

Conditions for perceptual transparency

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Abstract. We review the conditions that are necessary for the perception of transparency, and describe the spatiochromatic constraints for achromatic and chromatic transparent displays. These constraints can be represented by the generalized convergence model and are supported by psychophysical data. We present an alternative representation of the constraints necessary for transparency perception, which is based on an analogy with a model of color constancy and the invariance of cone-excitation ratios. We show that the invariant-ratios model is a special case of the generalized convergence model. We argue that the spatial relations in an image are preserved when a Mondrian-like surface is partially covered by a transparent filter, and therefore show an intriguing link between transparency perception and color constancy. Finally, we describe experiments to relate the strength of the transparency percept with the number of unique patches in the image display. We find that the greater the number of surfaces in the display that are partially covered by a transparent filter, the stronger the impression of transparency. © 2004 SPIE and IS&T. [DOI: 10.1117/1.1636764]

1 Introduction

In this study, we conduct two psychophysical experiments to investigate whether invariant cone-excitation ratios predict the perception of transparency. In one experiment, we quantitatively compare the strength of the transparency percept for stimuli defined by the invariant cone-excitation-ratio condition, the invariant ratio model,¹ with stimuli defined by the convergence model.² In a second experiment, stimuli were presented that simulated Mondrian-like surfaces partially covered by a transparent filter, and the effect of the number of partially covered surfaces in the display was measured in terms of the strength of the transparency percept.

Perceptual transparency is the phenomenon of seeing one surface behind another. For example, in Fig. 1, four opaque areas give rise to the perception of two opaque surfaces (large rectangles) seen behind a transparent filter (small rectangles). Many authors^{3,4} have stated that the filtered region is the area where we can simultaneously perceive both the filter and the opaque surface behind the filter. However, recovering the color of two surfaces from one set of strictly local cone excitations would seem to be intrac-

table. Furthermore, if an opaque surface is partially covered by a filter whose color is complementary (for example, a red surface and a green filter), the filtered patch will appear very dark and the red and green surfaces do not seem to be simultaneously observed.⁵

The first quantitative model of the photometric constraints for transparency perception was Metelli's *episcotister* model.^{4,6} The *episcotister* is a wheel with open sectors rotating in front of two opaque surfaces. During its rotation, the *episcotister* produces fusion colors between its sector color and the background color. According to Metelli, to perceive transparency, two photometric constraints must be preserved. Specifically, the PQ region (see Fig. 1) will be perceived to be transparent when: the difference $|(a-b)|$ is greater than the difference $|(p-q)|$, thus, $|(a-b)| > |(p-q)|$; and the direction of contrast is the same, thus, if $|(a > b)|$ then $|(p > q)|$; where a , b , p , and q are the reflectances of the areas A , B , P , and Q , respectively.

Photometric conditions, and more generally chromatic conditions (where we use the term chromatic quite generally to imply constraints on the color of stimuli) are necessary but not sufficient for perceiving transparency. Metelli⁴ proposed three main figural conditions that are also necessary for transparency perception: figural unity of the transparent region, continuity of the boundary line, and adequate stratification. Some recent studies have proposed further additional constraints for the perception of transparency. It has been conjectured that the presence of X junctions formed at the intersection of the opaque and transparent areas is a necessary element in the image.⁷⁻⁹ To have an X junction, a minimum of four areas is needed. However, other studies have shown that even with only three areas, perceptual transparency can occur,¹⁰ and they have questioned the role of X junctions.¹¹

The *episcotister*-based approach has been adopted more or less in its original formulation by most of the researchers investigating perceptual transparency, but some minor changes have been suggested. For example, Gerbino *et al.*¹² proposed that the computations carried out by the visual system when perceiving transparency might be in terms of luminance values rather than reflectance⁶ or lightness values.¹³ The perception of colored stimuli was studied to

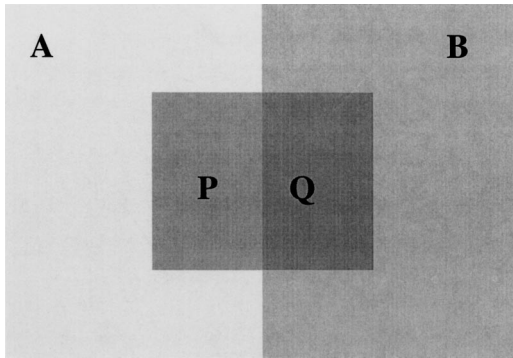


Fig. 1 Four opaque areas give rise to the perception of two opaque surfaces covered by a homogeneous transparent filter. A and B are opaque surfaces and P and Q are the corresponding filtered areas.

generalize Metelli's results with achromatic additive color mixture to the three dimensions of color space.^{5,13} Faul investigated the conditions under which transparency perception held, and demonstrated that both luminance and chromatic constraints were necessary.¹³ Although luminance relationships may be necessary for the perception of transparency in achromatic images, they are not sufficient when the objects in the image do not have the same chromaticities. In fact, it has been shown that the perception of transparency holds even when opaque and filtered surfaces have identical luminance and differ only in their chromaticities.^{2,14} Whereas Faul treated luminance and chromatic constraints separately in his models,¹³ D'Zmura *et al.* considered the overall effect of luminance and chromatic constraints, and suggested that some tristimulus representation of the colors of the filtered surfaces must converge to a point in color space. They show evidence that observers are able to adjust the color of a filtered surface to make the central region appear transparent. For example, if the tristimulus values of two opaque surfaces A and B are represented by the 3×1 matrices \mathbf{x}_A and \mathbf{x}_B , respectively, the adjusted colors would lie on lines passing through \mathbf{x}_A and \mathbf{g} , and \mathbf{x}_B and \mathbf{g} , respectively, where \mathbf{g} is a 3×1 matrix that defines the tristimulus values of the convergence point.

The generalized convergence model can be expressed by the following equations:

$$\mathbf{x}_P = (1 - \alpha)\mathbf{x}_A + \alpha\mathbf{g}, \quad (1)$$

$$\mathbf{x}_Q = (1 - \alpha)\mathbf{x}_B + \alpha\mathbf{g}, \quad (2)$$

where α is a 3×3 diagonal matrix (a diagonal matrix is one with only main diagonal entries that are nonzero) that defines the amount by which the surface colors \mathbf{x}_A and \mathbf{x}_B are shifted toward the convergence point \mathbf{g} .

A special case of the generalized convergence model, named by D'Zmura *et al.*² the convergence model, has been described where the three diagonal entries of the matrix α have identical values. The performance of the convergence model has been compared with other models—including models based on cone scaling, such as von Kries—and has been quantitatively demonstrated to fit the color shifts that correspond to transparency better than the other models.¹⁵ More recently, it has also been shown that

the convergence model can also account for the color changes that take place when surfaces are viewed through a fog.¹⁶

The convergence model defines chromatic conditions under which transparency perception can occur. Our approach was inspired by a simple computational model of color constancy, based on the invariance of cone-excitation ratios.¹⁷ Perception of transparency poses the general question of how the visual system can correctly recognize the color of a surface when its color has been altered in some way by, for example, covering a surface by a transparent filter. An analogous problem has been investigated in color constancy: when the color signal of a surface is altered by illuminating it with a different light source, its color appearance remains approximately constant. (We note, however, that the constraints on the color signals introduced are different than in the case of transparency.)

In the case of a change in the illumination, it has been found that, within each cone class, cone-excitation ratios between surfaces seen under one illuminant and cone-excitation ratios for the same surfaces seen under another illuminant are almost invariant, and this may be a cue for color constancy.¹⁷ In the case of transparency perception, we make the same predictions, since certain changes to the illuminant are approximately equivalent to passing the illuminant through a transparent filter.¹

The phenomenon of invariance of cone-excitation ratios states that the ratio of the cone excitations between two opaque surfaces and the ratio between the same surfaces covered by a filter is almost statistically invariant within each cone class.¹⁸ The invariant-ratios model for a simple image, such as that in Fig. 1 can be expressed by the equations:

$$\mathbf{x}_P = \beta\mathbf{x}_A, \quad (3)$$

$$\mathbf{x}_Q = \beta\mathbf{x}_B, \quad (4)$$

where \mathbf{x}_P , \mathbf{x}_Q , \mathbf{x}_A , and \mathbf{x}_B are the cone excitations for the areas P, Q, A, and B, and β is a 3×3 diagonal matrix, where the entries on the main diagonal represent the ratios of the cone excitations for each of the three classes of cones. Equations (3) and (4) define the chromatic conditions that must be met for Fig. 1 to appear transparent. For many conditions, the predictions made by the invariant-ratios model and the convergence model are very similar.¹⁹

This is not surprising, since the two models are both special cases of the generalized convergence model. For the generalized convergence model [Eqs. (1) and (2)], the relationship between the opaque and transparent areas is defined by a scaling (the linear transform denoted by the diagonal matrix) and a translation. The special condition for the convergence model is that the scaling is identical for each of the three color dimensions, whereas the invariant-ratios model retains separate scaling for each of the three cone channels, but does not include a translation. The study of the invariant-ratios model is therefore of interest for two reasons: first, a comparison with the convergence model may indicate whether, for the generalized convergence model, the perception of transparency depends more on the translation component or the independence of the scaling for each of the channels; second, the close relationship be-

tween the invariant-ratios model and Foster's work on color constancy¹⁷ may reveal an intriguing link between the perception of transparency and color constancy.

It is important to note, however, that the hypothesis that perceptual transparency can be predicted by the invariance of cone-excitation ratios does not rely on such ratios being invariant for all physically transparent systems. Indeed, it relies on such ratios not being invariant for all physically transparent systems, since not all physically transparent systems are perceptually transparent. For example, consider the case where an opaque surface is overlapped by a filter whose color is complementary to the opaque surface's one. In a previous study,¹⁸ a Monte Carlo simulation was conducted to show that, although the cone-excitation ratios were close to being invariant for some physically transparent systems, the invariance was poor for filters with narrow-band spectral transmission properties. A further example is given by the case in which an opaque surface is completely overlapped by a transparent filter with identical spatial dimensions. In this case, it is almost impossible to perceive two different surfaces, one of which being an opaque surface covered by a transparent surface.⁴ The key issue that needs to be addressed is whether the degree of invariance of the cone-excitation ratios for psychophysical stimuli can predict the strength of the transparency percept when those stimuli are viewed.

2 Experiment 1: Comparison of Convergence and Invariant-Ratios Models

2.1 Aims

The purpose of the experiment was to ascertain whether the invariant model or the convergence model best predicts the strength of the transparency percept. In the first experiment, we simulated two sets of stimuli according to whether they were generated using the invariant-ratios model or the convergence model. The two sets of stimuli had the same opaque areas but different filtered regions (the filtered regions are here defined as the regions where the simulated transparent filter was overlapping the opaque surfaces). The *invariant* stimuli consisted of Mondrian-like patterns, whose filtered areas had colors produced by a transparent filter defined by the invariant-ratios model, whereas the *convergent* stimuli consisted of Mondrian-like patterns whose filtered areas had colors produced by the convergence model. The pairs of stimuli were presented side by side to observers who were asked to respond which of the two stimuli contained the strongest impression of a transparent filter. The invariant-ratios model predicts that in each trial, the presentation containing the most-invariant cone-excitation ratios would be considered to be the presentation containing the most transparent filter.

2.2 Methods

2.2.1 Observers

Six naïve observers participated in the experiment, all of whom had normal or corrected-to-normal visual acuity and had been assessed as color normal on the Farnsworth-Munsell 100-hue test. None of them was aware of the nature or purpose of the experiment.

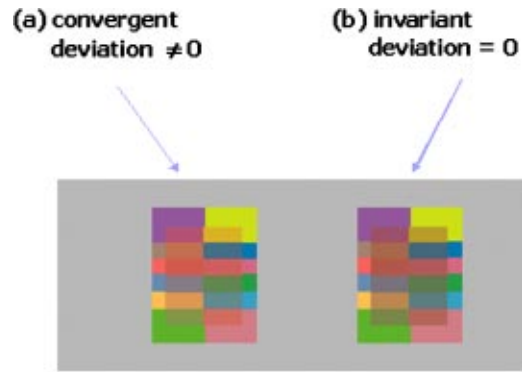


Fig. 2 Schematic representation of the stimulus patterns used in Experiment 1. Each experimental trial was composed of two Mondrian-like patterns (*convergent* stimulus, *invariant* stimulus) presented simultaneously. The position (right-hand side or left-hand side) of each stimulus was randomized.

2.2.2 Apparatus

A Sony Trinitron GMD500 color monitor driven by a VSG2/3 video card of a personal computer was used for presenting the stimulus patterns. The resolution was 1152×864 pixels and the frame rate was 120 Hz. The monitor had been characterized²⁰ using a Minolta spectroradiometer and was gamma corrected.²¹

2.2.3 Stimuli

Stimuli contained Mondrian-like patterns (4.52×3.58 deg of visual angle) composed of 12 surfaces displayed in a 12×6 arrangement and partially covered by simulated transparent filters (3.38×0.95 deg). Spectral reflectances of the opaque surfaces were selected from 1269 samples²² of the *Munsell Book of Color* (1976).

The filters were generated using the convergence model. We used Eq. (1) to simulate each single-filtered region with the constraint of α being constant within each filter simulation. The *convergent* stimuli were compared with *invariant* stimuli where the Mondrian-like patterns were partially covered by a simulated transparent filter, whose cone-excitation ratios were systematically made invariant. For each *convergent* stimulus, a corresponding *invariant* stimulus was generated, where the colors of the filtered areas were modified to make the cone-excitation ratios perfectly invariant. The first step in generating the *invariant* stimulus was the computation of the cone-excitation ratios generated by the *convergent* stimulus for CIE illuminant D65 for each opaque-transparent pair (ratio between \mathbf{x}_p and \mathbf{x}_A , for example). The cone sensitivity functions were computed using Smith and Pokorny's cone sensitivity functions.²³ The second step was the manipulation of those ratios to give rise to cone-excitation ratios that were perfectly invariant. Given the ratios between \mathbf{x}_p and \mathbf{x}_A and the ratio between \mathbf{x}_Q and \mathbf{x}_B , we manipulated \mathbf{x}_Q such that $\mathbf{x}_p/\mathbf{x}_A$ was equal to $\mathbf{x}_Q/\mathbf{x}_B$. This manipulation was performed on a patch-by-patch basis rather than on a pixel-by-pixel basis.

We generated *convergent* stimuli that varied according to the value α of the diagonal entry for the scaling matrix (which could be 0.1, 0.3, 0.5, 0.7, or 0.9), and the translation term \mathbf{g} (which could be one of five randomly selected terms). Figure 2 shows a schematic representation of the

stimulus patterns.

In each trial, the two stimulus patterns (the one covered by the convergent filter and the one covered by the invariant filter) were presented simultaneously side by side (Fig. 2). The invariant filter could randomly appear either on the left- or right-hand side. In a 2-alternative-forced-choice (2AFC) paradigm, observers were asked which of the two stimulus patterns simulated a uniform transparent filter over opaque surfaces. Each presentation lasted two seconds on screen. The next trial was presented two seconds after the observer indicated their response with a button press. Each trial was repeated three times for a total of 150 trials [3 (repetition) \times 2 (left or right position of the invariant filter) \times 5 (α) \times 5 (g)].

2.3 Results

For each trial, we calculated the degree of deviation from invariance in spatial cone-excitation ratios for all the possible pairs of surfaces seen directly and under the filter displayed in each stimulus. The degree of deviation was equal to:

$$\text{deviation}_i = 1 - r_i, \quad \text{if } r_i \leq 1, \quad (5)$$

$$\text{deviation}_i = 1 - 1/r_i, \quad \text{if } r_i > 1,$$

where r_i is the ratio of cone-excitation ratios, defined as

$$r_i = (e_{i,1}/e_{i,2}) / (e'_{i,1}/e'_{i,2}), \quad (6)$$

where the cone excitation is given by $e_{i,j}$ for cone class i (where $i \in \{L, M, S\}$ denoting long-, medium-, and short-wavelength-sensitive cone classes), for a surface j seen directly, and the prime superscript denotes the excitations for the surface viewed through a filter.

Note that for the *invariant* stimuli, the deviations were always equal to zero, whereas for the convergence filters, the deviations varied between 0 and 0.2 (sometimes the convergence model generated stimuli whose ratios were already invariant or close to being invariant, and in these cases the deviations for the two classes of stimuli were very similar; other times the deviations for the convergence model were quite large, and the two classes of stimuli were quite different). Observers' abilities to discriminate between the *convergent* stimulus and the *invariant* stimulus were tested by measuring the discriminability index *d prime* (d') of signal detection theory. For the purposes of our analyses, a correct response was deemed to be the *invariant* stimulus, and an incorrect response was deemed to be the *convergence* stimulus.

Figure 3 shows means of d' values plotted against deviations computed for the *convergent* stimulus. Each point represents a trial (averaged by the number of repetitions) in which observers saw a convergent stimulus (whose deviations are indicated by the value on the x axis) and an invariant stimulus (whose deviations were almost 0). Our hypothesis is that when the *convergent* stimulus deviations are far from 0, observers prefer the *invariant* stimulus. Whereas when the *convergence* stimulus deviations are close to 0, observers' preferences are chance. In Fig. 3, positive values of d' indicate a preference for the invariant

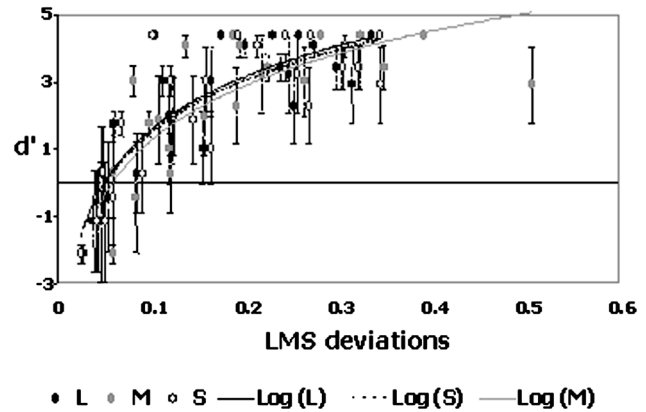


Fig. 3 Mean values of d' for Experiment 1 have been plotted versus the degree of deviation from invariance in spatial cone-excitation ratios for all the possible pairs of surfaces seen directly and under the filter. Black circles represent deviations for the long-wavelength-sensitive cone class, gray circles represent deviations for the medium-wavelength-sensitive cone class, and white circles represent deviations for the short-wavelength-sensitive cone class. Bold, gray, and dashed curves represent logarithmic curve fit for deviations for long-, medium-, and short-wavelength-sensitive cone classes, respectively. $d' < 0$ indicates observers' preferences for convergent filter; $d' = 0$ no preference; $d' > 0$ indicates observers' preferences for the invariant filter.

filter, negative values indicate a preference for the convergent filter, and chance performance is indicated by $d' = 0$.

Observers generally preferred the invariant filter to the convergent filter (positive values of d'). However, we found no significant preference ($d' = 0$) when the convergent filter had deviations close to 0. Negative values of d' represent observers' preference for the convergent filter; however, they were not significantly different from 0 (chance performance).

3 Experiment 2: Effect of Number of Surfaces in the Image

3.1 Aims

In the second experiment, we investigated the effect of varying the number of surfaces that composed the Mondrian-like patterns. With an increased number of surfaces, there is a corresponding increase in the number of pairs of surfaces from which invariant cone-excitation ratios could be recovered. Our hypothesis is that the number of invariant cone-excitation ratios could affect the strength of the psychophysical cues for transparency.

To test this hypothesis, we generated Mondrian-like patterns that differed according to the number of opaque (and subsequently filtered) surfaces. Each of these Mondrian-like patterns was simulated, overlaid by a transparent filter, defined by the invariant-ratios model (for more details about how we generated such a filter, see Ripamonti and Westland.²⁴ We used a discrimination task procedure, whereby observers had to discriminate between a *physical* stimulus and a *comparison* stimulus. The *physical* stimulus consisted of a Mondrian-like pattern composed by N opaque surfaces covered by a physically plausible filter that generated cone-excitation ratios almost invariant. The *comparison* stimulus consisted of a Mondrian-like pattern com-

posed by the same number of N opaque surfaces, but with filtered areas that were manipulated by adding random noise. In a previous study, we showed that when observers are asked to choose which of two presentations (which corresponded to the *physical* stimulus and the *comparison* stimulus) contains a mosaic of opaque surfaces covered by a transparent filter, observers significantly choose the *physical* stimulus.²⁴ In the present experiment, we have used the same two presentations that we used in the previous study, but varied the number of opaque surfaces composing the Mondrian-like pattern. The pairs of stimuli were simultaneously presented to observers who were asked to respond which of the two stimuli contained a homogeneous transparent filter. We expect observers' performances in the discrimination task to depend on the number of surfaces (and thus number of cone-excitation ratios) available in the display. In particular, we expect that observers will be more likely to choose the physical stimulus as the number of surfaces increases. Such a result would also support Da Pos and Izzinosa's findings,²⁵ according to which, image complexity affects perceptual transparency, in particular the greater the image complexity, the stronger the transparency perception.

3.2 Methods

Stimuli contained Mondrian-like patterns (4.52×3.58 deg of visual angle) composed of 2, 4, 6, or 8 opaque surfaces partially covered by physically plausible transparent filters (3.38×0.95 deg). Spectral reflectances of the opaque surfaces were selected from the same set as in Experiment 1. Effective spectral reflectances $R'(\lambda)$ for the filtered surfaces $R(\lambda)$ were computed according to Wysecki and Stiles.²⁶ The formula is illustrated by Eq. (7).

$$R'(\lambda) = R(\lambda)[T(\lambda)(1-r)^2]^2, \quad (7)$$

where r is the internal reflectance of the filter set equal to 0.1, and $T(\lambda)$ is the filter transmittance defined by a Gaussian distribution, such that:

$$T(\lambda) = 0.4 + 0.6 \exp[-(\lambda - \lambda_m)^2 / 2\sigma^2], \quad (8)$$

where λ_m was randomly selected in the range 400 nm $\leq \lambda_m \leq$ 700 nm, and σ was 150 nm.

In Ripamonti and Westland,²⁴ we used filter transmittances that varied according to σ . We found that as σ increases (i.e., as the filter becomes broader), the closer the cone-excitation ratios are to the invariance, and the stronger is the percept of transparency. In the present experiment, we used very broad filter transmittances so that the *invariant* stimuli were perceived as transparent. The cone-excitation ratios of these *physical* stimuli were not exactly invariant, but were close to invariance. These stimuli were compared with noisy *comparison* stimuli, where the colors of each transparent patch were subject to up to 4% noise.

Note that the aim of this experiment was not to test whether observers perceive the *physical* stimuli as transparent, instead it was to test whether the discrimination between the *physical* stimulus and the *comparison* stimulus would be affected by varying the number of surfaces. Our model states that the invariance of cone-excitation ratios is

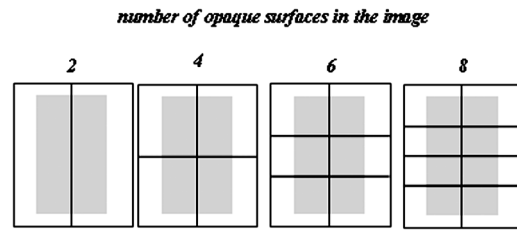


Fig. 4 Schematic representation of stimuli used in Experiment 2. Stimuli varied according to the number of opaque surfaces (2, 4, 6, and 8) present in each image. Lighter areas represent opaque surfaces, darker areas represent transparent filters.

a necessary condition for perceiving transparency, and here we tested whether it is also sufficient for such a percept.

We were also interested to test whether ratios of all cone classes must be invariant, or whether the invariance of only one or two cone classes is sufficient to perceive transparency.

Thus, we generated three different comparison stimuli which could be: 1. a simulation in which cone-excitation ratios for all three cone classes were perturbed, 2. a simulation in which cone-excitation ratios for single-cone classes were perturbed, and 3. simulation in which cone-excitation ratios for pairs of cone classes were perturbed. In each trial, the two stimulus patterns (the one covered by the physically plausible filter and the one covered by the comparison filter) were presented sequentially in random order (Fig. 4). In a 2AFC paradigm, three observers were asked which of the two stimulus patterns simulated a uniform transparent filter over opaque surfaces. Each presentation lasted two seconds on screen. The interstimulus interval lasted one second. The next trial was presented two seconds after the observer indicated their response with a button press. Each trial was repeated three times for a total of 168 trials [3 (repetitions) \times 7 (combinations of cone-classes perturbed) \times 4 (number of surfaces) \times 2 (randomized presentation order)]. The complete session of 168 trials was repeated twice. A training run of 20 trials was given before each session and subsequently discarded. No feedback was provided during the experiment.

4 Results

Performance was quantified by d' , where values of d' equal to zero indicate chance performance (d' greater than zero indicates preference for the physically plausible filter; d' less than zero indicates preference for the comparison). We statistically tested whether d' means differed from 0 by performing independent student t-test analyses of the seven combinations of perturbed cone classes.

We found that d' means significantly differed from 0 for all the combinations of cone classes perturbed, with the exception of when the perturbation was applied only to the S-cone class. Figure 5 illustrates d' means versus the number of surfaces in the Mondrian-like display. It has been suggested that at least two surfaces are required for transparency perception⁴; we note, however, that discrimination performance is relatively poor when only two Mondrian-like surfaces were partially covered by a transparent filter. In this experiment, we did not test whether a stimulus looked transparent or not, but rather whether observers

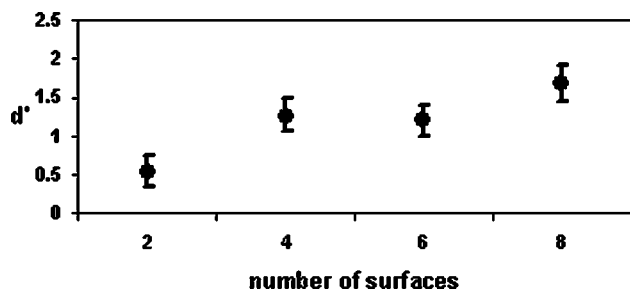


Fig. 5 Means of d' values from Experiment 2. d' values seem to vary according to the number of surfaces in the Mondrian-like display. $d' < 0$ indicates observers' preferences for the comparison filter; $d' = 0$ no preference; $d' > 0$ indicates observers' preferences for the physically plausible filter.

were able to discriminate the strength of the transparency percept of stimuli that were approximately invariant, and those that were noisy. It is evident from the figure that discrimination is reliable for four or more surfaces, and that discrimination performance generally improves with the number of surfaces.

5 Discussion

We have demonstrated that the human visual system is able, under certain constraints, to separate the color properties of the transparent filter from the color properties of the underlying surfaces, and thus recognize surfaces seen through the filter as belonging to those surfaces seen in plain view. However, we do not suggest that the human visual system is able to extract the color of the filter, merely that it is able to discriminate simulations of filtered surfaces where ratios of cone-excitations remain invariant from simulations where the cone-excitation ratios are not invariant. In a previous study,¹⁸ we used a simple model of physical transparency to show that the cone-excitation ratios for pairs of surfaces viewed directly and for the same surfaces viewed through a physically transparent filter were close to being equal in certain conditions (in particular, for filters with broadband transmission properties). Although it is interesting that some physically transparent systems can be shown to have invariant cone-excitation ratios (at least to a first approximation), it is clear that such ratios will not be invariant for all physically transparent systems. This work addresses the question of whether the invariance of cone-excitation ratios for surfaces covered by a transparent filter is a cue for perceptual transparency. Two experiments were carried out, and in each experiment observers were asked to discriminate between two simulations of Mondrian-like patterns partially covered by a transparent filter. Observers were asked to select which of the two stimuli simulated a homogeneous transparent filter.

In Experiment 1, we directly compared the invariant-ratios model with the convergence model, and found that in most cases observers preferred the stimulus defined by the invariance model. However, this is not to say that the stimuli generated by the convergence model did not appear to be transparent. Moreover, many of the convergent stimuli were psychophysically indistinguishable from the invariant stimuli. When the difference between the two stimuli increased, as indicated by the deviation (see Fig. 3)

for the *convergence* stimulus, then observers increasingly preferred the *invariant* stimulus. Since the invariant-ratios model and the convergence model are both special cases of the generalized convergence model, it is not surprising that there may be a wide range of conditions for which the two models perform similarly, but certain conditions where the predictions of the two models would be different. In some studies, the performance of the convergence model has been quantitatively demonstrated to fit the color shifts that correspond to transparency better than a simple cone scaling model.¹⁵ However, we show that the invariance model makes better predictions than the convergence model for the stimuli that we used. Thus, it seems that there are stimuli that are better predicted by the convergence model and other stimuli that are better predicted by the invariance model. The convergence model contains an additive (translation term) component, and might be expected to make good predictions for stimuli with substantial specular reflectance. Stimuli with scattering components, such as turbid media, may also be predicted well by the convergence model (however, such systems would be more accurately described as translucent rather than transparent). Similarly, we might predict that the situations where the invariance model would outperform the convergence model would be those where the ratios of the cone excitations are close to being invariant, but are very different for each of the cone classes.

In Experiment 2, we found that in discrimination experiments between simulations of filters giving small deviations from invariance and filters giving large deviations, performance improved with the number of surfaces in the display. Our hypothesis was that with an increased number of surfaces, there would be a corresponding increase in the number of pairs of surfaces from which invariant cone-excitation ratios could be recovered. For computational models of perceptual transparency that make use of X junctions and T junctions,^{8,27} the number of X junctions also increases with the number of surfaces in the image. It is likely that the number of surfaces is one of several factors that could affect the strength of psychophysical cues for transparency; we might reasonably expect other factors to include the variance²⁸ of the surfaces and their spatial relationships. For real scenes, we would expect many additional factors (such as surface specularity and the degree of spatial uniformity of surfaces) to be involved.^{29,30}

In conclusion, our psychophysical data support the hypothesis that invariant cone-excitation ratios may provide a cue for transparency perception. However, such invariance seems to be a necessary but not sufficient condition for transparency perception. Furthermore, the invariance constraint may not be uniquely represented as invariant cone-excitation ratios; indeed, other models (such as the convergence model²) may provide approximately alternative representations of the same constraint.

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