Local versus global contrasts in texture segregation

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Received June 5, 1998; revised manuscript received November 2, 1998; accepted November 12, 1998

In a texture pair (TP) yielding a vertical or horizontal edge, the local (luminance or color) contrast or the local orientation of the individual textels is traded off with the global strength of the luminance-, color-, or orientation-defined TP edge so as to keep the latter at the detection threshold. Local and global contrasts are defined along the same (within-domain conditions) or along distinct physical dimensions (transdomain conditions). In the latter case local luminance or color contrast is traded off against global orientation. In all cases TP's are presented for 66.7 or 333.3 ms. Textels differ from the background in either luminance or color so that the TP's are respectively equichromatic or equiluminant. TP edge strength is modulated by means of swapping variable proportions of textels between the two textures in the TP. The observed local–global relationships are fitted with a version of the equivalent noise model for contrast coding modified to include the presentation time factor. The extension of the standard model in the time domain is meant to allow comparison between equivalent noise estimates for variable duration stimuli. Model fits of the within-domain data yield equivalent noise energy values significantly different for color- and luminance-defined TP's but are not applicable for the transdomain experiments, which indicates that global orientation processing is independent of both local luminance and local color contrast insofar as the latter are above the detection threshold. Finally, this study points to the equivalence among the local–global, the equivalent noise, and the statistical approaches to texture segregation. [S0740-3232(99)02003-7]

OCIS codes: 330.4060, 330.5510.

1. INTRODUCTION

"Visual texture is a 2D visual stimulus characterized by a visible grain. Visual grain consists in local modulations along dimensions such as luminance, color and shape, which may or may not be discriminable. Two textures are visually different if they do not share the same grain and/or if they do not share, in the statistical sense, the same grain distributions across space."[1] This generic definition prompts a fundamental question in visual psychophysics: What is the relationship between the local (at the grain level) and the global (at the statistical level) characteristics of two images at their segregation threshold? In the process of addressing this problem from both an experimental and a modeling perspective, it became clear that it can be formulated in at least two other, strictly equivalent ways. One refers to the assessment of the equivalent noise in a given processing domain (such as luminance, color, or orientation) by means of studying texture segregation within that domain. Another relates to the relevant statistics involved in texture segregation.

The local–global problem is central in visual processing and has been stated at least since the Gestalt era. From a computational point of view, this problem has been frequently related to the issue of multiple-scale processing, but little stress has been put on the possibility of interactions across scales.[2–4] An enduring debate focused on the issue of parallel versus serial processing of local and global properties and, in the latter case, on the temporal order in which they are processed.[5–8] To our knowledge, the relationship between local and global properties of an image characterizing its segregability from another image has not been formulated in the context of visual texture processing.

The notion that texture segregation can be quantified in terms of some sort of feature statistics may be traced back to work on the information-limiting characteristics of photographic granularity in the 1940's.[2] In the context of visual psychophysics, the statistical approach was most certainly set off by Julesz[9] and Beck.[10] It led to Julesz's[11] texton theory but was eventually absorbed by the (presumably) more tractable approach of multiscale, local Fourier analysis complemented by some sort of nonlinear processing.[4] As noted by some,[12] this approach is not intuitive in the sense that predicting the discriminability of two images (textures) requires the actual computation of differences in their Fourier spectra. As a consequence, the statistical approach in texture segregation has been recently revived by a number of studies that demonstrated the significance of the first-order (the

0740-3232/99/030728-14$15.00

mean) and the second-order (the variance) statistic differences.[12–14]

Going along with the spirit of allowing a better intuition into whether two images will be segregated, a number of studies[15–19] capitalized on the notions of equivalent noise and of noise masking. This classical approach in electrical engineering is meant to assess the efficiency of an input–output device in terms of its resistance to external noise.[15,16] In vision research the equivalent endeavor is reminiscent of Barlow's[20,21] measurements of dark light. In contrast to the standard multiscale modeling, which requires the specification of a large number of filter parameters, the characterization of the contrast detection system in terms of the "distribution of a noise, the equivalent noise of the system referred to its input" (Ref. 17, p. 1133), requires one single global parameter.[22] Here we pursue this line of thought as it relates to texture segregation.

Whereas the techniques of modeling texture segregation in terms of a local–global relationship or as a statistical operation or by means of specifying the equivalent noise of the system appear to be three distinct theoretical approaches, it can be shown that they are strictly equivalent. It is easier to make this point clear if we refer to the stimulus design used in the present experiments to trade off local versus global contrasts in texture segregation.

2. STIMULUS DESIGN AND THE LOCAL–GLOBAL TRADE-OFF

Figure 1 illustrates two types of texture pair (TP) whose segregation is based on global differences in luminance contrast (top four panels) and in orientation (bottom four panels). (Replacing the two shades of gray of the textels with two equiluminant hues would yield a global color contrast discrimination task for the top four TP's and a chromatically defined orientation discrimination task for the bottom four.) The original question that we asked concerned the relationship between these global, just-detectable differences and the contrast (or orientation) of their local (constituent) elements. We thus manipulated the local/textel contrast (or orientation) along the discriminant dimension (maximum luminance contrast and 90° local orientation difference in the first and third rows of Fig. 1, respectively; lower luminance contrast and smaller orientation difference in the second and fourth rows) and measured TP segregation in terms of what we refer to herein as the dilution parameter, P. The left-hand TP's in Fig. 1 illustrate the case of 0 dilution: All the elements in each texture of the TP are identical along the discriminant dimension, i.e., either luminance polarity or orientation. The right-hand panels illustrate TP's with 50% dilution: 25% of the textels on each side of the TP were randomly swapped. Thus dilution $P = 2p$, with $p \leq 0.5$, the actual proportion of swapped textels in each texture, so that for $p = 0.5$, $P = 1$, i.e., 100% dilution. The experimental design then allows us to relate local and global contrasts at the segregation threshold or, alternatively, to assess the law governing global contrast computation by the visual system for an arbitrary stimulus dimension.

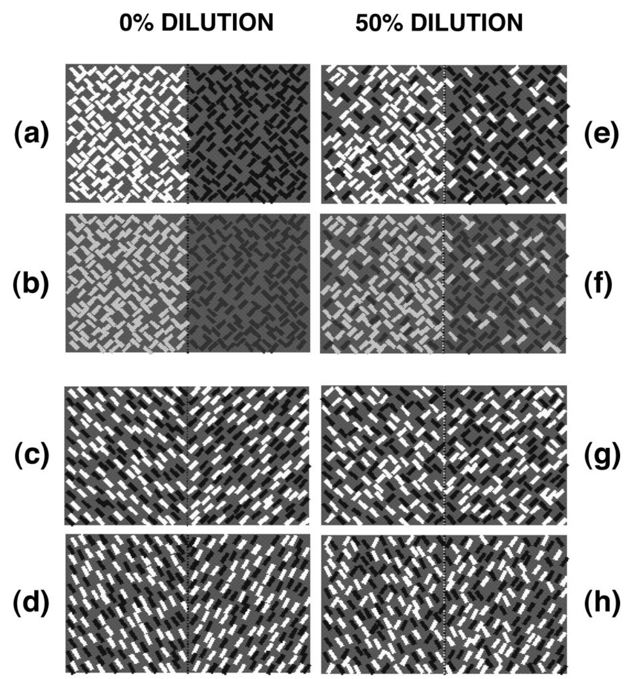

Fig. 1. Illustration of two types of texture pair (TP) used in the present study. For the top four TP's segregation is based on global differences in luminance contrast. The bottom four TP's illustrate the case of a global orientation difference. Replacing the two shades of gray of the textels with two equiluminant hues (in this case, red and green) would yield a global color contrast discrimination task for the top four TP's and a chromatically defined orientation discrimination task for the bottom four. Local textel contrast, or local textel orientation difference, is maximal for panels (a), (c), (e), (g), and it is reduced in panels (b), (d), (f), and (h). Left-hand TP's [(a)–(d)] yield zero dilution, that is, all the textels in each texture of the TP are identical along the discriminant dimension, namely, luminance polarity or orientation. The right-hand TP's [(e)–(h)] illustrate the 50% dilution case: 25% of the textels on each side of the TP are randomly swapped. Illustrations are not to actual scale, and textel density is larger than in the experiments.

3. LOCAL–GLOBAL TRADE-OFF AND ITS BEARING ON EQUIVALENT NOISE AND ON RELEVANT TEXTURE STATISTICS

A. Within-Domain Local–Global Trade-Off

It can easily be shown[23] that the global contrast, C_G, of a TP edge is given by

$$C_G = C_L d|1 - P|, \tag{1}$$

where C_L is the local contrast or local orientation difference, d is the textel spatial density, and P is the dilution factor.[24] The relation in which we are interested is

$$C_{G\_\theta} = f(C_L), \tag{2}$$

where C_{G_θ} is the global contrast at threshold. The equivalence of Eqs. (1) and (2) would mean that C_{G_θ} does not depend on C_L, so any increase of the latter would be compensated by a corresponding increase of the dilution. The implication of such a proportionality would be that the critical parameter determining the segregation threshold is the arithmetic mean contrast over the textures to be discriminated. An obvious alternative is that the threshold behavior is governed by the signal-to-noise (S/N) ratio rather than by the signal alone.

Following standard conventions,[16] we pose that noise power, N^2 in the stimulus is well approximated by its squared rms contrast:

$$N^2 = (\mathrm{rms})^2 = C_L{}^2\mathrm{d}. \tag{3}$$

Given the spatial homogeneity of the relevant feature yielding the TP edge in the present experiments (see Fig. 1), the rms contrast is independent of the area over which it is computed. The overall noise power in the system is given by the sum of the external noise power and of the equivalent noise power of the system, $N_{\mathrm{Eq}}{}^2$, which is unknown. The S/N ratio at threshold (weighted by a sensitivity parameter) is then fixed, and it is given by

$$K = \frac{C_{G\_\theta}}{(C_L{}^2 d + N_{\mathrm{Eq}}{}^2)^{1/2}}. \tag{4}$$

Since C_L is known, K and N_{Eq} can be estimated based on measurements of C_{G_θ}. This is what we did when local and global contrasts were defined in the luminance, color, and orientation domains.

Equation (4) has been extensively used to account for human detection performances in noise,[15–18,25] but to our knowledge it was never applied in the context of texture segregation. Note that in this context Eq. (4) can be viewed in three different ways: (i) It provides the relationship between local and global contrasts at the detection threshold; (ii) it describes the system's behavior in terms of basically one single parameter (if sensitivity is ignored), namely, its equivalent noise; (iii) it poses the issue that the relevant statistics accounting for this behavior are nothing but the mean texture contrast, C_G, normalized by the standard deviation (σ) within the relevant stimulus dimension, $(C_L{}^2 d + N_{\mathrm{Eq}}{}^2)^{1/2}$; this ratio is nothing but d' up to a scale factor.[26] If Eq. (4) were to provide a good fit to the empirical texture segregation data, one may say that this type of performance had been characterized in three equivalent ways, each of which illustrates a different approach to the problem.

B. Transdomain Local–Global Trade-Off

In the TP's illustrated in Fig. 1, textels across the TP edge differ along one single dimension; C_G, C_L, and N_{Eq} in Eq. (4) are all given in contrast units within that dimension (e.g., luminance contrast or color contrast). However, one may be interested in the dependence of the TP contrast threshold, say, an orientation contrast, on the local contrast within a different domain such as luminance or color. The general question then becomes, Is averaging within one domain dependent on the local contrast in a different domain? Phrased differently, the question bears on the transdomain local–global relationship or, equivalently, on whether signal processing within one visual domain is to be related to the noise within a different domain. For such a transdomain trade-off, Eq. (4) becomes

$$K = \frac{C_{L1}|1 - P|d}{(C_{L2}{}^2 d + N_{\mathrm{Eq2}}{}^2)^{1/2}}, \tag{5}$$

where C_{L1} and C_{L2} stand for the local contrasts in dimensions 1 and 2 (say, orientation and luminance) characterizing the textels and N_{Eq2} is the equivalent noise in dimension 2. Note that C_{L1} is the contrast yielding the TP edge, whereas C_{L2} is, in principle, irrelevant for this task. If the two dimensions are orthogonal, C_{G1} (i.e., $C_{L1}d|1 - P|d$) should not depend on C_{L2}. For Eq. (5) to yield such a constant C_G, N_{Eq2} should be much larger than C_{L2} so that the manipulation of the latter will not modify K (i.e., the S/N ratio at threshold). However, N_{Eq} is assumed to characterize a given processing domain once and for all, independently of the experimental format. Thus, for Eq. (5) to be an accurate description of the transdomain local–global trade-off, N_{Eq2} should be the parameter inferred from Eq. (4) for the within-domain conditions.

4. METHODS

A. Stimuli

The stimuli were displayed on a Sony GDM-17E11 red–green–blue monitor 1280 pixels wide and 1024 pixels high under the control of a Silicon Graphics Indy workstation. The screen subtended 21.8 × 17.1 deg at a distance of 76 cm in all the experiments. All the experiments were run in a dimly illuminated room.

B. Main Experiments

The stimuli consisted of textels 5.4 arc min (5 pixels) wide and 35.4 arc min (33 pixels) long presented on a yellow background (*x, y* chromatic coordinates averaged across observers: 0.413, 0.451; see Appendix A) of 27 cd/m^2. Intertextel distance (computed from their centers) was 46.2 arc min on average. Textel density (computed as the area that the textels occupy relative to the total inspection area) was 10.07% (i.e., approximately 400 textels for each texture in the TP). Luminance-defined textels were equichromatic to the background and yielded a variable luminance contrast. Chromatic-defined textels were equiluminant to the background and yielded a variable chromatic contrast along the $L-M$ (long–medium) axis. At full chromatic contrast their chromatic coordinates were 0.554, 0.357 for red and 0.277, 0.542 for green. Textels were arranged so as to yield global luminance (or color) contrasts with orientation randomized over the TP or global orientation contrasts with luminance (or color) randomized over the TP (see Fig. 1).[27] Along each of these dimensions textels were binarized (i.e., dark–bright, red–green, $\pm X°$). These binary values were used as a parameter for all the experimental conditions, with the exception of the two transdomain conditions, where the orientation of the textels was fixed at +45° and −45° (i.e., the local orientation difference was 90°). For the luminance- and color-defined TP edges, and for the orientation-defined edges in the two transdomain conditions, the orientation of the TP edges was randomly vertical or horizontal; the edges were randomly jagged within a spatial range of 2 textels, with their mean position also randomized about the center of the screen within a range of 2 textels. This randomization (4 textels overall, i.e., 1.54° overall) was meant to minimize the chances of observers' inferring the orientation of the edge (which they were asked to report) by means of systematic eye movements. To this same end, they were repeatedly reminded to maintain fixation on a central, conspicuous cross. For the conditions in which local orientation difference was traded for the global orientation difference, the vertical/horizontal forced choice was not applicable, since the local textel orientation covaries with the orientation of the texture edge. Hence the orientation-defined edges in the within-domain conditions were always vertical and were randomly presented 3.2 deg to the left or to the right of the fixation point. This eccentricity was chosen based on preliminary experiments to yield the highest discrimination performance (i.e., beyond the 79% convergence point of the psychophysical staircase) for the smallest local angle differences with the chromatic stimuli. Observers were asked to report on the position of the (left-hand or right-hand) edge.[30] In all the cases presentation time was 66.7 or 333.3 ms, with no mask.

C. Preliminary (Calibration) Experiments

If performances obtained with color- and luminance-defined stimuli are to be compared, one needs to make sure that (1) the hues defining the texture elements (red and green) are equiluminant, and that (2) they yield equal chromatic contrasts relative to the background so that they are equally salient (i.e., the hue of the equiluminant background must be unique yellow). In addition, it is useful to know (3) the equivalent luminance contrast for at least the highest red–green chromatic contrast available on the monitor. The specific stimulus formats and psychophysical procedures used to assess these points are extensively described in Gorea *et al.*[31] [for (1) above] and in Papathomas *et al.*[32] [for (2) and (3) above]. They are summarized in Appendix A. Equiluminance and unique-yellow values were assessed for each observer. Equivalent contrast assessments were made for three observers, only two of which served in the present experiments. Typically, these values are quite consistent across observers.[33] Suffice here to note that the equivalent luminance contrast of the maximum chromatic modulation was close to 40% for all three tested observers.

D. Observers

The results of responses from two naïve undergraduate students and from the second author were run in all the experimental conditions, with the exception of those in which local orientation was traded for global orientation. For the latter only two of those conditions were used. The three observers had normal color vision as assessed with Ishihara plates. They had normal or corrected-to-normal acuity.

E. Procedure

All the main experiments were run with a two-alternative forced-choice (2AFC) staircase procedure. The pair of binary values (i.e., local contrast) of a TP was fixed, and the staircase was monitoring the P value, i.e., the dilution parameter (normalized so as to range between 0 and 1; see above).

Within-domain and transdomain local–global contrast trade-off was assessed with the following six experimental formats: (i), (ii) The dilution threshold, P_θ, for luminance- and color-defined TP edges was measured as a function of the local luminance contrast and the local color contrast, respectively; textels were +45° and −45°, with the two orientations being randomly distributed over the two textures in the TP; (iii), (iv) P_θ for orientation-defined TP edges was measured as a function of the local orientation difference between textels. Luminance-defined textels (dark and bright) were set at 32% contrast. Color-defined textels (red and green) were set at the equivalent luminance contrast (i.e., 85% of the total available modulation along the red–green axis). Luminance or color polarities were randomized over the two textures in the TP. Formats (i)–(iv) are of the within-domain type. (v), (vi) P_θ for orientation-defined TP edges with both luminance- and color-defined textels was measured as a function of the local luminance contrast and the local color contrast. In this case textel orientations were fixed at +45° and −45° as in (i) and (ii). Formats (v) and (vi) are of the transdomain type. Each of the six experimental formats was run with 66.7 and 333.3 ms presentation times so that overall there were 12 experimental conditions, each of which was repeated at least three times for each observer. The order was randomized across observers.

Observers reported on the orientation (vertical or horizontal) of the luminance- or color-defined edges [conditions (i) and (ii)] and of the orientation-defined edges in the transdomain conditions [(v) and (vi)]. For the orientation-defined edges in the within-domain conditions [(iii) and (iv)], observers reported on the position (left or right) of the TP edges. Dilution was decreased with a 0.02 step after every wrong response, and it was increased by the same amount after three correct responses in a row. This rule yields an average of 79% correct. One session was completed after 20 reversals, and the P_θ value was computed as the average of the last 12 reversals.

5. RESULTS

While the dependent variable was the dilution percentage, $|1 - P|$, the data are presented as $C_G = C_L|1 - P|[d]$, i.e., as the space-averaged TP edge contrast (global contrast). Displaying the data in this format is meant to facilitate the direct interpretation of the results: C_G independence of local luminance contrast, color contrast, or orientation contrast (C_L) would yield a zero-slope function of C_L. The density parameter d is shown between brackets because its status is uncertain in the computation of the orientation C_G (see Section 7). The fits of the data shown below for the global versus local orientation experiment [see Eqs. (4) and (7)] were obtained with $d = 1$ (different d values would yield different estimates of both K and N_{Eq} parameters; see Subsection 6.B).

For the experiments with color-defined textels, chromatic contrasts are given in equivalent luminance contrast (EqLC) units. With the maximum chromatic modulation available [i.e., from full red (0.554, 0.357 chromatic coordinates) to full green (0.277, 0.542 chromatic coordinates) along the L–M axis] being referred to as 1, any measured chromatic contrast in this range was scaled by 0.4, the measured EqLC for a raw chromatic contrast of 1.

A. Within-Domain Local–Global Trade-Off

Figure 2 displays C_G luminance contrast (open symbols) and chromatic contrast (filled symbols) thresholds for 66.7 [Fig. 2(a)] and 333.3 ms [Fig. 2(b)] presentations. Different symbols are for different observers. Smooth curves are best fits of the average data (not shown) with Eq. (4) (dashed and solid curves are for the luminance and the chromatic conditions, respectively). Local contrast (abscissas) for the chromatic condition is expressed in EqLC units. Vertical arrows show the estimated equivalent noise contrasts for the two conditions (see Section 6).

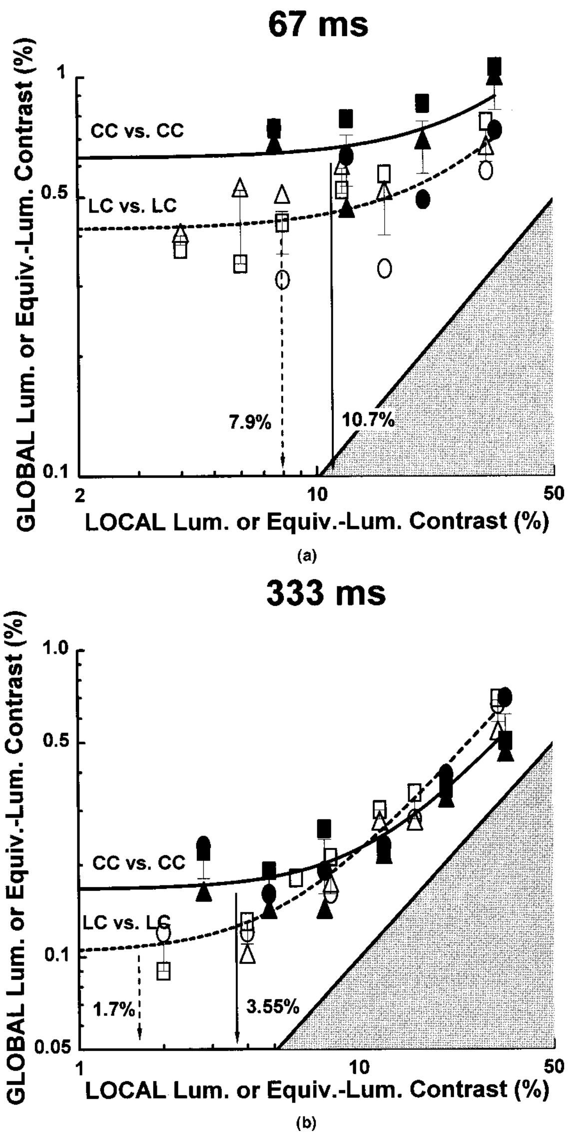

Fig. 2. Global luminance contrast (open symbols) and global chromatic contrast (filled symbols) thresholds as a function of local contrast for (a) 66.7-ms and (b) 333.3-ms presentations. Local contrast for the chromatic condition is expressed in equivalent luminance contrast units. Different symbols are for different observers. Smooth curves are best fits with Eq. (4) of the average data (not shown); dashed and solid curves are for the luminance and chromatic conditions, respectively. Vertical thin bars are ± 1 SE of the mean data. Vertical arrows show the estimated equivalent noise contrasts for the luminance-defined (dashed) and color-defined (solid) textures. The oblique line limiting the gray areas in each plot represents the upper 95% confidence interval of the binomial distribution for a 100% dilution (see text).

The oblique line limiting the gray areas in each plot represents the upper 95% confidence interval of the binomial distribution for the dilution parameter $P = 1$ (i.e., 100% dilution; proportion of swapped textels, $p = 0.5$). Any measured p threshold, p_θ, smaller than $0.5 + z_{[0.975]}0.5/20 = 0.549$ (i.e., $P - 1 = 0.098$), would show up within the shaded area and could not be set apart from purely statistical sampling errors of the binomial distribution around $p = 0.5$.[34]

The most obvious observation that can be made from Fig. 2 is that global contrast thresholds increase with local contrast for both luminance and chromatic stimuli and for the two presentation times. This amounts to saying that the space-averaged contrast is not the critical value determining TP segregation. Instead, the good theoretical fits of the data support the notion that the critical quantity determining threshold behavior is the S/N ratio as defined in Eq. (4). The absence of data points within the shaded areas indicates that the increase in C_G with C_L (i.e., the flattening of the measured P_θ with C_L) cannot be attributed to statistical noise.

A closer look at the data of Fig. 2 reveals a visible trend of the color–color data (especially those shown as circles and triangles) to deviate from the monotonic relationship between C_{G_θ} and C_L imposed by Eq. (4). While this deviation might be accidental, it may also be a consequence of the nonlinear processing of contrast (see Section 7).

For the luminance–luminance trade-off Eq. (4) yields N_{Eq} fits of 7.9 and 1.7% for 66.7 and 333.3 ms, respectively. For the color–color trade-off the respective N_{Eq} values are 10.7% and 3.55%. Short presentation times thus yield equivalent noises that are a factor of 4.64 and 3.01 larger than long presentation times for the luminance and color domains, respectively. The equivalent noise, however, should not depend on presentation time. The observed duration dependency can be accounted for if one considers that N_{Eq} in Eq. (4) is not equivalent noise but rather equivalent noise energy. As such, these parameter fits should be weighted by the presentation time for which they were obtained. Equation (4) does not include a time parameter. If the increase from 66.7- to 333.3-ms presentations were to yield full integration (that is, be within the regime of Bloch's law), then the N_{Eq} estimates for a duration of 333.3 ms should be scaled (with respect to a 66.7-ms presentation) by a factor of 5. The estimated equivalent noise energies then become $7.9 \times 66.7 = 526.9$, and $1.7 \times 333.3 = 566.6$, for the luminance domain; and $10.7 \times 66.7 = 713.7$, and $3.55 \times 333.3 = 1183.2$, for the chromatic domain. The estimated energy values are moderately close across durations (given that they are obtained from independent sets of data) for the luminance but not for the chromatic domain. One possible implication of this difference is that temporal integration is shorter in the latter than in the former. In all events, Bloch's law does not hold perfectly[35] within the temporal range used here, so adjustments of the ratios between the nominal durations used should be made. This procedure is described in detail in Section 6.

As inferred here, the equivalent noises are, in average, a factor of 1.72 ($10.7/7.9 = 1.35$ at 67 ms, and $3.55/1.7 = 2.09$ at 333 ms) larger in the chromatic than in the luminance domain. When amended so as to account for the relative temporal integration efficiency at the two durations (see Section 6), the equivalent noise energy ratio between the two domains is 1.8. Thus the present data indicate that contrast processing operates at a substantially higher internal noise level for chromatic than for luminance-defined stimuli.

For 66.7-ms presentations C_G is asymptotic to approximately 0.42% and 0.62% for luminance and chromatic conditions, respectively. For 333 ms this asymptotic value decreases by a factor of approximately 4 for the luminance condition (i.e., 0.11%) and by a factor of approximately 3.8 for the chromatic condition (i.e., 0.17%). This decrease is attributable to the imperfect temporal integration in this temporal range (full integration should have yielded a fivefold threshold decrease). Thus, when the input noise is significantly below the equivalent noise, the estimated TP segregation thresholds are close to the optimum of the standard contrast transfer function for luminance- and color-defined stimuli.[36]

Figure 3 displays global orientation thresholds as a function of the local orientation differences for 66.7-ms [Fig. 3(a), left] and 333.3-ms [Fig. 3(a), right] presentations. Open and filled symbols are for luminance- and color-defined textels, respectively. The data show no obvious difference between the global orientation thresholds in the two domains. Presentation of the data for the two durations in the same plot [Fig. 3(b)] demonstrates that stimulus duration (and therefore contrast energy) is of little consequence as well (see Section 6).

One formulation of the question that this experiment was supposed to answer concerned the rule used by the visual system to average orientation over space at the segregation threshold. The data appear to tell the same story as for the luminance–luminance and the color–color experiments: Space-averaged orientation is not the determining quantity at threshold. Instead, a constant S/N ratio model as defined in Eq. (4) [or Eqs. (7); see below] nicely fits the data [averaged over the two observers; see dashed and solid curves in Fig. 3(a) for luminance and color, respectively]. Fits of the data obtained with Eq. (4) at 67 ms and with the density parameter arbitrarily set at 1 yield equivalent noises in the orientation domain of 13.9° and 10.5° (ratio of 1.32), for the luminance- and the color-defined textures, respectively. At 333 ms the respective values are 12.8° and 10.45° (ratio of 1.22). These estimated values do depend on the density parameter but not on their ratios. As an example, equivalent noises estimated with $d = 0.1$ are 4.4° and 3.3° (ratio of 1.33) at 67 ms and are 4.05° and 3.3° (ratio of 1.22) at 333 ms. Thus, once the luminance-defined and color-defined stimuli are equated for visibility (in EqLC units), orientation discrimination is processed at a higher (by an average factor of 1.27) equivalent orientation noise in the luminance than in the chromatic domain. When Eq. (4) is used to fit the data averaged over the two durations and the two domains (again with $d = 1$), it yields an overall equivalent noise of 11.9° [Fig. 3(b)]. Note that the authors of previous studies that have modeled global orientation discrimination performances have implicitly used a density parameter of 1 independently of the actual density of the stimuli.[12,14,37]

In contrast with the luminance–luminance and the color–color trade-off data (Fig. 2), the orientation–orientation trade-off appears to have little, if any, dependence on presentation time. As is discussed in Section 6, this behavior implies that, at the contrast used here, the information required for an orientation discrimination task is already fully integrated by 66.7 ms.

Orientation discrimination thresholds obtained with isolated long lines or gratings at full luminance contrast and long presentation times are typically between 0.5° and 2°.[38–42] For 100 ms and difference-of-Gaussian-like luminance-defined textels, Dakin and Watt[14] obtained global orientation thresholds between 1.2° and 2.5°. The lowest global orientation thresholds obtained in the present experiments are ~8° and ~6.5° for the luminance- and color-defined textures, respectively. The Dakin–Watt difference-of-Gaussian values had a σ of 3.48 arc min and were clipped at $\pm 3\sigma$ from their centers, yielding a total extent of 21 arc min. In the present experiments textels were 35.4×5.4 arc min rectangles (aspect ratio, 6.56). The difference between their thresholds and the present ones may be partly due to the fact that, whereas they used very-narrow-band textels, ours were broadband. However, in view of the present results, the most likely source for this difference is the zero variance of the local orientation distributions used by Dakin and Watt.[14] Indeed, the present experiments yield up to approximately 50° global orientation thresholds for the largest variance (i.e., 90° local orientation differences).

B. Transdomain Local–Global Trade-Off

In these experimental conditions, the orientation of the textels was fixed at ±45°, and the TP edge was defined as a global orientation difference dependent on their dilution. Figure 4 displays global orientation thresholds as a function of either local luminance contrast (open symbols) or local chromatic contrast (in EqLC units; filled symbols) for 66.7 ms [Fig. 4(a)] and 333.3 ms [Fig. 4(b)] presentations. Different symbols are for different observers. With the exception of the luminance-defined TP at the shortest duration, the global orientation discrimination thresholds decrease with local luminance contrast and color contrast up to some critical value and stabilize thereafter. Fitting the descending segment of the data with a straight line of slope −1 and getting its intersection point with a horizontal line fitted to the flat range of the data yields critical luminance and chromatic contrasts of ~7% and ~18%, respectively, for the 66.7-ms presentation. For 333 ms, global orientation thresholds are independent of the local luminance contrast at least beyond 2% contrast but do decrease with chromatic contrast up to ~6%. Thus, to reach optimal performance, color-defined orientation discrimination appears to require approximately three times more contrast than the luminance-defined orientation discrimination. However, this optimal level is roughly the same in the two domains, namely, approximately 40°.

The decrease of the orientation C_{G_θ} with local luminance contrast or chromatic contrast up to some critical, rather low-contrast, value has repeatedly been documented[40,42] and should be expected on pure detectability grounds. When integrated over time, this critical value presumably represents the contrast energy beyond which orientation tuning is optimal. The present data suggest that this critical energy is roughly three times larger in the chromatic than in the luminance domain. Note that, for the chromatic condition, an increase in the presentation time by a factor of 5 yields a decrease of the critical color contrast by a factor of approximately 3. This observation is in good accord with the one made for the within-domain experiment and confirms the fact that temporal integration is less than perfect in this temporal range.

Inspection of the data yields two additional observations. First, Eq. (5) cannot deal with the decrease in the orientation C_{G_θ} (i.e., $C_{L1}|1 - P|d$) when local luminance

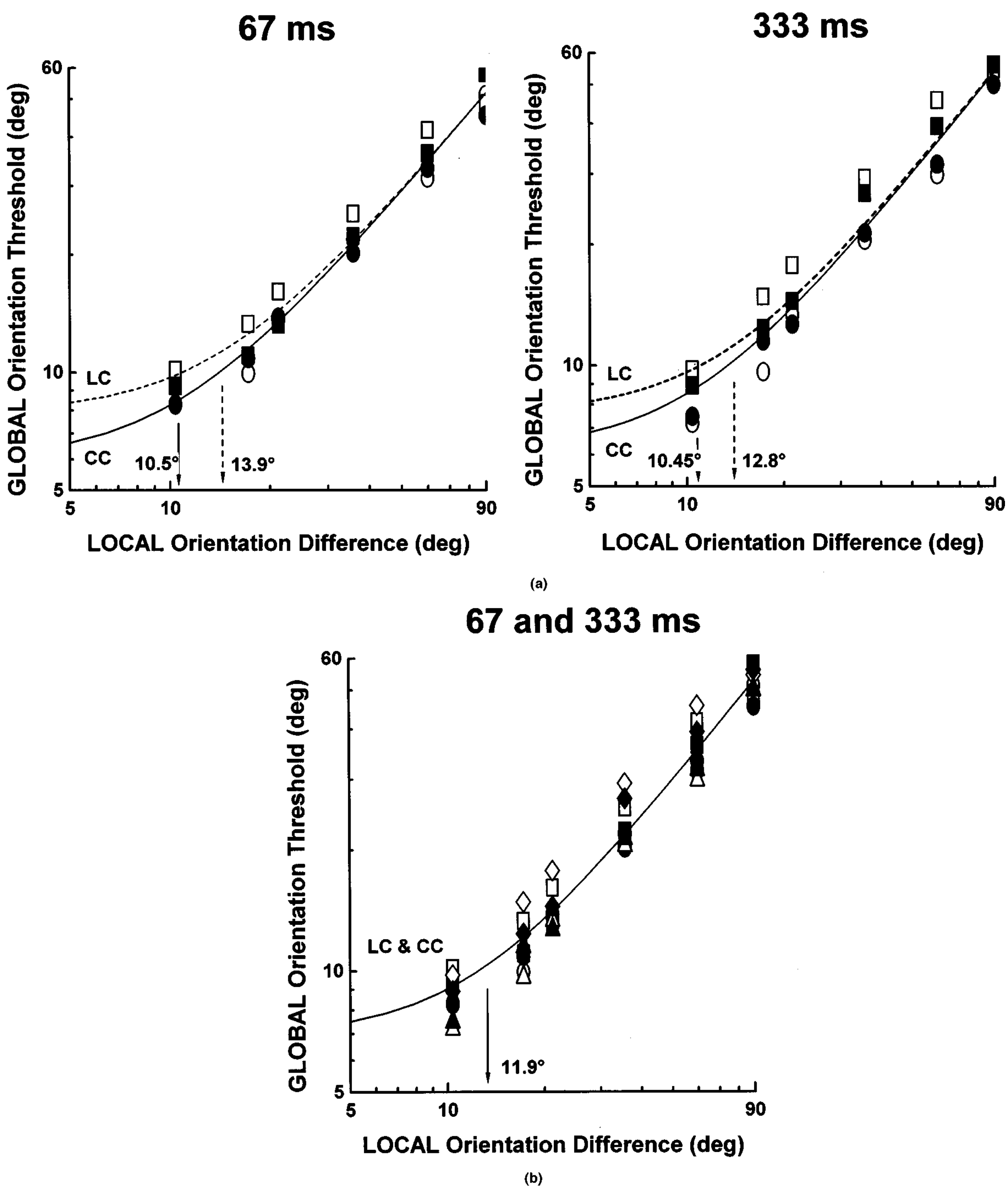

Fig. 3. Global orientation thresholds as a function of the local orientation differences for [(a), left] 66.7-ms and [(b), right] 333.3-ms presentations. In (b) the data obtained for the two durations are presented together. Open and filled symbols are for luminance- and color-defined textels, respectively. In (a) the circles and squares are for the two observers, TEC and TVP, respectively. In (b) the circles and triangles are for observer TEC under 66.7- and 333-ms presentations; squares and diamonds are for observer TVP for the same durations. Smooth curves are best fits with Eq. (4) of the average data (not shown); dashed and solid curves are for the luminance and chromatic conditions, respectively. In (a) the vertical arrows show the estimated equivalent noise contrasts for the luminance-defined (dashed) and color-defined (solid) textures. In (b) the solid arrow shows the equivalent orientation noise estimated from the average of all the data. The upper 95% confidence interval of the binomial distribution for a 100% dilution (see text) are out of the range of the plot.

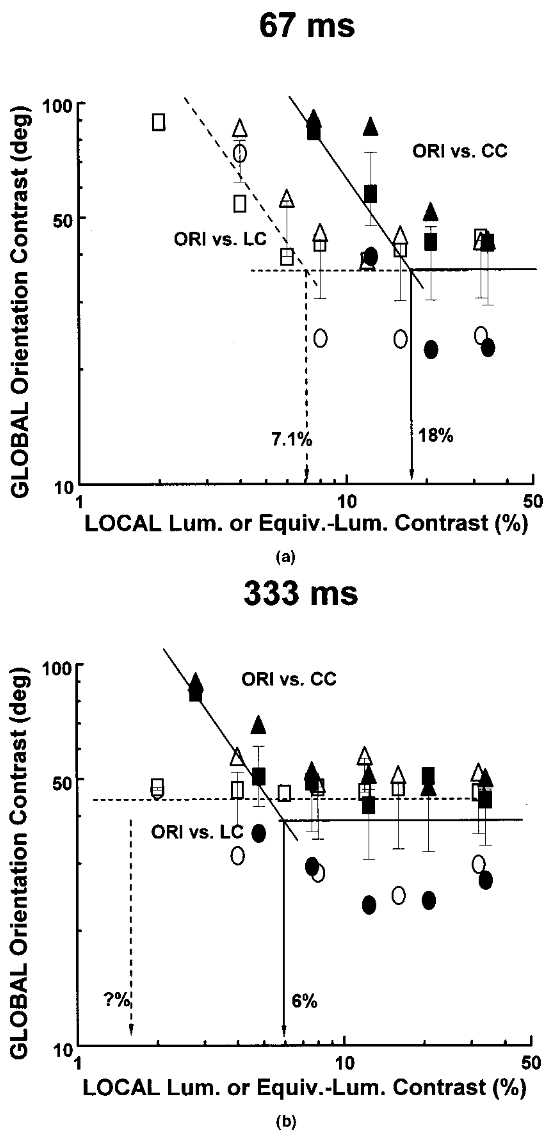

Fig. 4. Global orientation thresholds as a function of either local luminance contrast (open symbols) or local chromatic contrast (in EqLC units; filled symbols) for (a) 66.7-ms and (b) 333.3-ms presentations. Different symbols are for different observers. Straight dashed lines (for the luminance condition) and straight solid lines (for the chromatic condition) are best fits to the descending (slope, -1) and the flat (slope, 0) ranges of the data. Vertical arrows show the intersection points of these lines. There is no descending range for the luminance-defined textures under the 333-ms presentation, so this intersection point is not defined in (b).

contrast or color contrast (C_{L2}) increases. This global threshold decrease requires that K, the S/N ratio, not be constant at threshold, contrary to the basic assumption of the model. Second, under this same assumption, the flat C_G function of C_{L2} beyond some critical value requires a very large (in fact infinite) N_{Eq} in the luminance and chromatic domains. The estimated N_{Eq} in these domains are, however, below 12%. In conclusion, Eq. (5) is not an accurate description of the transdomain data. The straightforward implication of this observation is that global orientation discrimination is independent of the noise in the domains in which orientation is defined, that is, in the luminance and chromatic domains.

6. MODEL FITTING

As noted by Pelli,[16] all the studies that modeled contrast processing by means of Eq. (4) or by similar equivalent noise approaches (see Section 1) have used a single presentation time, say, T_S. Equation (4) can be used to estimate the equivalent noise, $N_{\mathrm{Eq}1}$, from data obtained with a fixed value of $T_S = T_{S1}$. However, when it is used to get a new estimate $N_{\mathrm{Eq}2}$ from another set of data, obtained with $T_S = T_{S2}$, it is not clear how $N_{\mathrm{Eq}1}$ and $N_{\mathrm{Eq}2}$ should be compared in relation to T_{S1} and T_{S2}.

To expand such models so as to include the role of time, one simple approach is to consider how the relative lengths of the stimulus duration, T_S, and a putative decision time interval, T_D,[35] affect performance.[43] A reasonable approach is to replace contrast C with its time-integrated energy, which can be approximated by the product CT, where T is the interval over which C is present. This approximation is valid within the regime of Bloch's law, where sensitivity is indeed determined by the integration of contrast over time. Since the stimulus as well as any externally applied noise are present for a duration of T_S, whereas the equivalent noise is present throughout the decision interval T_D, Eq. (4) can be modified by replacement of C_L, C_{G_θ}, and N_{Eq} with $T_S C_L$, $T_S C_{G\_\theta}$, and $T_D N_{\mathrm{Eq}}$, respectively. This results in Eq. (6):

$$K = \frac{T_S C_{G\_\theta}}{(T_S{}^2 C_L{}^2 d + T_D{}^2 N_{\mathrm{Eq}}{}^2)^{1/2}}. \tag{6}$$

Equation (6) is valid as long as $T_S \leqslant T_D$. When $T_S > T_D$, T_S must be replaced by T_D, since the decision operator acts on a time window of T_D. Note that Eq. (6) reduces to Eq. (4) for $T_S = T_D$. Overall, for any value of T_S, the S/N ratio K is given by Eqs. (7):

$$K = \frac{T_S C_{G\_\theta}}{(T_S{}^2 C_L{}^2 d + T_D{}^2 N_{\mathrm{Eq}}{}^2)^{1/2}} \qquad \text{for } T_S \leqslant T_D, \tag{7a}$$

$$K = \frac{C_{G\_\theta}}{(C_L{}^2 d + N_{\mathrm{Eq}}{}^2)^{1/2}} \qquad \text{for } T_S > T_D. \tag{7b}$$

The product of time and contrast in Eq. 7(a) implies a full temporal integration regime. However, this is not a mandatory condition, provided that T_D and T_S are scaled with respect to each other in proportion to their relative integration efficiencies as given by Bloch's law. The decision time, T_D, and the equivalent noise, N_{Eq}, are considered fixed, unknown parameters, and the present experiments were not designed to assess their values separately. Nevertheless, the experimental results can be used to estimate their product, which is the (fixed) equivalent noise energy $E_{\mathrm{Eq}} = T_D \times N_{\mathrm{Eq}}$ (within the regime of Bloch's law). It is this product, rather than N_{Eq} *per se*, that is expected to stay constant within a given processing domain. Since the model can estimate only E_{Eq}, the value of N_{Eq} can be known only up to a factor of T_D.

Consider two values of stimulus duration, $T_{S1} = 100$ ms and $T_{S2} = 500$ ms, and assume that T_D is 500 ms. The effective ratio T_{S1}/T_{S2} is not 1:5, since within

Table 1. Estimated Parameters of Eqs. (7) for the Best Fit of the Global versus Local Trade-Off in Luminance and Color[a]

	Global versus Local Luminance Contrast → Physical Duration (ms)			Global versus Local Chromatic Contrast → Physical Duration (ms)		
	66.7	333.3		66.7	333.3	
Parameter	Step 1	Step 3a	Step 3b	Step 1	Step 3a	Step 3b
K	Fit: $\mathbf{K_1 = 0.053}$	Fixed: 0.053	Fit: **0.061**	Fit: $\mathbf{K_1 = 0.059}$	Fixed: 0.059	Fit: **0.047**
E_{Eq}	Fit: $\mathbf{E_{Eq1} = 526.7}$	Fixed: 526.7	Fixed: 526.7	Fit: $\mathbf{E_{Eq1} = 713.7}$	Fixed: 713.7	Fixed: 713.7
T_S	Fixed: 66.7 ms	Fit: **333/1.54** =**216** ms	Fit: **333/1.07** =**311** ms	Fixed: 66.7 ms	Fit: **333/1.05** =**316.8** ms	Fit: **333/1.65** =**201.4** ms
	←			←		
	Step 4a	Step 4b	Step 2	Step 4a	Step 4b	Step 2
K	Fixed: 0.061	Fit: **0.053**	Fit: $\mathbf{K_2 = 0.061}$	Fixed: 0.047	Fit: **0.059**	Fit: **0.047**
E_{Eq}	Fixed: 563.0	Fixed: 563.0	Fit: $\mathbf{E_{Eq1} = 563.0}$	Fixed: 1182.2	Fixed: 1182.2	Fit: **1183.2**
T_S	Fit: $\mathbf{66.7 \times 1.31}$ =**87.3** ms	Fit: $\mathbf{66.7 \times 1.07}$ =**71.4** ms	Fixed: 333.3 ms	Fit: $\mathbf{66.7 \times 1.26}$ =**84.2** ms	Fit: $\mathbf{66.7 \times 1.66}$ =**110.7** ms	Fixed: 333.3 ms

[a] Arrows indicate the order in which the procedure for fitting T_S progressed. Fitted parameters are shown in boldface font (see text for more details).

this temporal range a fivefold increase in presentation time yields only a twofold (or less) sensitivity increase.[35] Using Eq. (4) to assess N_{Eq} with 100- and 500-ms stimuli should yield values in a ratio of 2:1 (or less). However, if Eqs. (7) are used with $T_{S2} = T_D$ for the 500-ms condition and with the effective duration $T_{S1,\mathrm{eff}} = T_D/2$ (or less) for the 100-ms condition, the two sets of data should yield identical E_{Eq} values. This logic is strictly true under the reasonable assumption that T_D is a constant.[35] If T_D were to covary with T_S, the estimated equivalent noise energy should increase proportionally with stimulus duration. The estimates given in Table 1 and discussed below do not follow this trend; instead, Eqs. (7) yield E_{Eq} values that are almost equal for the 333.3- and 66.7-ms presentations. We take this as strong evidence that T_D is indeed a constant. Moreover, temporal integration experiments with high-pass spatial stimuli indicate performance improvement up to at least 500 ms.[35] We may thus be confident in assuming that T_D is larger than the longest duration used here. E_{Eq} can therefore be estimated from the data obtained with both 66.7- and 333-ms stimuli.

A. Model Fits to the Luminance–Luminance and Color–Color Trade-Off Data

Model fits were obtained with MICROCAL ORIGIN 4.1 software for the data averaged over observers. Below we describe, step by step, our fitting procedure for incorporating the role of stimulus presentation time in the model, using the data of Fig. 2. These steps are described with reference to the data obtained for luminance–luminance trade-off conditions. The same steps were repeated for the chromatic–chromatic and the orientation–orientation trade-off conditions. The results for the luminance–luminance and the color–color trade-off data are summarized in Table 1; those for the orientation–orientation trade-off data are given in Table 2.

1. Set $T_S = T_{S1} = 66.7\,\mathrm{ms}$, and estimate K and E_{Eq} by fitting Eq. 7(a) to the data obtained with 66.7 ms; this equivalent noise energy is denoted by E_{Eq1}. The equivalent noise model asserts that this is the quantity that stays fixed across temporal presentations. Its value was estimated to be $E_{\mathrm{Eq1}} = 526.7$, and K was estimated to be $K_1 = 0.053$.

2. Having obtained a value for E_{Eq}, we now turn to the data with $T_S = T_{S2} = 333\,\mathrm{ms}$. The model's prediction is that the values of K and E_{Eq} should be the same as in step 1 above. One obtains these values by fitting Eq. 7(a) to the data obtained with 333 ms. The resulting values are $E_{\mathrm{Eq2}} = 563.0$ and $K_2 = 0.061$, which are quite close to those of step 1, considering the oversimplifying assumptions.

3. To get a better idea of how the temporal integration deviates from the oversimplified treatment described above, we can work backward to estimate the effective time $T_{S2,\mathrm{eff}}$ for the stimulus duration $T_{S2} = 333\,\mathrm{ms}$ relative to T_{S1}. Namely, under the assumption that K and E_{Eq} remain fixed across stimulus durations, we can estimate the value of $T_{S2} = T_{S2,\mathrm{eff}}$ that keeps the value of

E_{Eq} fixed at the level obtained in step 1 above. There are two possibilities toward this end.

3.a. *Constrained-K fit*: Here we set $K = K_1 = 0.053$, as in step 1, and we look for a value of T_{S2} that results in $E_{\mathrm{Eq}} = E_{\mathrm{Eq1}} = 526.7$ when Eq. 7(a) is fitted to the data obtained with 333 ms. The resulting value is $T_{S2,\mathrm{eff}} = 216$ ms; thus the effective time is smaller than the actual stimulus time of 333 ms by a factor of 1.54, indicating less than full temporal integration between 66.7 and 333 ms.

3.b. *Unconstrained fit*: Here we try to find a value of T_{S2} that results in $E_{\mathrm{Eq}} = E_{\mathrm{Eq1}} = 526.7$ when Eq. 7(a) is fitted to the data obtained with 333 ms, without constraints on the value of K. This results in $T_{S2,\mathrm{eff}} = 311$, which is smaller than the actual stimulus time of 333 ms by a factor of 1.07. The corresponding value of K was $K_{3.\mathrm{b}} = 0.061$.

4. Step 3 can be repeated to estimate the effective time $T_{S21,\mathrm{eff}}$ relative to T_{S2}.

4.a. *Constrained-K fit*: Here we set $K = K_1 = 0.061$, as in step 2, and we look for a value of T_{S1} that results in $E_{\mathrm{Eq}} = E_{\mathrm{Eq2}} = 563.0$ when Eq. 7(a) is fitted to the data obtained with 66.7 ms. This results in $T_{S1,\mathrm{eff}} = 87.3$ ms; thus the effective time is larger than the actual stimulus time of 66.7 ms by a factor of 1.31.

4.b. *Unconstrained fit*: When the value of K is unconstrained, the effective value $T_{S1,\mathrm{eff}}$ that yields $E_{\mathrm{Eq}} = E_{\mathrm{Eq2}} = 563.0$ when Eq. 7(a) is fitted to the data obtained with 66.7 ms is 71.4 ms, which is larger than the actual stimulus time by a factor of 1.07. The corresponding value of K was $K_{4.\mathrm{b}} = 0.053$.

When the constraint of a constant E_{Eq} across stimulus duration is relaxed, the estimated values of E_{Eq} for the luminance–luminance and the color–color trade-off data are reasonably close (given that they are obtained from independent sets of data) but are definitely unequal. When this constraint is maintained and T_S and T_D are appropriately scaled, the average equivalent noise energy in the luminance domain is 539.0 (with a standard error of ±42.3). The equivalent calculations for the chromatic domain yield an average equivalent noise energy of 970.3 ± 91.0. Thus the present experiments yield an equivalent noise energy that is 939.3/539.0 = 1.8 times larger in the chromatic than in the luminance domain.

To conclude, the above discussion points to the fact that the fit of the equivalent noise energy (but not of N_{Eq}) is independent of both the decision time, T_D, and the stimulus duration, T_S, as long as T_S and T_D are related with respect to their relative temporal integration efficiency.

B. Model Fits to the Orientation–Orientation Trade-Off Data

The main observation for this set of data (Fig. 3) is that the global orientation thresholds as a function of orientation noise are quite close across domains (luminance and color) and are practically independent of the temporal presentation. Obviously, the N_{Eq} parameters estimated by means of Eq. (4) are also very similar. However, according to the above logic, the use of Eq. (4) implies that T_D covaries with T_S, and, as a consequence, it should have yielded, under the assumption of a constant E_{Eq}, smaller N_{Eq} values for the longer durations. By compari-

Table 2. Estimated Parameters of Eq. (6) for the Best Fit of the Local versus Global Trade-Off in Orientation[a]

	Luminance-Defined Orientation $\longrightarrow$			Chromatically Defined Orientation $\longrightarrow$		
	Physical Duration (ms)			Physical Duration (ms)		
	66.7	333.3		66.7	333.3	
Parameter	Step 1	Step 3a	Step 3b	Step 1	Step 3a	Step 3b
K	Fit: **K_1 = 0.57**	Fixed: 0.57	Fit: **0.59**	Fit: **K_1 = 0.57**	Fixed: 0.57	Fit: **0.59**
E_{Eq}	Fit: **E_{Eq1} = 927.1**	Fixed: 927.1	Fixed: 927.1	Fit: **E_{Eq1} = 700.3**	Fixed: 700.3	Fixed: 700.3
T_S	Fixed: 66.7 ms	Fit: **333/5.36** =**62.0** ms	Fit: **333/4.58** =**72.7** ms	Fixed: 66.7 ms	Fit: **333/5.88** =**56.7** ms	Fit: **333/5.0** =**66.7** ms

	$\longleftarrow$			$\longleftarrow$		
	Step 4a	Step 4b	Step 2	Step 4a	Step 4b	Step 2
K	Fixed: 0.59	Fit: **0.57**	Fit: **K_2 = 0.57**	Fixed: 0.59	Fit: **0.57**	Fit: **0.59**
E_{Eq}	Fixed: 4266.2	Fixed: 4266.2	Fit: **E_{Eq1} = 4266.2**	Fixed: 3483.0	Fixed: 3483.0	Fit: **3483.0**
T_S	Fit: **66.7 × 4.54** =**303** ms	Fit: **66.7 × 5.43** =**362.3** ms	Fixed: 333.3 ms	Fit: **66.7 × 4.06** =**271.0** ms	Fit: **66.7 × 5** =**333.3** ms	Fixed: 333.3 ms

[a] Arrows indicate the order in which the procedure for fitting T_S progressed. Fitted parameters are shown in boldface font (see text for more details).

son, the luminance and color trade-off data support the notion of a fixed T_D. To account for this apparent paradox, one must conclude that the constancy of the orientation N_{Eq} across the two stimulus durations reflects the fact that temporal integration in the orientation domain is already completed by 66.7 ms, provided that the local elements of the TP are beyond their detection threshold. In this context, the decision time, T_D, may take any value equal to or larger than 66.7 ms (or less). Phrased differently, one could say that orientation N_{Eq} is constant for any presentation duration that, for a given contrast, yields performances above the detection threshold. According to Regan,[44] this critical energy (i.e., contrast multiplied by time) should in fact be 8–14 times the detection threshold. Table 2 displays the results of the fitting procedure for the orientation–orientation trade-off data with Eqs. (7) according to steps 1–4 described above. The average equivalent noise energy for the luminance- and color-defined textures are 2596.9 and 1965.7, respectively (for $d = 1$; they scale down by a factor of 3.17 for $d = 0.1$). Thus the equivalent orientation noise energy is $2596.9/1965.7 = 1.32$ times larger in the luminance than in the chromatic domain.

7. DISCUSSION

The present study contributes to the texture segregation literature in the following ways:

(i) It presents a new technique for the study of texture segregation by means of relating local and global information in this type of task.

(ii) It points out the equivalence among three apparently distinct ways of characterizing texture segregation performance, namely, in terms of (a) the above-mentioned local–global relationship, (b) the equivalent noise energy limitations of the visual system, and (c) the relevant statistics used in this kind of task. Concerning (c), texture segregation performance appears to depend on the ratio between the mean (in this case, the global contrast at threshold, C_{G_θ}) and the variance (the sum of external and internal noise) yielded by the features (or properties) along which the textures differ. This constant ratio is none other than d' (weighted by a sensitivity coefficient).

(iii) It provides a characterization of texture processing within the luminance, chromatic, and orientation domains in terms of the equivalent noise energies specific to these domains. The fit of the experimental data with Eqs. (7) yields an equivalent noise energy approximately 1.8 times larger in the chromatic than in the luminance domain. As for the orientation domain, the same fitting procedure yields an orientation equivalent noise energy roughly 1.3 times larger for the luminance-defined textures than for the chromatic-defined textures. With a density parameter equal to unity and assuming an effective temporal integration of 67 ms (or less), the estimated orientation equivalent noise is ~14° and ~10.5° for the luminance- and chromatic-defined textures, respectively. These values are scaled down by a factor of 3.2 if the density parameter is set to 0.1.

The nature and significance of the density parameter in global orientation processing remains unclear. According to Nothdurft[45] and Sagi and Julesz,[46] density is a relevant factor in feature discrimination insofar as it yields (orientation) gradient detection. The Sagi–Julesz data suggest that orientation-gradient extraction occurs when the lines to be discriminated fall within a spatial region not larger than twice their length. Within this range performance increases with density (scaled relative to the line length) up to a plateau, but out of this range it decreases with density. Thus performance follows a nonmonotonic function of density. For their 1° × 6 arc min lines, Sagi and Julesz obtain a minimum performance at a density (computed as it was in the present study; see Section 4) of approximately 0.5–0.75% [*sic*] and a plateau at densities above 2–2.5%. Assuming (as suggested by these authors and as shown by Nothdurft[45]) that these critical values are inversely proportional to the line length (rather than to the aspect ratio), they should be increased in the present case (line length of 35.4 arc min) by a factor of 1.7; minimum sensitivity and plateau performance should then be attained for densities of 0.85–1.275% and 3.4–4.25%, respectively. Accordingly, the 10% density used in the present study is well within the steady-state range for orientation-gradient extraction.

(iv) The present study demonstrates that global orientation thresholds are independent of both local luminance and local chromatic contrast insofar as the available local energy is beyond the detection threshold (transdomain experiments). More generally, the present experiments establish that, insofar as the noise in the luminance or color domain does not modify the orientational spectrum of the stimulus, it does not affect orientation-based texture segregation above the detection threshold. This independence is to be expected, based on both psychophysical[40,42,44] and electrophysiological[47–49] findings. According to Regan,[44] it is in fact achieved for stimuli 8–14 times beyond their detection threshold. Under the present experimental conditions the data indicate that, to reach optimal performance, color-defined orientation discrimination requires approximately three times more energy than the luminance-defined orientation discrimination. This difference should be scaled with respect to the detection thresholds in the two domains (not measured here). The optimal performance level, however, is roughly the same in the two domains, namely, approximately 40°.

(v) Finally, the present study extends the standard equivalent noise modeling of contrast detection to incorporate the presentation time factor and shows that the empirical data comply with the concepts of a constant equivalent noise energy and of a constant decision time over stimulus duration.

It should be borne in mind that any of the three approaches referred to in point (ii) above makes implicit use of the existence of a single processing channel (within the relevant stimulus domain[17,18,22]) for both the local and the global characteristics of the stimuli. As such, it does not bear on the issue of the temporal order (if any) in which local and global stimulus characteristics are processed.[5–8] Obviously, this one-channel model is an oversimplification of the visual processing of contrast (and orientation), but, at least in the present experimental context, it provides reasonable fits to the texture segmentation performances, as well as a straightforward (and hence intuitive) characterization of the processing modes in terms of their limiting internal or equivalent noise.

The orientation–orientation trade-off data (Fig. 3) lie close to a straight line. Linear fits of the data yield slopes (in linear coordinates) of approximately 0.52–0.60, with intercepts at the origin at 2.1–3.8°. Since data could not be collected for local orientation differences smaller than 10°, the possibility exists that global orientation thresholds keep on decreasing with a decrease in local orientation up to the detection threshold of the latter. Given the additive equivalent noise model used here, the implication of this behavior would be that the internal noise in the orientation domain is close to zero. Under this assumption, Eqs. (4) and (7) should yield a straight line that passes through the origin, a characteristic not supported by the data (the intercepts of the linear fits are well beyond zero). It may therefore be that a nonlinear response incorporated in these equations would allow better fits. However, the linear, additive noise model appears to provide reasonable fits to the ensemble of the present data as well as to other noise masking data.[15,16,18]

Related approaches making use of both nonlinear contrast processing[50–52] and multiplicative noise[25,26,52] appear to be necessary to account for some attentional and learning effects on contrast detection in noise. In the present context, the consideration of the contrast transducer should, at least in principle, account for the nonmonotonic behavior (the dipper) observed on some occasions (four of the twelve conditions tested; see Fig. 2). The transducer is an accelerated function until the detection threshold is reached and is progressively decelerated thereafter.[50–54] Assuming a reference local contrast C_{L0} above its own threshold, its increase to C_{L1} would yield a response increment of $R(C_{L1})/R(C_{L0}) = L < C_{L1}/C_{L0}$. At the detection threshold (that is, in the accelerated range of the transducer), this same C_{L1}/C_{L0} increment would yield a proportionally larger increase in the response to the global contrast $R(C_G)$, so that $R(C_{G1})/R(C_{G0}) = G > C_{L1}/C_{L0}$. To keep C_G constant, the dilution parameter should be increased proportionally to C_{L1}/C_{L0} [see Eq. (1)]. However, to keep $R(C_{G\_\theta})$ constant, dilution should be increased by a factor G, so that $C_{G1\_\theta} < C_{G0\_\theta}$ (hence the dipper). Eventually external noise will start dominating the detection process, so that facilitation will be overtaken by inhibition. Fitting the present data with a model incorporating the contrast transducer would have required a significant increase in the number of free parameters,[50–53] the assessment of which was beyond the scope of the present investigation.

The original objective of this study did not include plans to investigate in detail the role of the temporal factor on N_{Eq}. However, processing the luminance–luminance and the color–color trade-off data by means of the standard analysis [i.e., Eq. (4)] yielded N_{Eq} values strongly dependent on stimulus duration, T_S. This was not the case for the orientation–orientation trade-off. The extension of the model to include the concept of equivalent noise energy, $E_{\mathrm{Eq}} = T_D N_{\mathrm{Eq}}$ (with T_D, the decision time), so as to account for the effects of T_S [see Eqs. (7)] led to the conclusion that a fivefold increase in presentation time (from 66.7 to 333 ms) corresponds to only an approximately 3.9-fold increase in effective temporal integration for both the luminance and the chromatic domains (see Table 1) and to practically no increase at all in the effective integration for orientation (see Table 2). The fact that the estimated integration continues to increase up to at least 333 ms for the first two domains also indicates that decision time is definitely equal to or larger than 333 ms, as previously established.[35] One then must pose the point that decision time is also equal to or larger than 333 ms for the orientation judgments. Given that the estimated equivalent noise energy value for these conditions increases linearly with the nominal T_S, the inescapable conclusion is that orientation-related information under the present stimulation conditions has been integrated to saturation by 66.7 ms (or less).

Finally, the present experiments led us to the conclusion that internal noise is higher by a factor of 1.8 in the chromatic than in the luminance domain insofar as contrast processing is concerned. Also, they demonstrated the opposite tendency for orientation processing: Internal orientation noise is higher by a factor of 1.3 in the luminance domain relative to the chromatic domain. While the latter factor may reflect measurement variability, the 1.8 interdomain ratio observed for contrast processing is large enough to ensure that it reflects a genuine difference between the two domains. We do not know of any psychophysical or electrophysiological study that has focused on this aspect of contrast or orientation processing in the visual system.

APPENDIX A: DETAILS ON THE PRELIMINARY EXPERIMENTS

1. Obtaining Equiluminant Colors

The generic problem is cast as follows. Find the equiluminant setting for color A against a background of color B and luminance L_{B0}. Our approach[31] is to display four frames, each lasting for 33 ms with no interstimulus interval, showing a target that moves in one direction, with background B. Its color changes every other frame from B_+ (an equichromatic patch of color B and luminance $L_{B+} > L_{B0}$) to A (a patch of color A with variable luminance L_A). If observers base their responses on a purely luminance-based first-order motion system, they would always perceive the veridical direction when $L_A > L_{B0}$ and the opposite direction when $L_A < L_{B0}$, owing to reverse ϕ motion. (The inequalities relate to the perceptual comparisons of luminance across colors A and B.) Equiluminance is thus attained when $L_A = L_{B0}$. This approach thus enables one to find the value of L_A (call it L_{A+}) for which the perceived motion direction is ambiguous. This value was obtained by a staircase procedure that incremented or decremented L_A every time the observer saw the reverse-ϕ or the veridical direction, respectively. To account for second-order motion influences, the actual equiluminant settings were estimated as the average of L_{A+} and L_{A-} where the latter was obtained by means of an identical procedure, except that elements B_+ were replaced by B_-, that is, equichromatic patches of color B and luminance $L_{B-} < L_{B0}$. This process was carried out once to yield a red patch (R) equiluminant to a yellow background and was then repeated for a green patch (G).

2. Obtaining a Background of Unique Yellow

The original yellow background was arbitrarily set to consist of a mixture of red and green components, R and G, respectively. The values of R and G were averages of equiluminant R and G settings from observers who participated in an earlier experiment.[32] The mixture of R and G in the original yellow background was then adjusted to yield a unique-yellow background as follows. Observers were shown a stimulus with equiluminant red and green small squares displayed against the equiluminant yellow background along diagonal lines of orthogonal orientations. Presentation duration was 66 ms. Observers indicated which orientation was dominant. This was done by a staircase procedure in which the red component in the yellow mixture (R_Y) was increased [while the green component in the yellow mixture (G_Y) was decreased to keep equiluminance] anytime the observer preferred the orientation of the red pattern; inversely, a preference for the green pattern entailed an increase in the G_Y component (and an equivalent decrease in the R_Y component) in the yellow mixture. The rationale is that, when the red pattern dominates, the background is somewhat greenish, whereas it is reddish when the green pattern dominates. The staircase procedure was terminated after 15 reversals, and the averages of the R_Y and G_Y values over the last 10 reversals were used as the components for the final, unique-yellow background.

3. Obtaining Equivalent Luminance Contrast

The goal here was to find a luminance contrast equivalent to the maximum chromatic contrast of pure red to pure green available on the monitor. The luminance-contrast-defined stimuli were of the type illustrated in the top panels of Fig. 1. The chromatic stimuli were similar, with red and green substituting bright and dim texels, respectively. In the first stage, we determined the dilution level at which performance with the chromatic stimuli was 79% correct (by means of the staircase described in Subsection 4.E). In the second stage the dilution parameter was held fixed at the value obtained in the first stage; the staircase procedure was then run with the luminance contrast as the variable so as to again achieve 79% correct responses. The end result was a luminance contrast that yielded the same performance as the full-range chromatic contrast.

ACKNOWLEDGMENTS

We are very much indebted to Al Ahumada, who suggested that we model the present data in terms of equivalent noise. We thank Tiffany Conway, who patiently ran through the whole set of experimental conditions for all the observers, including herself. Akos Feher contributed to the software and to its numerous modifications while we were searching for the best experimental format. This work was supported by the Direction de la Recherche et de la Technologie (grant 95-1195/A000 to A. Gorea).

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22. This approach appears to characterize the rather complex visual processing stream without loss of generality. Threshold predictions based on this single, generic front-end filter (whose Fourier transform is the contrast transfer function of the visual system as a whole) are quite comparable with those yielded by more realistic models involving the parallel processing of the input image through a bank of front-end filters tuned to different spatial frequencies and orientations.[17,18]
23. Assume that there are 2 textels of luminance $L_0 + \Delta L$ and $L_0 - \Delta L$, with L_0 being the luminance of the background. Their contrast relative both to L_0 and to each other is $c = \Delta L / L_0$. The overall luminance in a TP is $L_{T1} = pd(L_0 + \Delta L) + (1 - p)d(L_0 - \Delta L) + (1 - d)L_0 = d\Delta L(2p - 1) + L_0$ for one texture and $L_{T2} = pd(L_0$

$-\ \Delta L) + (1-p)d(L_0 + \Delta L) + (1-d)L_0 = -d\,\Delta L(2p-1) + L_0$ for the other texture. The global TP contrast is given by $(L_{T1} - L_{T2})/(L_{T1} + L_{T2}) = c(P-1)d$, with $P = 2p$, so that 50% swapped textels ($p = 0.5$) yields 0% global contrast. As noted in the text, the status of the density parameter, d, is not clear when one is averaging second-order features such as orientation; mean orientation contrast could well be a nonmonotonic function of density.

24. In experiments in which presentation time, T, is a parameter (as was the case here), local contrast should be replaced by local energy, which can be approximated by $C_L T$ insofar as T is smaller than the temporal integration constant (see Section 6).
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27. In the terminology of Gorea and Papathomas,[28,29] these TP's are of the type luminance (or color) across orientation ($\mathrm{L} \times \mathrm{O}$ or $\mathrm{C} \times \mathrm{O}$) and orientation across luminance (or color) ($\mathrm{O} \times \mathrm{L}$ or $\mathrm{O} \times \mathrm{C}$). More generally, $\mathrm{A} \times \mathrm{B}$ TP's are those whose edges are defined by two (or more) values of attribute A with two (or more) values of the remaining attribute, B, randomized over the whole TP.
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30. Once the extraction of the TP edge is achieved, specifying edge orientation (vertical or horizontal) or edge location (±3.2-deg location discrimination) is a trivial task in the sense that these tasks do not limit texture segregation: They both yield 100% performance, provided that the edge itself is 100% visible; thus performances below 100% in any of the two tasks reflect only edge extraction limitations. Moreover, in the remainder of this paper the only comparative discussion between the luminance/color and the orientation data shall bear on the generality of the generic equivalent noise model and not on the details of the fits. The equivalent noises estimated for the luminance/color domains, on the one hand, and for the orientation domain, on the other, are not commensurable and therefore are not to be related even when estimated by means of identical procedures.
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34. The distribution of the two-valued attributes (luminance, color, or orientation) in the textures used here is binomial. The upper confidence limit of the binomial distribution with respect to p is given by $p + z\sqrt{pq/N}$, where $q = 1 - p$; N is the number of events considered (in this particular case, the number of textels); and z, the standard score in the normal distribution, with the upper $\alpha/2$ proportion of cases cut off. For $p = 0.5$, $N = 400$, and $\alpha = 0.05$, this expression yields a p' value of 0.549. When converted into $P' - 1 = 2p' - 1$ (see Ref. 23), it becomes 0.098. The linear function delimiting the shaded area is given by $0.098C_L d$, which is the limit below which the measured global contrast at threshold cannot be distinguished from random variations of the binomial distribution around $p = 0.5$.
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43. Obviously, the process responsible for the decision as to whether a signal is present receives inputs from both the external signal and noise and the internal noise.[16] Simulating it with an integrator that acts on a window of fixed duration is only a first approximation toward incorporating the effect of time into the model. It is assumed that the decision stage acts on the probabilistic sum of the outputs of several temporal integrators, each characterized by a critical integration time, τ.[35] For obvious reasons, T_D must be larger than the average integration time τ.
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