SPATIAL MASKING AND COLOR ADAPTATION FROM NON-LINEAR PCA

VNIVERSITAT DE VALÈNCIA
SPAIN

Valero Laparra
Jesús Malo

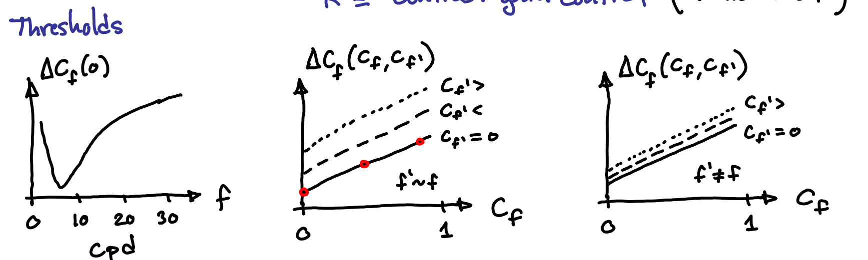
1 INTRODUCTION

PSYCHOPYSICS

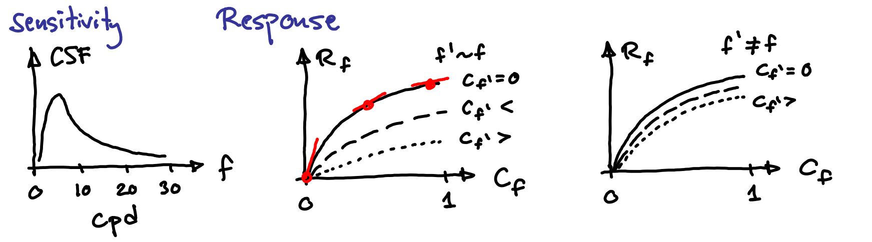
⊛ SPATIAL DIMENSIONS: NON-LINEAR Spatial frequency analyzers

$x \xrightarrow{W} c \xrightarrow{F} c' \xrightarrow{R} r$

- $W \equiv$ Wavelet transform matrix (Watson 83)
- $F \equiv$ Diagonal CSF-based matrix (Campbell 68)
- $R \equiv$ Contrast gain control (Watson 97)

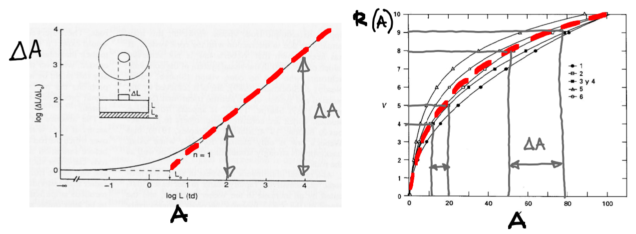


$$\frac{dR_f}{dC_f} \propto \frac{1}{\Delta C_f} \Rightarrow R_f = \int_0^c \frac{1}{\Delta C_f(c_f)} \cdot dc_f$$

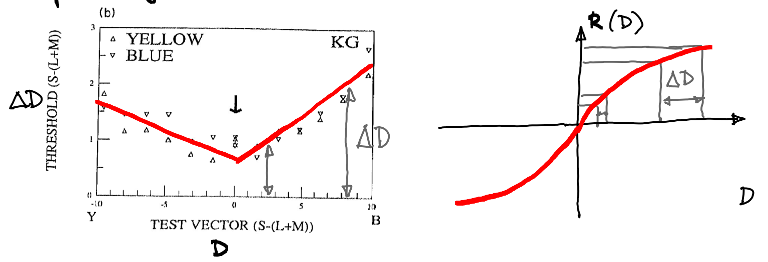


⊛ COLOR DIMENSIONS: Achromatic (A) and chromatic (T and D) mechanisms are NON-LINEAR

* Achromatic Channel: Weber law (e.g. Wyszecki & Stiles 82)



* Chromatic Channels: e.g. non-linearities in Yellow-Blue (D) channel (Krauskopf & Gegenfurtner 92, Romero et al. 93)



PREVIOUS (RESTRICTED) THEORETICAL DERIVATIONS

⊛ SPATIAL DIMENSIONS

- $W \equiv$ (Olshausen & Field 96, Bell & Sejnowski 97) → Global linear ICA
- $F \equiv$ (Atick 92) → Wiener Filter-like argument
- $R \equiv$ (Schwartz & Simoncelli 01) → Independence using divisive normalization
  (Malo & Gutierrez 06) → Non-linear (local-to-global) ICA

⊛ COLOR DIMENSIONS

- (Linear) opponent channels are similar to global PCA (e.g. Simoncelli & Olshausen 01)
- ATD non-linearities from (Mahalanobis) non-linear PCA (Laparra & Malo 08)

2 OUR WORK:

- ⊛ Joint derivation of F and R using non-linear PCA
- ⊛ Derivation of ATD non-linearities using non-linear PCA
- ⊛ Better foundation of non-linear PCA

3 (LOCAL-TO-GLOBAL) NON-LINEAR PCA

⊛ General ideas (from local-to-global ICA Malo & Gutierrez 06)

- + Describe manifolds with curved coordinates with metric related to the local density
- + Integrate local behavior into global description

Stimulus x $\underset{T^{-1}}{\overset{T}{\rightleftarrows}}$ Response r

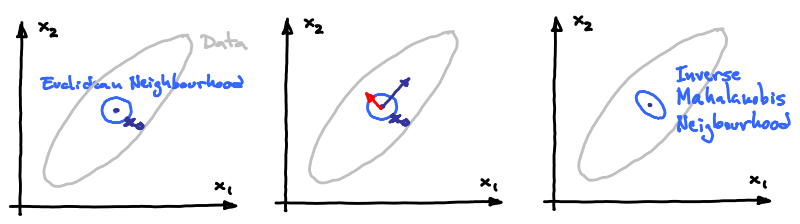
(Lin 99) $\quad \nabla T(x') = A_\ell(x')$

(Malo & Gutiérrez 06) $\quad T(x) \equiv r = r_0 + \int_{x_0}^{x} A_\ell(x')\,dx' \qquad T^{-1}(r) \equiv x = x_0 + \int_{r_0(x_0)}^{r} A_\ell(x'(r'))\,dr'$

⊛ Assumptions:

- A.1 Local linear axes describe local structure of the PDF (local indep.)
- A.2 Integration of locally independent variables lead to global independence

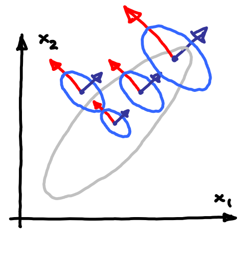
⊛ Approach I: Local Mahalanobis



$d^2 = (x - x_0)^T (x - x_0) \qquad C_{x_0}^{(E)} = B^{(E)}(x_0) \cdot \Lambda^{(E)}(x_0) \cdot B^{(E)}(x_0)^T \qquad d^2 = (x - x_0)^T C_{x_0}^{(E)} (x - x_0) \qquad C_{x_0}^{(M)} = B^{(M)}(x_0) \cdot \Lambda^{(M)}(x_0) \cdot B^{(M)}(x_0)^T$

$$\nabla T(x') = B^{(M)}(x') \cdot \lambda^{(M)}(x')^{\frac{1}{2}}$$

- * Local axes from local PCA (on ellipsoids)
- * Local metric from inverse Mahalanobis
- * Weakness: variance is not necessarily correlated to data density



⊛ Approach II: line element for constant mass variation

$$\nabla T(x') = B^{(E)}(x') \cdot \Delta(x')$$

- * Local axes from local PCA (on spheres)
- * Local metric for equal increment of the CDF in each dimension

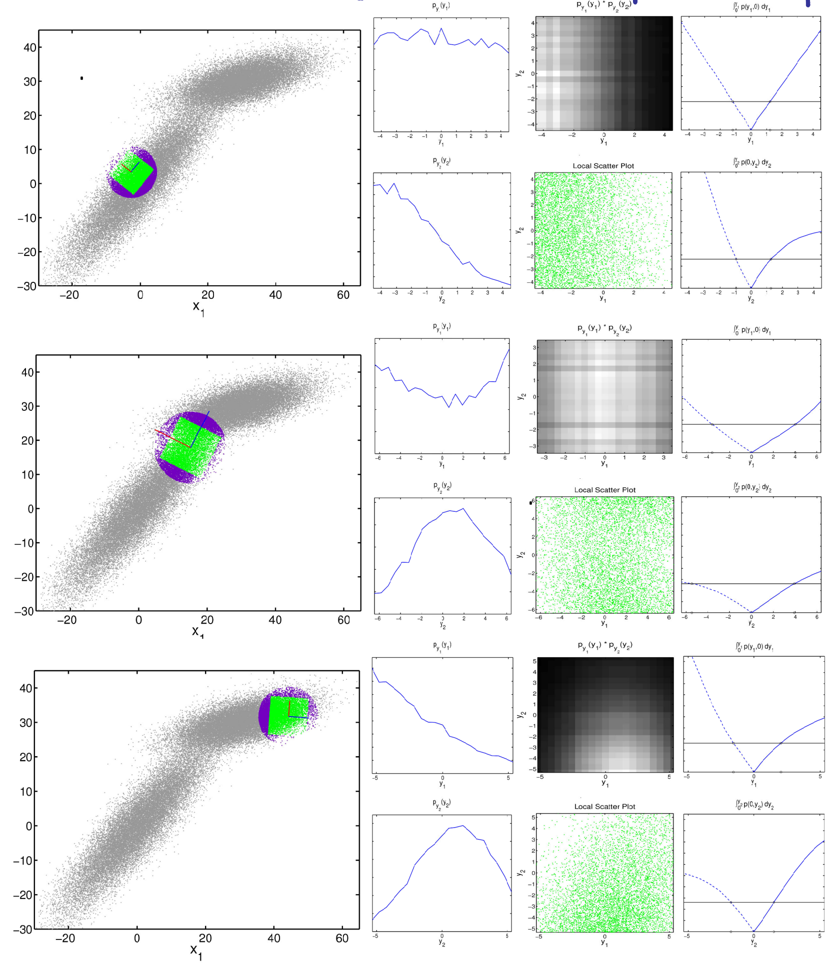
$\Delta_{ii} = \Delta y_i \quad / \quad \varepsilon = \int_0^{\Delta y_i} p(0, \ldots, 0, y_i, 0, \ldots, 0)\, dy_i$

where $y \equiv$ Project. on local axis: $\quad y = B^{(E)}(x')^T \cdot (x - x')$

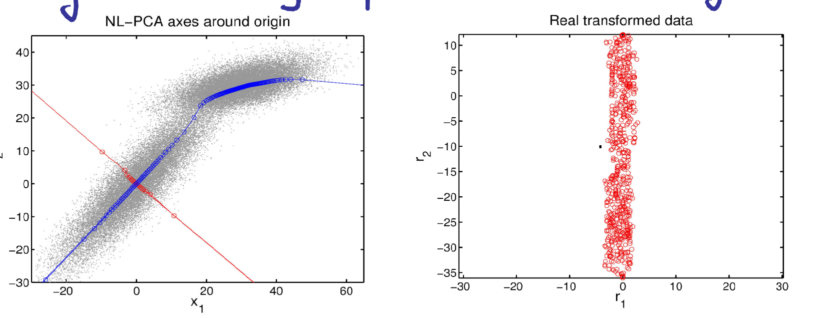
and $P(y) = \prod_i P_{y_i}(y_i)$ (y_i are locally independent)

4 DISCUSSION

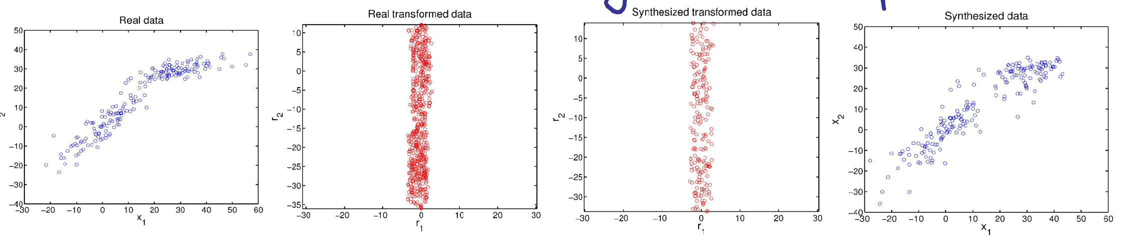
⊛ A.1 Local PCA is fine (enough) for local component independence



⊛ A.2 Integration of locally independent variables lead to global independence

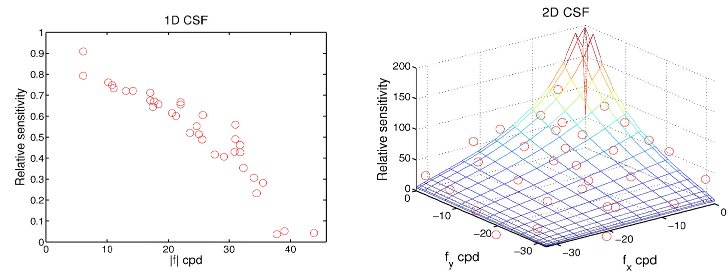


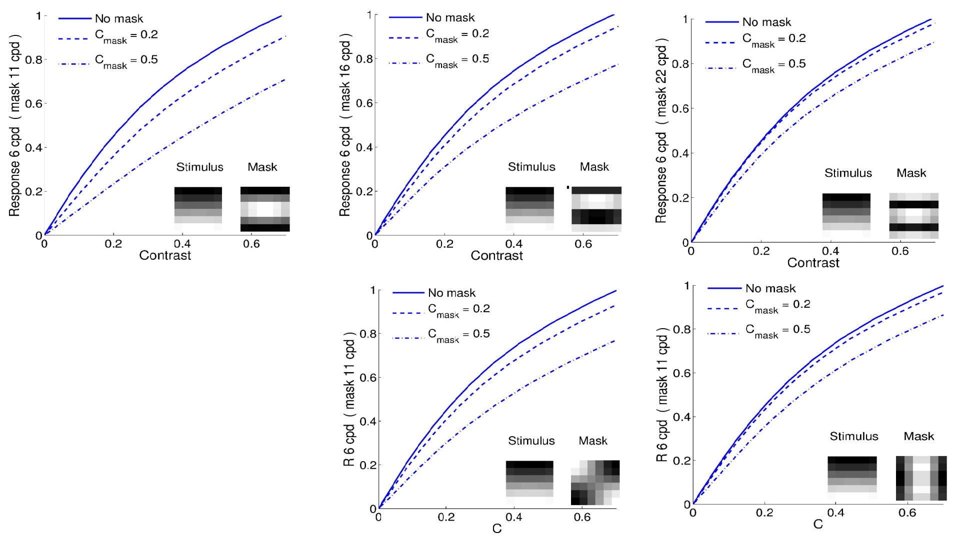
⊛ Transform and inverse: synthesis example



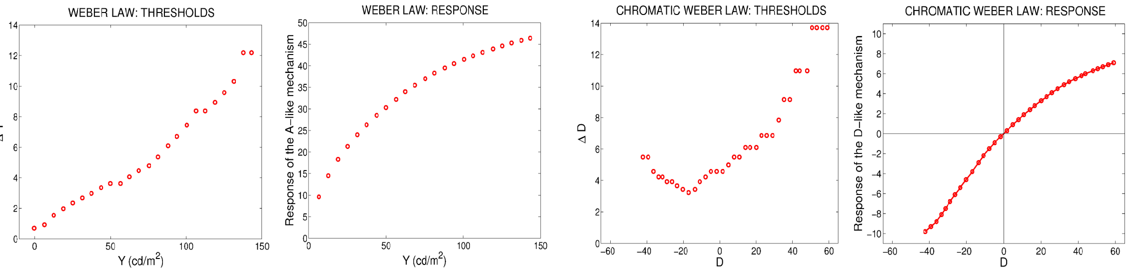
5 PERCEPTION RESULTS

⊛ SPATIAL DIMENSIONS





⊛ COLOR DIMENSIONS



6 CONCLUSIONS

(1) Non-linear PCA on a representative database reproduces the spatial frequency sensitivity, F, the gain control, R, and classical nonlinearities in achromatic and chromatic channels.

(2) Color results (Laparra & Malo 08) predict that specific environments or adaptation conditions may induce different non-linear behavior

(3) Further work includes: (i) systematical testing of the assumptions and robustness of the method, (ii) experimental test of the predictions in (2), and (iii) exploring the applications (automatic contrast and color correct, non-linear classification, vector quantization ...)

7 REFERENCES

[1] Wyszecky, G., & Stiles, W. S. Color science: Concepts and methods, quantitative data and formulae. New York, NY: John Wiley & Sons, 1982

[2] J Krauskopf and Gegenfurtner. Color Discrimination and Adaptation. Vision Research, 32(11) 2165-2175, 1992

[3] Romero, Javier; Garcia, José A.: Jiménez del Barco, Luis; Hita, E. Evaluation of color-discrimination ellipsoids in two-color spaces JOSA A, Volume 10, Issue 5, pp.827-837, May 1993

[4] E P Simoncelli and B Olshausen. Natural image statistics and Neural Representation. Annual Review of Neuroscience, 24: 1193-1216, 2001

[5] J Malo and J Gutierrez. V1 non-linearities emerge from local-to-global non-linear ICA Network: Comp. Neur. Syst., 17(1) 85-102, 2006

[6] V Laparra & J Malo. Color and Luminance Discrimination by Non-Linear PCA Computational Vision and Neuroscience symposium, 2008

[7] AB Watson and J. Solomon, "A model of visual contrast gain control," JOSA A 14, 2379-91, 1997

[8] F. W. Campbell and J. G. Robson , Application of fourier analysis to the visibility of gratings J Physiol Vol 197, Issue 3 pp 551-566 1968

[9] Watson, A. B. Detection and recognition of simple spatial forms. In O. J. Braddick, & A. C. Sleigh (Ed.), Physical and biological processing of images Berlin: Springer-Verlag. 1983

[10] Bruno A. Olshausen & David J. Field. Emergence of simple-cell receptive field properties by learning a sparse code for natural images Nature 381, 607 - 609 1996.

[11] Atick, J.J. Could information theory provide an ecological theory of sensory processing? Network: Computation in Neural Systems, 1992

[12] AJ Bell, TJ Sejnowski. The "independent components" of natural scenes are edge filters Vision Research, 1997

[13] O Schwartz, EP Simoncelli. Natural signal statistics and sensory gain control Nature Neuroscience, 2001

[14] Lin J. (1999). Factorizing probability density functions: Generalizing ICA. Proc. of the First Intl. Workshop on ICA and Signal Separation.

Acknowledgments: This work was supported by the project CICYT TEC2006-13845 MEC Spain