation of signals in distributed networks such as the brain.

3. Application to classification

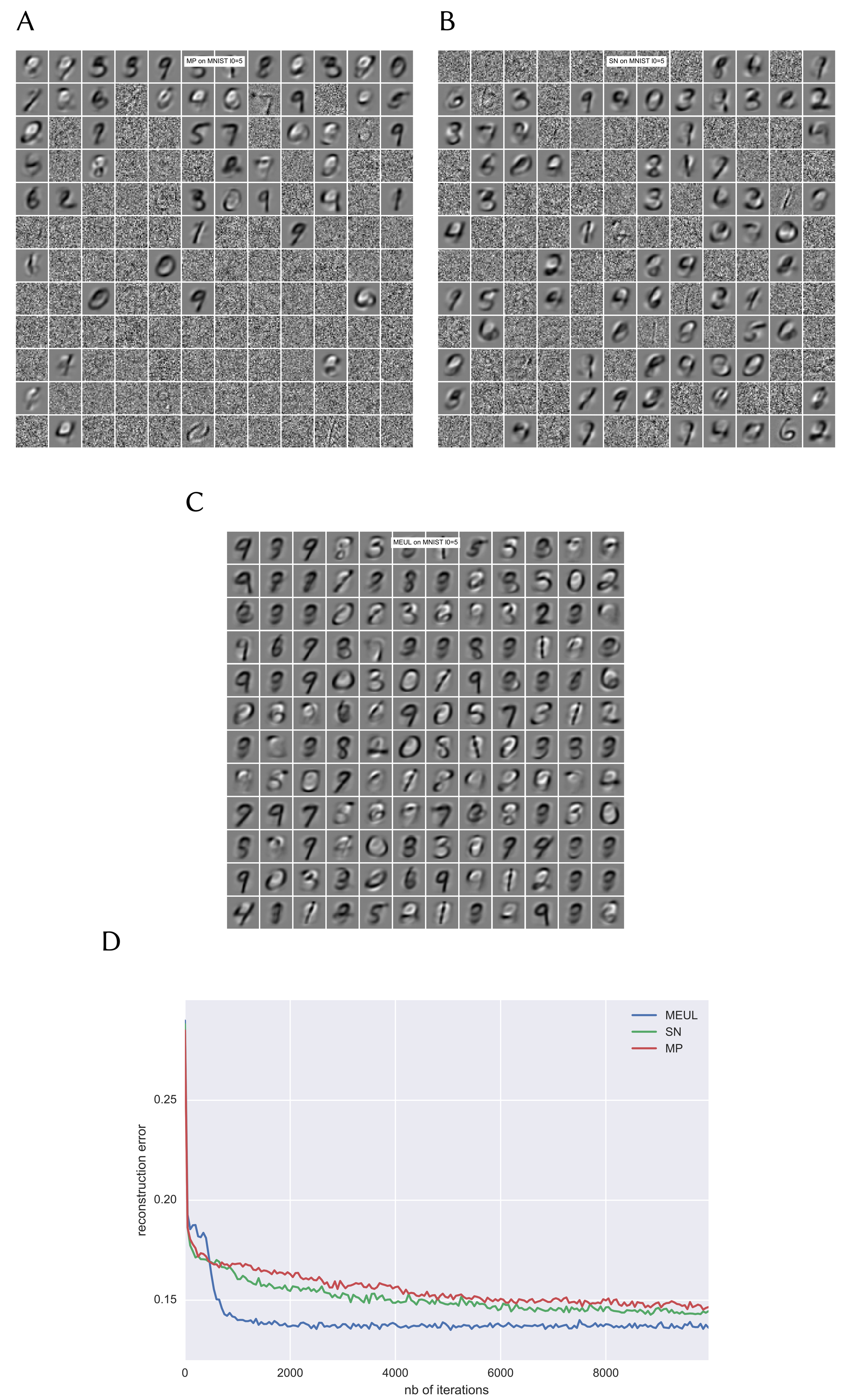

Figure 3: **Quantitative role of homeostasis in a classification network**: We used the generic MNIST protocol to assess the role of the homeostasis algorithm on classification. (A-C) 144 dictionaries learned from the MNIST database with a sparseness of 5 after 10000 iterations with (A) MP Algorithm ($\eta = 0.01$): No homeostasis regulation, only a small subset of dictionaries are selected with a high probability to describe the dataset. (B) SPARSENET Algorithm ($\eta = 0.01$, $\eta_h = 0.01$, $\alpha_h = 0.02$): The homeostasis regulation is made by normalizing the volatility. (C) MEUL Algorithm ($\eta = 0.01$, $\eta_h = 0.01$): All dictionaries are selected with the same probability to describe the dataset, leading to a cooperative learning. (D) Comparison of the reconstruction error (computed as the square root of the squared difference between the image and the residual) for the 3 algorithms (MEUL, SPARSENET, MP): The convergence velocity of MEUL is higher than SPARSENET and MP.

Presented Thursday, 18 May 2017 at **NeuroFrance 2017**, the International Conference from the Sociét'e des Neurosciences, Bordeaux, France