Supporting Information

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SI Text

Negative Contrast Excess Is Robust to Variations in the Receptive-Field Model. In the text, we measured local contrast distributions in natural scenes using a divisively normalized difference of Gaussians filter,

$$\text{Contrast}(x,y) = (I_c(x,y) - I_s(x,y))/I_d(x,y)^{\delta} \qquad \textbf{[S1]}$$

with $\delta = 1$. Here, I_c, I_s, and I_d are intensities measured by unit-normalized center, surround, and divisive normalization Gaussian filters centered at (x, y). The excess of negative contrasts was independent of the power of I_d appearing in the denominator in Eq. **S1**. This is because divisive normalization by a positive number does not change the sign of the center response minus the surround response. Thus, the fraction of dark contrasts exceeded the fraction of bright contrasts even without divisive normalization ($\delta = 0$). We tested how the precise shape of the contrast distribution depended on δ by measuring the skewness and kurtosis of the contrast distribution as a function of δ (Fig. S1).

We also tested how the precise shape of the contrast distribution depended on the size of the adaptation pool (Fig. S2, *Left*). As the size of the adaptation pool varied from the center size to the surround size, the skew in the contrast distribution shifted from negative to positive (Fig. S2, *Right*). When contrast was normalized by the center response, the contrast distribution had longer tails to the negative. When contrast was normalized by the surround response, the contrast distribution had longer tails to the positive. However, other than small effects on the contrast-detection threshold, the fraction of negative contrasts was independent of the adaptation-pool size and always exceeded the fraction of positive contrasts. This is again because divisive normalization by a positive number does not change the sign of the center response minus the surround response.

We also asked whether the shape of the center-surround filter could affect the excess of negative contrasts. We tested Gaussian weightings, flat weightings, rectangular filters, ellipisoidal filters, and different relative-surround sizes (K, the ratio of surround to center size). In each case, filters were convolved with an ensemble of natural images. We did not introduce a response threshold, and hence, the percentage of negative values was independent of the divisive normalization scheme. The percentage of negative filter values for each combination of parameters is given in Fig. 2. These results extend earlier reports of specific instances of a skew to negative contrasts (1–3) and show that the excess persists when center-surround models used to probe images differ in scale and shape.

1. Laughlin SB (1983) Matching coding to scenes to enhance efficiency. *Physical and Biological Processing of Images*, eds Braddick OJ, Sleigh AC (Springer, Berlin).
2. Ratliff CP (2007) Toward a theory of the functional organization of the retina. PhD dissertation (University of Pennsylvania, Philadelphia, PA).
3. Burkhardt DA, Fahey PK, Sikora MA (2006) Natural images and contrast encoding in bipolar cells in the retina of the land- and aquatic-phase tiger salamander. *Vis Neurosci* 23:35–47.
4. Borghuis BG, Ratliff CP, Smith RG, Sterling P, Balasubramanian V (2008) Design of a neuronal array. *J Neurosci* 28:3178–3189.

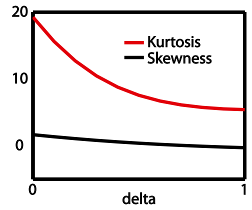

Fig. S1. The skewness and kurtosis of contrast distribution varies with the power δ of the divisive normalization in ref. 1. Here, the SDs of the surround Gaussian and the divisive normalization Gaussian were both taken to be 1.5 times the SD of the center Gaussian.

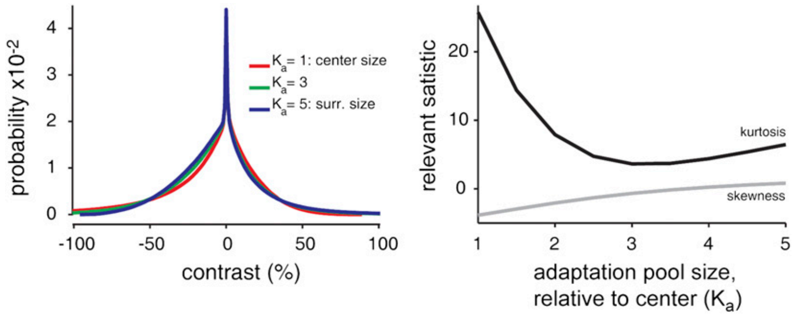

Fig. S2. Variation of contrast distributions with adaptation pool size. (*Left*) The SD of the surround Gaussian was fixed at 5 times the center SD (similar results for other surround widths). The center-surround response was divisively normalized by the response of a Gaussian with SD of K_a times the center SD. Thus, K_a = 1 represents an adaptation pool of size comparable with the center, and K_a = 5 is an adaptation pool of size comparable with the surround. Large positive and negative contrast values are cut off here, but the contrast distribution for K_a = 1 has long tails to the negative and the contrast distribution for K_a = 5 has long tails to the positive. Regardless of shape, all distributions have the same proportion of positive or negative contrasts. (*Right*) Skewness and kurtosis of contrast distributions vary with adaptation pool size. Skewness and kurtosis were computed for contrast distributions as a function of adaptation pool size. Skewness was negative for center-sized adaptation pools and was positive for surround-sized adaptation pools. All distributions were somewhat kurtotic.

Table S1. Negative contrasts robustly predominate in natural images

Shape	Center size	% Negative (K = 1.5)	% Negative (K = 5)
Gaussian	$\sigma = 2$	56.6	58.5
	$\sigma = 20$	56.7	60.4
Square	$L = 4$	54.9	57.6
	$L = 40$	53.8	57.9
Rectangle	$L = 2$; $W = 8$	53.6	57.0
	$L = 20$; $W = 80$	52.7	57.4
Circle	$R = 2$	55.0	57.4
	$R = 20$	53.7	57.8
Ellipse	$A = 1$; $B = 3$	54.7	56.8
	$A = 10$; $B = 30$	53.3	57.5

In all cases except the Gaussian, the center and surround filters had a flat weighting across their domain. We did not include a response threshold. Parameters: σ, Gaussian SD; L, length of rectangle; W, width of rectangle; R, radius of circle; A, semi-minor axes of ellipse; B, semi-major axes of ellipse.