Towards a functional explanation of the connectivity LGN - V1

Marina Martinez-Garcia*[1,2], Borja Galán[1], Luis M. Martínez[2] and Jesús Malo[1]

[1]Image Processing Lab. Parc Científic, Universitat de València, Spain
[2]Instituto de Neurociencias, CSIC, Universidad Miguel Hernandez, Spain

Motivation The principles behind the connectivity between LGN and V1 are not well understood. Models have to explain two basic experimental trends: (i) the combination of thalamic responses is *local* and it gives rise to a variety of oriented Gabor-like receptive fields in V1 [1], and (ii) these filters are spatially organized in orientation maps [2]. Competing explanations of orientation maps use purely geometrical arguments such as optimal wiring or packing from LGN [3–5], but they make no explicit reference to visual function. On the other hand, explanations based on functional arguments such as maximum information transference (infomax) [6,7] usually neglect a potential contribution from LGN local circuitry. In this work we explore the ability of the conventional functional arguments (infomax and variants), to derive *both* trends simultaneously assuming a plausible sampling model linking the retina to the LGN [8], as opposed to previous attempts operating from the retina.

Methods Here we take a purely linear approach [8]. In this setting, the response of a population of simple V1 cells r_{V1}, is related to the set of responses of antecedents LGN cells, r_{LGN}, and to the retinal image, x, through a couple of matrices: $r_{V1} = K \cdot r_{LGN} = K \cdot M_{LGN} \cdot x$, with $r_{LGN} = M_{LGN} \cdot x$, where the rows of M_{LGN} contain the (vectorized) center-surround receptive fields of LGN cells tuned to random locations in the visual field. M_{LGN} may be a rectangular matrix reflecting the undersampling in the retina-to-LGN pathway. In this formulation, the rows of the matrix $M_{V1} = K \cdot M_{LGN}$ should contain (vectorized) the experimental Gabor-like receptive fields and the rows of K would describe the way LGN responses are pooled to form the V1 sensors. Here we assume that the goal of K is the maximization of the transmitted information from LGN to V1. In the low noise limit, this is equivalent to looking for K that minimizes the redundancy in r_{V1}. In our specific case we minimized this given a set of r_{LGN} responses for natural images. This can be done through linear Independent Component Analysis [9]: $K = R \cdot (\Lambda^{-1/2} \cdot B^T)$, where B and Λ respectively contain the eigenvectors and eigenvalues of the covariance matrix of the LGN responses to remove 2nd order relations in r_{LGN}, and R is an extra rotation (orthonormal matrix) that maximizes the sparsity of the final responses. We also explored extensions of ICA that consider residual dependence between the responses [6,7]. In the simulations we used a definition of orientation maps more consistent with the experimental literature.

Reproducible results[1] When taking into account LGN, linear infomax does not fully account for all the facts listed above. On the positive side, it explains the first trend: we obtain local pooling regions in K (novel result) and Gabor-like receptive fields in M_{V1} (consistently with [10–12]). Interestingly, the Gabors obtained from LGN are shifted to high frequencies with regard to previous work using ICA on retinal images. On the negative side, both linear ICA and even topographic ICA lead to random-like spatial distribution of sensors. This is ok for some animals like rodents [2], but it is not satisfactory for others like cats or humans [13].

Conclusion Consistently with other aspects of human vision [14–16], additional constraints should be added to plain infomax to understand the second trend of the LGN-V1 connectivity. Possibilities include energy budget [11], wiring constraints [8], or error minimization in noisy systems, either linear [16] or nonlinear [14, 15]. In particular, consideration of high noise (neglected here) would favor the redundancy in the prediction (which would be required to match the relations between spatially neighbor neurons in the same orientation domain).

[1] Ringach DL. Spatial structure and symmetry of simple-cell receptive fields in macaque primary visual cortex. *J. Neurophys*, 88:455–463, 2002.

[2] K. Ohki, SY. Chung, YH. Chang, P. Kara, and RC. Reid. Microarchitecture of visual cortex: functional maps with single-cell precision. *Nature*, 433:597–603, 2005.

[3] M. Schottdorf, S. J. Eglen, F. Wolf, and Keil W. Can retinal ganglion cell dipoles seed iso-orientation domains in the visual cortex? *PLoS ONE*, e86139, 2014.

[4] V. R. A. Hore, J. B. Troy, and S. J. Eglen. Parasol cell mosaics are unlikely to drive the formation of structured orientation maps in primary visual cortex. *Visual Neuroscience*, 29:283–299, 2012.

[5] S. Paik and D. L. Ringach. Retinal origin of orientation maps in the visual cortex. *Nature Neuroscience*, 14:919–925, 2011.

[6] A. Hyvärinen and P. O. Hoyer. A two-layer sparse coding model learns simple and complex cell receptive fields and topography from natural images. *Vision research*, 41(18):2413–2423, 2001.

[7] Libo Ma and Liqing Zhang. Overcomplete topographic independent component analysis. *Neurocomputing*, 71(10):2217–2223, 2008.

[8] LM. Martínez, M. Molano, X. Wang, F. Sommer, and J. Hirsch. Statistical wiring of thalamic receptive fields optimizes spatial sampling of the retinal image. *Neuron*, 81(4):943–956, 2014.

[9] A. Hyvärinen, J. Karhunen, and E. Oja. *Independent Component Analysis*. John Wiley and Sons, New York, USA, 2001.

[10] B. A. Olshausen and D. Field. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature*, 281:607–609, 1996.

[11] M. Rehn and FT. Sommer. A network that uses few active neurones to code visual input predicts the diverse shapes of cortical receptive fields. *J Comput Neurosci.*, 22:135–146, 2007.

[12] J. Malo and J. Gutiérrez. V1 non-linear properties emerge from local-to-global non-linear ICA. *Network: Computation in Neural Systems*, 17:85–102, 2006.

[13] K. Ohki, SY. Chung, P. Kara, M. Hubener, T. Bonhoeffer, and RC. Reid. Highly ordered arrangement of single neurons in orientation pinwheels. *Nature*, 442:925–928, 2006.

[14] D. A. MacLeod. *Colour discrimination, colour constancy, and natural scene statistics*. Oxford University Press, May 2003.

[15] V. Laparra and J. Malo. Visual aftereffects and sensory nonlinearities from a single statistical framework. *Frontiers Human Neuroscience*, 9:557, 2015.

[16] M. Gutmann, V. Laparra, A. Hyvarinen, and J. Malo. Spatiochromatic adaptation via Higher-Order Canonical Correlation Analysis. *PLoS ONE*, 2(9):e86481, 2014.

*Correspondence: marina.martinez@uv.es, jesus.malo@uv.es
[1]Supplementary material (model, code and results) http://isp.uv.es/docs/MODVIS16linear.zip