Visual discrimination and adaptation using non-linear unsupervised learning

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ABSTRACT

Understanding human vision not only involves empirical descriptions of *how it works*, but also organization principles that explain *why it does so*.[1] Identifying the guiding principles of visual phenomena requires learning algorithms to optimize specific *goals*. Moreover, these algorithms have to be flexible enough to account for the non-linear and adaptive behavior of the system.

For instance, linear redundancy reduction transforms certainly explain a wide range of visual phenomena.[2–9] However, the generality of this organization principle is still in question:[10] it is not only that and additional constraints such as energy cost may be relevant as well,[11] but also, statistical independence may not be the better solution to make optimal inferences in squared error terms.[12–14] Moreover, linear methods cannot account for the non-uniform discrimination in different regions of the image and color space: linear learning methods necessarily disregard the non-linear nature of the system. Therefore, in order to account for the non-linear behavior, principled approaches commonly apply the trick of using (already non-linear) parametric expressions taken from empirical models.[15–17] Therefore these approaches are not actually explaining the non-linear behavior, but just fitting it to image statistics. In summary, a proper explanation of the behavior of the system requires flexible unsupervised learning algorithms that (1) are tunable to different, perceptually meaningful, goals; and (2) make no assumption on the non-linearity.

Over the last years we have worked on these kind of learning algorithms based on non-linear ICA,[18] Gaussianization,[19] and principal curves.[14,20] In this work we stress the fact that these methods can be tuned to optimize different design strategies, namely statistical independence, error minimization under quantization, and error minimization under truncation. Then, we show (1) how to apply these techniques to explain a number of visual phenomena, and (2) suggest the underlying organization principle in each case.

Keywords: Color discrimination, Color Adaptation, Color after-effects, Contrast Masking, Non-linear opponent channels, Unsupervised learning, Infomax, Error minimization, Dimensionality reduction

1. NON-LINEAR TECHNIQUES SUITED TO VISION SCIENCE

Explanation of visual phenomena through unsupervised learning is based on considering the stimuli (colors, images or even sequences) as vectors, $\mathbf{x}$, in a multidimensional space.[8] Then, one assumes a set of sensors or mechanisms that transform the input stimulus into a set of responses (the vector $\mathbf{r}$):

$$\mathbf{x} \underset{R^{-1}}{\overset{R}{\rightleftarrows}} \mathbf{r} \tag{1}$$

The idea is designing the set of sensors (or the transform R) so that it achieves certain criterion. If this procedure reproduces some empirical behavior one may conclude that the visual system behaves like that *because* it is optimized for such stimuli and such goal. Nevertheless, note that a plausible organization principle is not the only requirement in vision science applications: it is also necessary that the algorithm makes experimentally testable predictions. To this end, invertibility and easy computation of discrimination measures in the input

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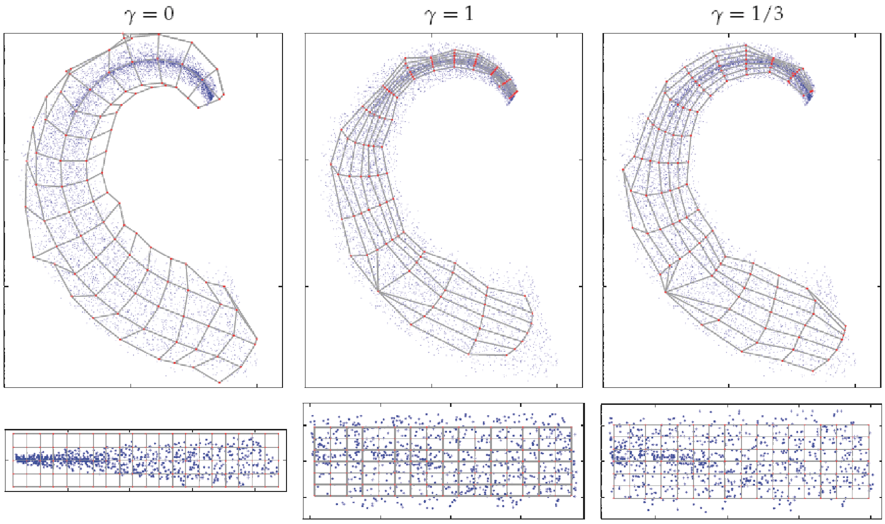

RMSE	0.55	0.56	0.53
MI (bits)	0.27	0.05	0.06

Figure 1. **Learning approach 1: identifying the curvilinear features in the data**. Here the 2D synthetic distributions (top row) are unfolded and equalized (bottom row) using Sequential Principal Curves Analysis[14] using either Euclidean metrics (left), PDF-dependent infomax metric (center) or error minimization metric (right). The error and Mutual Information numbers below indicate the optimality according to different criteria. The same sequential strategy is used in Principal Polynomial Analysis (Fig. 4).

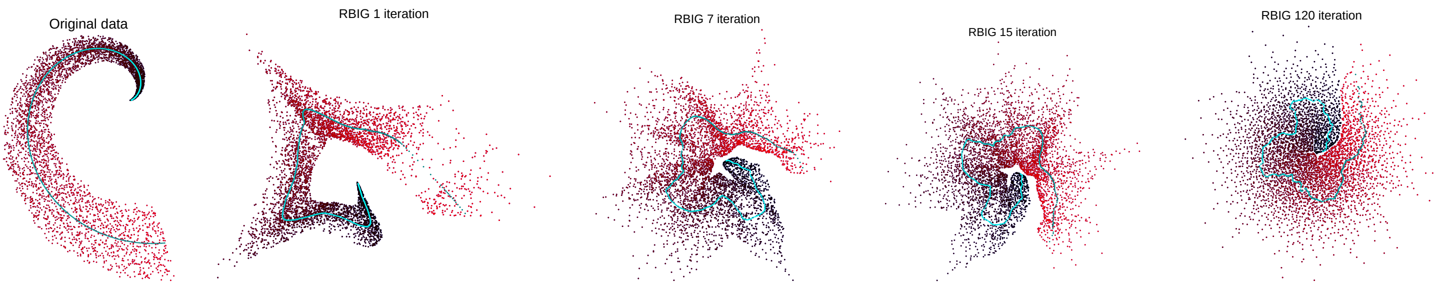

Figure 2. **Learning approach 2: ignoring the relevant features to transform the data into a multivariate Gaussian.** Transform of the same synthetic data as in Fig. 1 using Rotation-Based Iterative Gaussianization.[19]

space is highly desirable. Note that these are unusual properties in the plethora of techniques constantly emerging from the machine learning community. Invertibility implies that the relevant features for a particular goal can be analyzed in the stimulus domain, where perception experiments operate. The ability to derive discrimination metrics is a fundamental issue since threshold measurement is a major paradigm in psychophysics.

According to the above, we developed *invertible* methods to learn the transform R under different optimality criteria (information maximization or error minimization) assuming limited resources: either limited number of sensors (dimensionality reduction) or sensors with limited resolution (quantization). In order to adapt the transform to the stimulus statistics one may take two different strategies:

- Identify the meaningful directions determined by the regularities of the data (Fig. 1).
- Mapping the input into a domain where the statistical properties are perfectly determined (in our case transformed data have a Gaussian distribution). This strategy implies no restriction in the transformation thus ignoring regularities in the data (Fig. 2).

In the past years we pursued both. The first approach gave rise to sequential algorithms in which one curvilinear feature is identified after the other, namely, our Sequential Principal Curves Analysis (SPCA),[14] and our Principal Polynomial Analysis (PPA)[20]*. The second approach gave rise to a Probability Density Estimation algorithm

*While SPCA is non-parametric, PPA (much faster) assumes that the relevant features are flexible polynomials.

Figure 3. RBIG discrimination ellipsoids using infomax metric (left) or error minimization metric (right) for the synthetic data in red. The metrics are computed estimating the local PDF and using the appropriate exponent.[12,14] As in the SPCA case (Fig. 1) infomax leads to bigger differences in the size of discrimination ellipses.

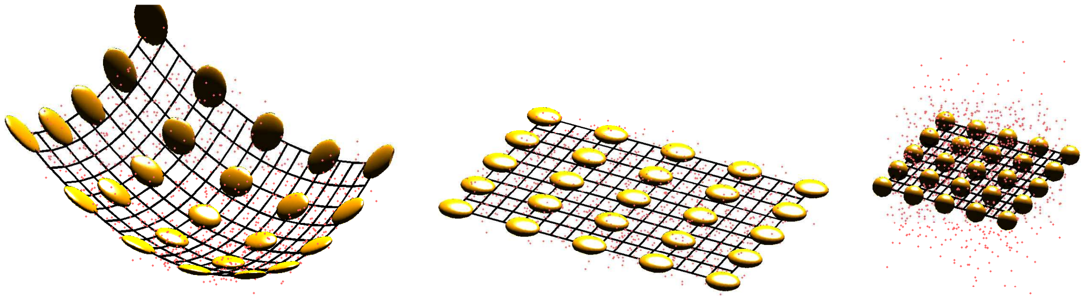

Figure 4. PPA transform and discrimination ellipsoids. Left: input domain and samples from a curved manifold in 3D space. Center: PPA representation by unfolding along the identified curvilinear features (in black). Right: whitened PPA domain. The PDF adapted metric in the input domain is computed by assuming Euclidean discrimination in the final domain (spheres at the right).

that is able to turn any training dataset into a multivariate Gaussian, namely our Rotation-Based Iterative Gaussianization (RBIG).[19]

Invertibility together with basic Riemannian geometry allows to compute the discrimination metric in the stimulus domain as previously done with empirical divisive-normalization models.[21,22] Moreover, using the local density information SPCA and RBIG can be tuned to compute discrimination metrics optimized according to either *infomax* or error minimization criteria under quantization [†]. On the other hand, PPA is formulated to minimize the representation error under dimensionality reduction.

Figures 2-4 illustrate how these transforms work and the discrimination ellipsoids obtained according to different optimality criteria. The behavior illustrated here is used below to make particular predictions in visual adaptation and discrimination.

2. A GALLERY OF PREDICTIONS

Color discrimination from Gaussianization. Color discrimination is non-uniform across the color space due to the non-linear response of the opponent color sensors.[23,24] RBIG, originally developed for infomax,[19] can also be tuned to compute discrimination metrics according to an error minimization strategy (Fig. 3). Fig. 5 shows the MacAdam color discrimination ellipses predicted using RBIG under both criteria. In this case, in agreement with previous literature focused on cardinal axes only,[12,14] error minimization (for limited resolution sensors) seems to be a more plausible organization principle rather than component independence.

Contrast masking from Sequential Principal Curves Analysis. The response of pattern analyzers is non-linear, and it is strongly attenuated (masked) if the test pattern is shown on top of backgrounds of similar frequency, while it is not severely affected if the test pattern is shown on top of backgrounds of very different frequency.[25] Fig. 6 shows that this is the case for SPCA sensors, originally tested in color vision problems,[14]

[†]It is possible to tune PPA in the same way but the algorithm has to be slightly modified.

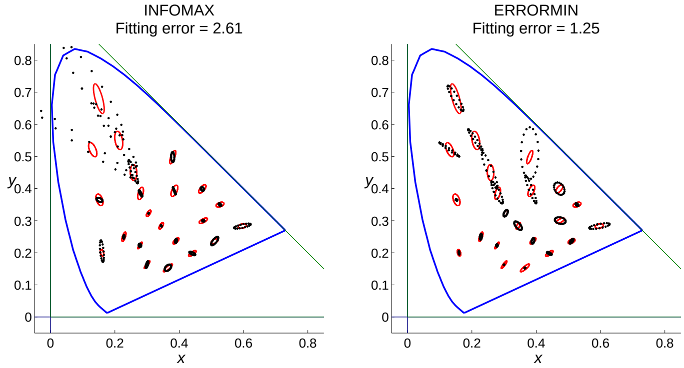

Figure 5. Color discrimination ellipses using Infomax and Error Minimization coding strategies using Gaussianization transforms. Predictions (in black) have to be compared with experimental MacAdam ellipses (in red).

optimized either using a infomax or error minimization criteria. Nevertheless, the steepness of the non-linearity is different so this can be used to determine which is actually the principle underlying this behavior.

Non-linear color sensors from Principal Polynomial Analysis. Color appearance is better explained using sensors tuned to curves (rather than lines) in the color space.[26,28] These curves can be explained according to an error minimization principle by using Principal Polynomial Analysis. See Fig. 7 for the predicted color sensors using this technique.

Color aftereffects from Sequential Principal Curves Analysis. It is known that adaptation to particular colored backgrounds induces specific color aftereffects (wrong color judgements) when looking at somewhere else.[28] Statistical analysis based on empirical models suggest that this could come from an adaptation to a biased statistics, e.g. a restricted environment made of samples with specific reflectance.[29] This effect can also be reproduced using non-parametric analysis (i.e. not based in the non-linear expressions of the empirical models), thus showing that the behavior directly emerges from data and the appropriate goal. Fig. 8 shows that the non-linear responses of Red-Green and Yellow-Blue mechanisms identified by Sequential Principal Curves Analysis (tuned for error minimization) shift under biased statistics.

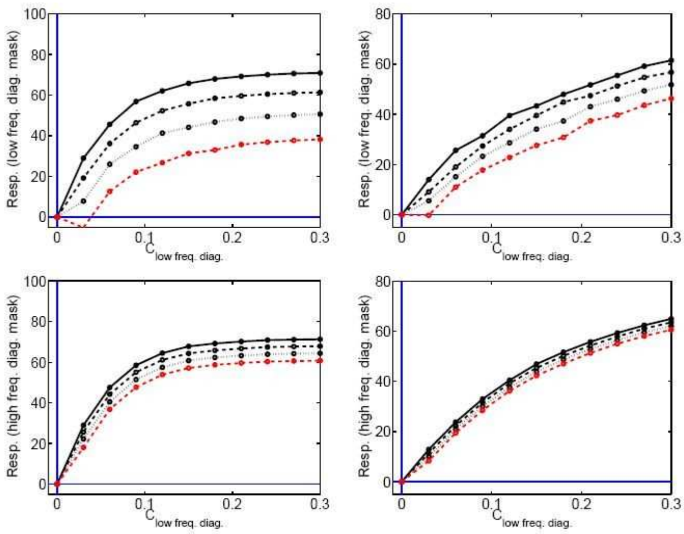

Figure 6. Non-linearities and masking of frequency sensors using Infomax (left) and Error Minimization (right) coding strategies through Sequential Principal Curves Analysis. Plots show the response of the sensors as a function of the contrast of the test for different masking conditions (form low contrast mask -solid line-, to high contrast mask -red line-). Top row shows the behavior when mask and test have similar frequency content. Bottom row shows the behavior when mask and test have different frequency content.

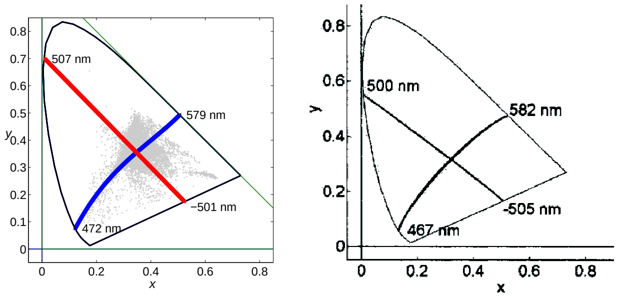

Figure 7. Non-linear color sensors identified by Principal Polynomial Analysis (left) compared to non-linear sensors of Guth[26] -as reported in Capilla et al.[27]-. Left plot also shows the natural image data (gray dots) used to train the statistical model.

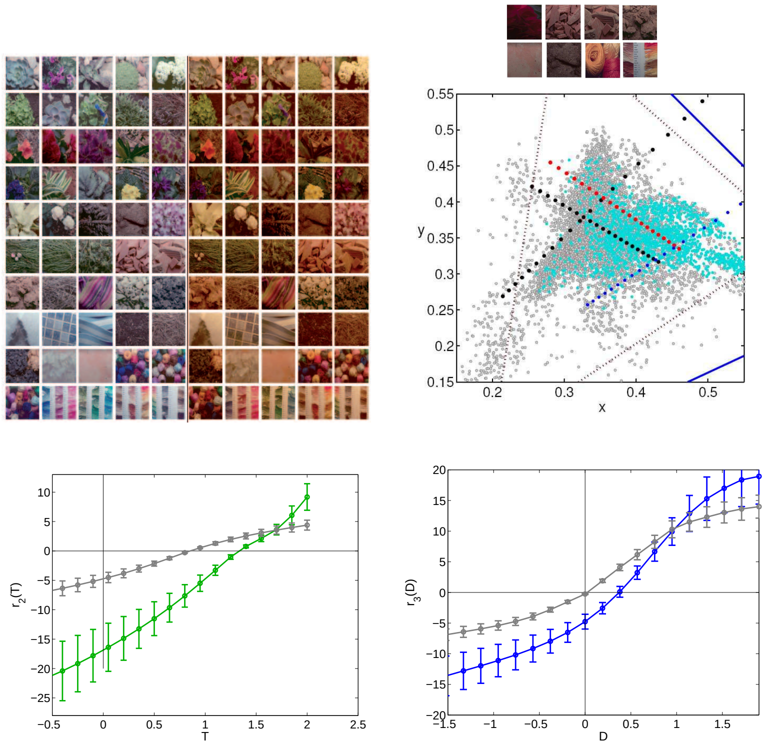

Figure 8. Shifts in the non-linear response of color sensors when adapted to a biased image statistics. The large panel of color images shows a *balanced* database consisting of a diversity of objects under CIE D65 and CIE A illuminants.[14] The colors of the objects under D65 are plotted in gray in the CIExy chromatic diagram at the right. The small panel of colored images at the right come from the D65 dataset but constitute a *biased* world with restricted reflectance (cyan dots in the chromatic diagram). When adapted to this biased environment, the responses of the sensors identified by our method (RG left and YB right) shift with regard to the curves in gray (adaptation to a diverse environment, large D65 database). Note that in this case, an stimulus eliciting zero responses (perceived as white) in the diverse environment situation, in the restricted environment would elicit negative responses in the RG and YB mechanisms, i.e. it would be perceived as blueish greenish (as is the case for human observers).

REFERENCES

[1] Barlow, H., "Possible principles underlying the transformation of sensory messages," in [*Sensory Communication*], Rosenblith, W., ed., 217–234, MIT Press, Cambridge, MA (1961).

[2] Buchsbaum, G. and Gottschalk, A., "Trichromacy, opponent colours coding and optimum colour information transmission in the retina," *Proc. Roy. Soc. B* **220**(1218), 89–113 (1983).

[3] Atick, J., Li, Z., and Redlich, A., "Understanding retinal color coding from first principles," *Neural Computation* **4**(4), 559–572 (1992).

[4] Atick, J., Li, Z., and Redlich, A., "What does post-adaptation color appearance reveal about cortical color representation?," *Vision Res* **33**(1), 123–129 (1993).

[5] Olshausen, B. A. and Field, D. J., "Emergence of simple-cell receptive field properties by learning a sparse code for natural images," *Nature* **381**, 607–609 (1996).

[6] Bell, A. J. and Sejnowski, T. J., "The 'independent components' of natural scenes are edge filters," *Vision Research* **37**(23), 3327–3338 (1997).

[7] Hoyer, P. and Hyvarinen, A., "Independent component analysis applied to feature extraction from colour and stereo images," *Network: Computation in Neural Systems* **11**, 191–210 (2000).

[8] Simoncelli, E. P. and Olshausen, B. A., "Natural image statistics and neural representation," *Annual Review of Neuroscience* **24**(1), 1193–1216 (2001).

[9] Doi, E., Inui, T., Lee, T., Wachtler, T., and Sejnowski, T., "Spatiochromatic receptive field properties derived from information-theoretic analysis of cone mosaic responses to natural scenes," *Neural Computation* **15**(2), 397–417 (2003).

[10] Barlow, H., "Redundancy reduction revisited," *Network: Comp. Neur. Syst.* **12**(3), 241–253 (2001).

[11] Laughlin, S. B., "The implications of metabolic energy requirements in the representation of information in neurons.," in [*The Cognitive Neurosciences III*], Gazzaniga, M., ed., 187–196, MIT Press, Cambridge MA (2004).

[12] MacLeod, D. A., "Colour discrimination, colour constancy, and natural scene statistics," in [*normal and defective colour vision*], Mollon, J., Pokorny, J., and Knoblauch, K., eds., 189–218, Oxford University Press (May 2003).

[13] Simoncelli, E. P., "Optimal estimation in sensory systems," *The Cognitive Neurosciences* **4**, 525–535 (2009).

[14] Laparra, V., Jiménez, S., Camps-Valls, G., and Malo, J., "Nonlinearities and adaptation of color vision from Sequential Principal Curves Analysis," *Neural Computation* **24**(10), 2751–2788 (2012).

[15] Schwartz, O. and Simoncelli, E., "Natural signal statistics and sensory gain control," *Nat. Neurosci.* **4**(8), 819–825 (2001).

[16] Kayser, C., Körding, K. P., and König, P., "Learning the nonlinearity of neurons from natural visual stimuli," *Neural Computation* **15**, 1751–1759 (2003).

[17] Lyu, S., "Dependency Reduction with Divisive Normalization: Justification and Effectiveness," *Neural Computation* **23**(11), 2942–2973 (2011).

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

[19] Laparra, V., Camps, G., and Malo, J., "Iterative gaussianization: from ICA to random rotations," *IEEE Trans. Neur. Nets.* **22**(4), 537–549 (2011).

[20] Laparra, V., Tuia, D., Jimenez, S., Camps, G., and Malo, J., "Nonlinear data description with Principal Polynomial Analysis," in [*IEEE Mach. Learn. Sig. Proc.*], (2012).

[21] Laparra, V., Muñoz Marí, J., and Malo, J., "Divisive normalization image quality metric revisited," *JOSA A* **27**(4), 852–864 (2010).

[22] Malo, J., Epifanio, I., Navarro, R., and Simoncelli, R., "Non-linear image representation for efficient perceptual coding," *IEEE Transactions on Image Processing* **15**(1), 68–80 (2006).

[23] Wyszecki, G. and Stiles, W., [*Color Science: Concepts and Methods, Quantitative Data and Formulae*], John Wiley & Sons, New York (1982).

[24] Krauskopf, J. and Gegenfurtner, K., "Color discrimination and adaption," *Vision Res.* **32**(11), 2165–2175 (1992).

[25] Watson, A. and Solomon, J., "A model of visual contrast gain control and pattern masking," *JOSA A* **14**, 2379–2391 (1997).

[26] Guth, S. L., "Further applications of the ATD model for color vision," *Proc. SPIE* **2414**, 12–26 (1995).

[27] Capilla, P., Díez, M., Luque, M. J., and Malo, J., "Corresponding-pair procedure: a new approach to simulation of dichromatic color perception," *J. Opt. Soc. Am. A* **21**(2), 176–186 (2004).

[28] Fairchild, M., [*Color Appearance Models, 2nd Ed.*], Wiley-IS&T, Chichester, UK (2005).

[29] Abrams, A., Hillis, J., and Brainard, D., "The relation between color discrimination and color constancy: When is optimal adaptation task dependent?," *Neural Computation* **19**(10), 2610–2637 (2007).