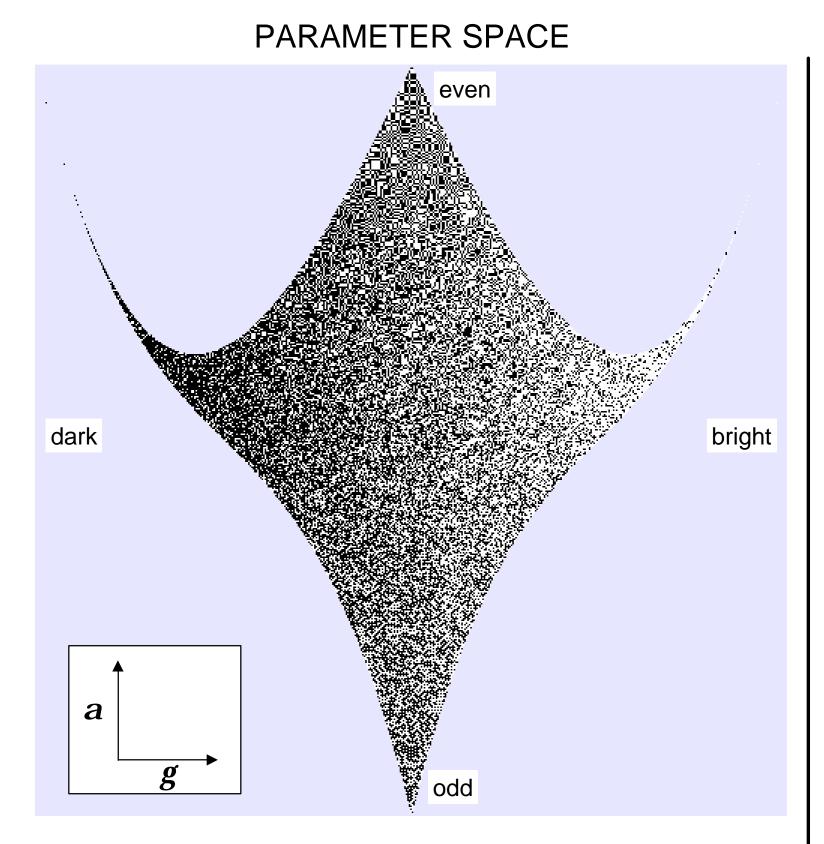
Interaction of first-order and isodipole statistics in a texture segregation task

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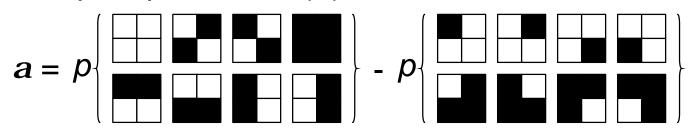
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PARAMETER SPACE DETAILS

Luminance parameter (g): $g = p \{ \Box \} - p \{ \blacksquare \}$

Isodipole parameter (*a*):



Textures are specified by two parameters, g and a. First-order (luminance) statistics are specified by g g = 0 specifies a texture that has an equal number of bright and dark checks; g = 1 specifies a texture that has only bright checks, and g = -1 specifies a texture that has only dark checks.

Fourth-order (isodipole) statistics are specified by a. a = 1 specifies a texture in which all 2x2 blocks contain an *even* number of bright checks, and a = -1 specifies a texture in which all 2x2 blocks contain an *odd* number of bright checks. There is no second- or third-order correlation structure. That is, the probability that any pair of checks is bright is $(1+g)^2/4$, and the probability that any triple of checks is bright is $(1 + g)^3/8$. Such textures can be constructed provided that $g^4 - (1-|g|)^4 \leq a \leq g^4 + (1-|g|)^4$. These inequalities define the stimulus space illustrated above. These textures generalize the decorrelated isodipole textures (Victor 1985, Victor and Conte, 1989).

Specification of the textures is completed by requiring that they are maximum entropy, subject to the constraints specified by the two parameters g and a. Such maximum-entropy textures may be constructed by a two-dimensional Markov process (Zhu, Wu, and Mumford, 1998). Following this construction, the probability of a particular 2x2 block that contains *n* bright checks is given by $[(1-g)^{4-n}(1+g)^n+(-1)^n(a-g^4)]/16.$

INTRODUCTION

Image statistics are often classified as first-order (e.g., luminance), second-order (e.g., contrast, autocorrelation, power spectrum) and high-order (e.g., fourth-order isodipole). Many studies of visual texture processing have considered texture discrimination based on one kind of image statistic, but few have examined how these statistics interact. To examine the interaction of isodipole statistics and luminance statistics, we construct a novel two-dimensional space of binary textures. One axis in this space, γ , specifies the bias in luminance statistics (γ =1 for all white, 0 for a 50:50 mix, -1 for all black). The second axis, α , specifies the bias in local fourth-order statistics (α =1 for the "even" texture, -1 for the "odd" texture). Long-range statistics and statistics of other orders are determined by maximizing entropy. This uniquely defines the textures in terms of α and γ (within predetermined limits), and thus describes a two-parameter perceptual space.

METHODS

TASK: Identify the location of the target stripe (4-AFC, top, right, bottom, left)

SUBJECTS: N=3, VA corrected to 20/20 Practice: MC - 2 hrs, AO - 3 hrs, CC - 3 hrs

STIMULI:

Size: 11.6 deg square, viewed binocularly at 57 cm Contrast 1.0, Luminance 57 cd/m², Duration 200 ms Refresh: 75 Hz (Dell Trinitron Monitor)

CONDITIONS:

288 trials per block

8 repeats of coordinate-axis points

16 repeats of diagonal points Conditions randomized in every block

15 blocks per subject (4320 trials per subject) Feedback on error in all practice and experimental blocks

PSYCHOMETRIC FUNCTIONS

For each of the three subjects, psychometric functions (fraction correct) along the isodipole (a)and luminance (g) axes were separately fit to Weibull functions via maximum-likelihood.

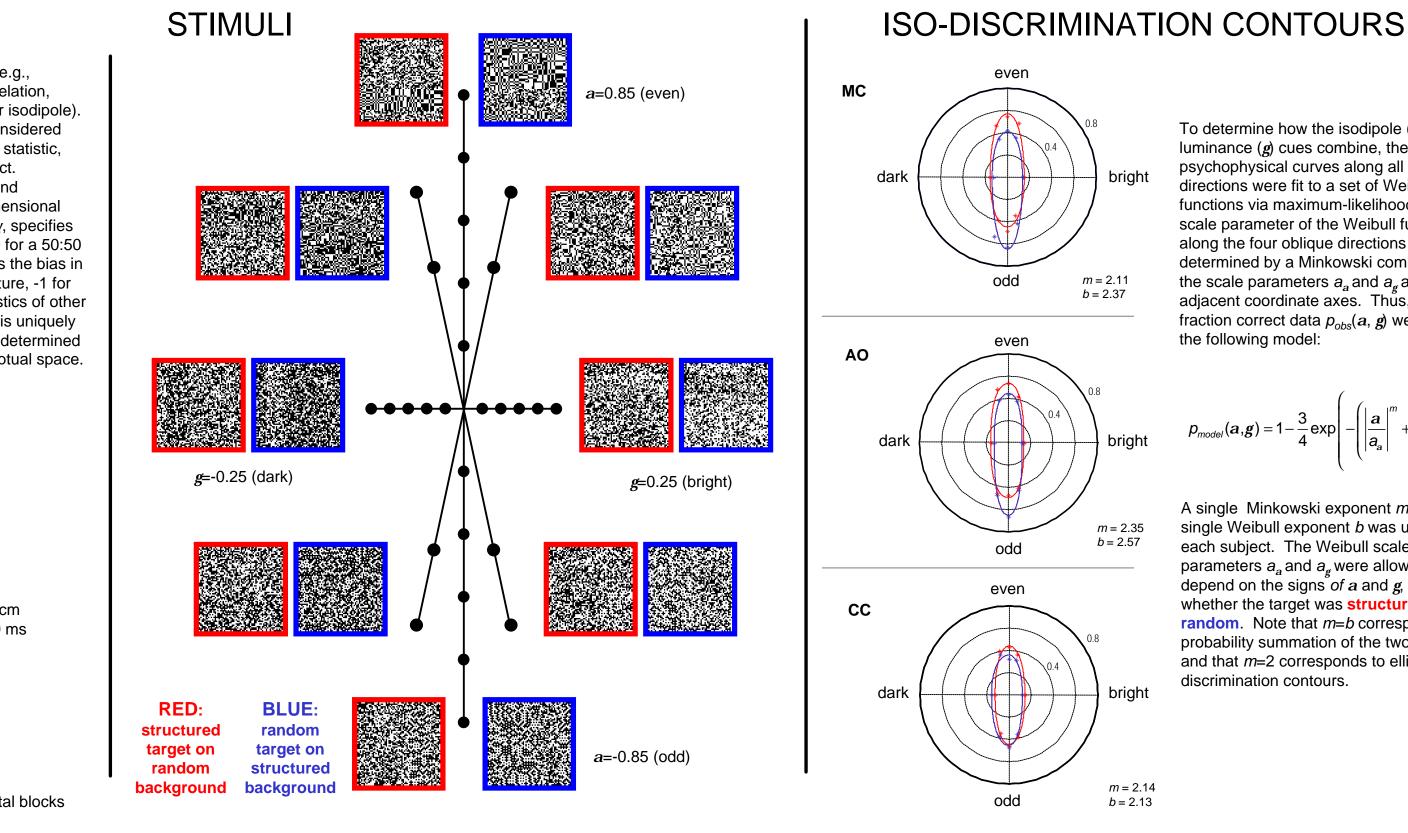
$$p_{model}(\boldsymbol{a},0) = 1 - \frac{3}{4} \exp\left(-\left|\frac{\boldsymbol{a}}{\boldsymbol{a}_{a}}\right|^{b}\right)$$
$$p_{model}(0,\boldsymbol{g}) = 1 - \frac{3}{4} \exp\left(-\left|\frac{\boldsymbol{g}}{\boldsymbol{a}_{g}}\right|^{b}\right)$$

The scale parameters a_{α} and a_{γ} of the Weibull functions were allowed to depend on the sign of a or g, and were also allowed to depend on whether the target was structured or random . A single Weibull exponent *b* was used for all eight curves within each subject.

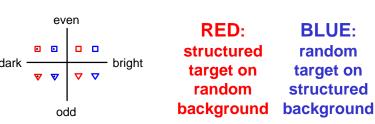
•The scale parameter in the isodipole direction, a_{α} , was about fourfold higher than the scale parameter in the luminance direction, a_{v} . This indicates a corresponding difference in sensitivity.

• In all directions except for the "odd" direction (*a*<0), performance for a structured target on a random background was better than performance for a random target on a structured background.

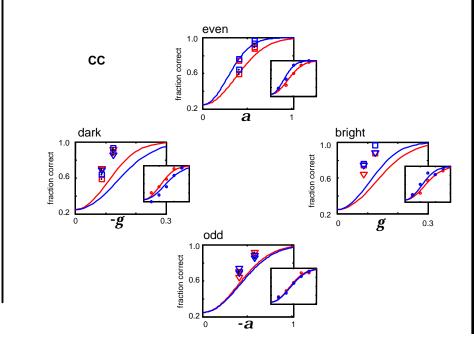
•Performance in the oblique directions ($a \neq 0, g \neq 0$) suggested that subthreshold isodipole and luminance cues could be combined.



Insets show observed fraction correct for stimuli along each of the coordinate axes (data points), along with the Weibull functions (curves) fit via maximum likelihood. Main graphs compare these Weibull functions (smooth curves) with the observed fraction correct for stimuli along adjacent oblique directions (isolated squares and triangles).



Key finding: when both cues were present (isolated squares and triangles), fraction correct was greater than when either cue was presented alone (smooth curves). This relationship held in all four oblique directions and in all three subjects.



- differences.
- difference in first-order (luminance) statistics.
- for the odd textures.
- exponent of 2.

- third-order statistics. Biological Cybernetics 31, 137-140.
- 1811-1827.
- dynamics. Visual Neuroscience 2, 297-313.
- Vision 27(2), 107-126.

To determine how the isodipole (a) and luminance (g) cues combine, the psychophysical curves along all eight directions were fit to a set of Weibull functions via maximum-likelihood. The scale parameter of the Weibull functions along the four oblique directions was determined by a Minkowski combination of the scale parameters a_a and a_a along the adiacent coordinate axes. Thus, the fraction correct data $p_{obs}(a, g)$ were fit to the following model:

$$\mathcal{D}_{model}(\boldsymbol{a},\boldsymbol{g}) = 1 - \frac{3}{4} \exp\left(-\left(\left|\frac{\boldsymbol{a}}{\boldsymbol{a}_a}\right|^m + \left|\frac{\boldsymbol{g}}{\boldsymbol{a}_g}\right|^m\right)^{\frac{b}{m}}\right)$$

A single Minkowski exponent *m* and a single Weibull exponent b was used for each subject. The Weibull scale parameters a_a and a_a were allowed to depend on the signs of a and g, and on whether the target was structured or **random**. Note that *m*=*b* corresponds to probability summation of the two cues, and that m=2 corresponds to elliptical isodiscrimination contours.

CONCLUSIONS

• Absolute sensitivity to differences in luminance statistics was approximately four times greater than sensitivity to isodipole

• Salience of a texture patch was *independent* of the sign of the

• Salience of a texture patch was strongly *dependent* on the sign of the difference in fourth-order (isodipole) statistics. A random patch on an even background was more readily detected than an even patch on a random background. The opposite was true

• Luminance and isodipole statistics behave like cardinal axes, and the corresponding cues combined according to a Minkowski

• This combination rule is consistent with probability summation.

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