The Wilson-Cowan model describes Contrast Response and Subjective Distortion

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The Wilson-Cowan equations were originally proposed to describe the low-level dynamics of neural populations (Wilson&Cowan 1972). These equations have been extensively used in modelling the oscillations of cortical activity (Cowan et al. 2016). However, due to their low-level nature, very few works have attempted connections to higher level psychophysics (Herzog et al. 2003, Hermens et al. 2005) and, to the best of our knowledge, they have not been used to predict contrast response curves or subjective image quality. Interestingly (Bertalmío&Cowan 2009) showed that Wilson-Cowan models may lead to (high level) color constancy. Moreover, these models may have positive statistical effects similarly to Divisive Normalization, which is the canonical choice to understand contrast response (Watson&Solomon 1997, Carandini&Heeger 2012): while Divisive Normalization reduces redundancy due to predictive coding (Malo&Laparra 2010), Wilson-Cowan leads to local histogram equalization (Bertalmío 2014), another route to increase channel capacity.

Here we show that the functional (statistical) similarities between Wilson-Cowan and Divisive Normalization actually hold and may be extended to contrast perception. Specifically, first we fitted the Wilson-Cowan model using a procedure reported for Divisive Normalization: following (Watson&Malo 2002, Laparra&Malo 2010), we maximized the correlation with human opinion in quality assessment. Secondly, we used the resulting model to predict the visibility of textured patterns on top of backgrounds of different frequencies and contrasts as in classical masking experiments. Finally, we checked the redundancy reduction of Wilson-Cowan and Divisive Normalization in the same way (as in Malo&Laparra 2010). Results show that (1) Wilson-Cowan is as good as Divisive Normalization in reproducing image distortion psychophysics, (2) Wilson-Cowan dynamics induces saturating responses that attenuate with the contrast of the background, particularly when the background resembles the test; and (3) mutual information between V1-like responses after the Wilson-Cowan interaction decreases similarly as in Divisive Normalization.

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Supplementary Material: ***The Wilson-Cowan model describes Contrast Response and Subjective Distortion***

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In order to compare the psyhophysical and statistical behavior of the Wilson-Cowan model, here we unplug the cortical Divisive Normalization of a successful contrast perception model [Martinez-Garcia et al. VSS-MODVIS 2016], and we substitute it by a Wilson-Cowan layer.

The baseline model consists of four stages: (1) a luminance-to-brightness point-wise nonlinearity, (2) a center-surround contrast computation stage, (3) a CSF-like filtering plus contrast masking nonlinearity, and (4) a wavelet-like filterbank followed by inhibition between neighbor sensors. Here we substitute the last Divisive Normalization (the one at the cortical stage, after the wavelets) by a dynamic layer that operates according to the Wilson-Cowan equations.

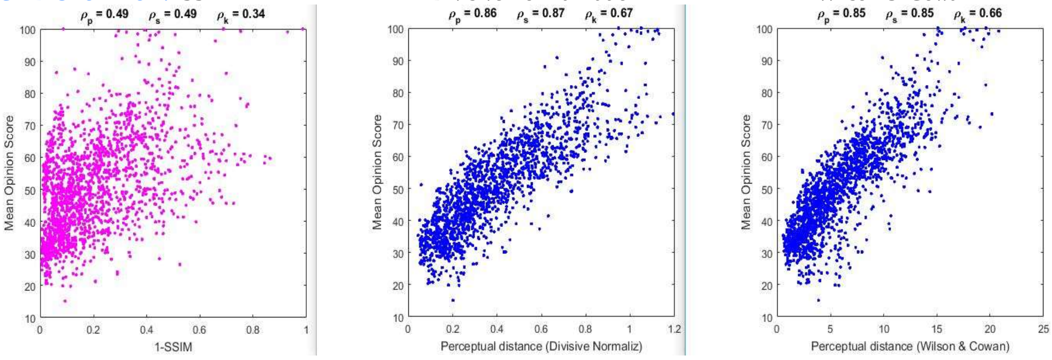
For a fair comparison, we set the parameters of this last nonlinear stage (either Divisive Normalization or Wilson-Cowan) in the same way: following [Watson&Malo IEEE ICIP 2002, Malo&Laparra JOSA A 2010], we choose the parameters that maximize the correlation between the experimental mean opinion score in subjective distorion tasks and the computed perceptual distance (using the L_2 norm in the response space).

SUBJECTIVE IMAGE DISTORTION: Both models (DN and WC scatter plots in blue) get substantially better correlations with human opinion than the widely used Structural Similarity Index (SSIM) [Wang et al. IEEE Tr. Im. Proc. 04] over a recent subjective image quality set (the TID database [Ponomarenko et al. Sig. Proc: Im. Comm 2015]). See the Pearson, Spearman and Kendall correlation coeffcients.

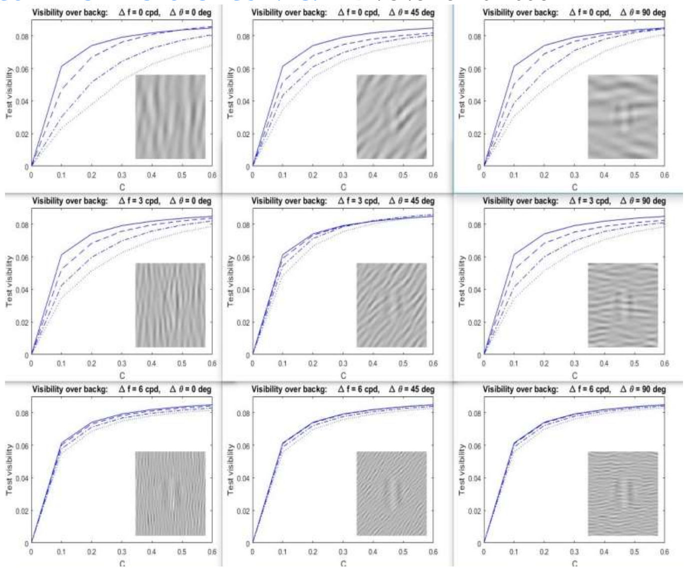
CONTRAST RESPONSE CURVES: Insets in the contrast response panels below show examples of the same low frequency pattern (3 cpd test in the center with fixed 0.2 RMSE-contrast) shown on top of backgrounds of 3, 6 and 12 cpd with different orientations and the same contrast. Increasing the contrast of the central test certainly increases its visibility, but not in the same way depending on the background [Watson&Solomon JOSA A 1997]: note that the test is barely visible on top of the pattern of the same frequency and orientation while it is clearly visible on top of very different bakgrounds. Curves show the increase in the average response of the neurons optimally tuned to the pattern with regard to the response to the isolated background, for backgrounds of different contrast (zero contrast – no mask-, in solid, and progressively bigger contrast in lighter dashed styles). The nonlinear response of Wilson-Cowan sensors (right panel) is attenuated by the contrast of the background in a similar way as the response of sensors that went through a Divisive Normalization (left panel): bigger attenuation over backgrounds of similar features and bigger visibility (less attenuation) the other way around.

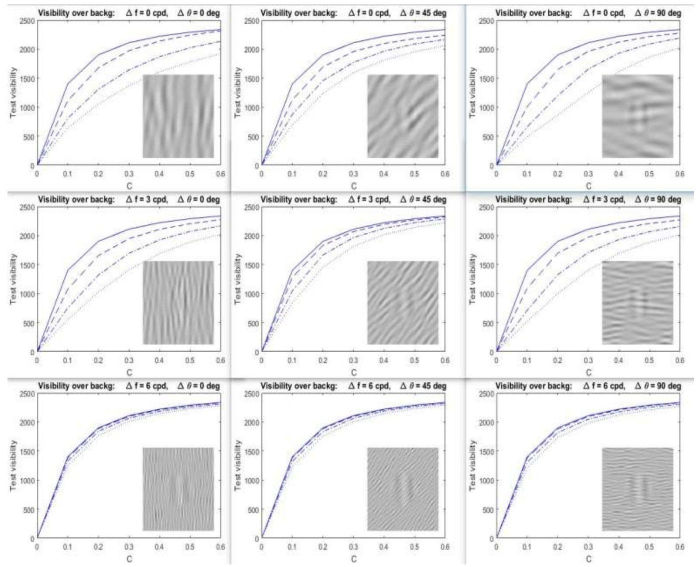
REDUNDANCY REDUCTION: Wavelet-like multiscale/multiorientation diagrams at the bottom show the statistical relation (mutual information) between the responses of a specific sensor (the one in black in the second scale, diagonal orientation) and the rest of the sensors computed over a calibrated image database [VanHateren Proc.RoySoc. 1998] in a linear wavelet representation (left) and in the two considered nonlinear representations. We used the same mutual information estimator as in (Malo&Laparra Neural Comp. 2010) where it was shown to have proper accuracy for heavy-tailed PDFs suitable to model images. Errors indicate the standard deviation of the mean over 50 estimations with 10^4 images. In the images white and black respectively stand for bigger and lower mutual information values. Gray levels are scaled according to the same range ([0, 0.6] bits) in all cases. Wilson-Cowan results are consistent with the redundancy reduction previously found in Divisive Normalization (Malo&Laparra Neural Comp. 2010) suggesting an infomax principle in the organization of the retina-cortex architecture.

SUBJECTIVE IMAGE DISTORTION: **SSIM** **Divisive Normalization** **Wilson & Cowan**



CONTRAST RESPONSE CURVES: **Divisive Normalization** **Wilson & Cowan**





REDUNDANCY REDUCTION: **Linear Wavelet ($9.6 \pm 0.1{\times}10^{-2}$ bits)** **Divisive Normalization ($3.2 \pm 0.1{\times}10^{-2}$ bits)** **Wilson & Cowan ($7.8 \pm 0.2{\times}10^{-2}$ bits)**