

# Clouds are not normal occluders, and other oddities: More interactions between textures and lightness illusions

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Identical textured disks can appear white or black depending on the luminance properties of the surrounding textured region (B. L. Anderson & J. Winawer, 2005, 2008). This occurs when the stimulus is perceptually segmented in three layers: (1) a uniform foreground disk, (2) a uniform background surface, and (3) a cloud-like layer that covers parts of the foreground and background regions. However, local occlusion cues fail to predict the pattern of data observed, suggesting that in some cases a different strategy may be adopted depending on texture characteristics (F. J. A. M. Poirier, 2009). Here, we produced a variety of stimuli using three different textures and several luminance configurations (including the White and inverse White configurations and the Anderson–Winawer illusion), for which participants reported the perceived characteristics of the central disk (e.g., lightness, transparency, whether the disk was textured). The results show several interactions between textures and luminance configurations, which we account for using mathematical models of previously documented strategies. We show how the strategies chosen depend on an interaction between texture properties and luminance configuration.

Keywords: lightness model, surface segmentation, contrast enhancement, White effect, texture

Citation: Poirier, F. J. A. M., Gosselin, F., & Arguin, M. (2012). Clouds are not normal occluders, and other oddities: More interactions between textures and lightness illusions. *Journal of Vision*, 12(1):21, 1–22, <http://www.journalofvision.org/content/12/1/21>, doi:10.1167/12.1.21.

## Introduction

The perceived lightness of a surface depends on scene interpretation, which integrates over several cues such as depth relationships, lighting conditions, and transparency (e.g., Adelson, 1993; Fine, MacLeod, & Boynton, 2003; Heinemann, 1955; Horeman, 1963; Kelly & Grossberg, 2000; Kingdom & Moulden, 1988; Li, 2000; White, 1979, 1981). Anderson and Winawer (2005) presented a “dramatic lightness illusion, causing identical texture patches to appear either black or white” (p. 79), which they claimed was much stronger than any other known lightness effect. The illusion was produced by varying the contrast of a cloudy texture such that a central region was at high contrast whereas the surrounding region had a somewhat lower contrast with its luminance shifted either toward lighter or darker values (see Figures 1 and 2 for examples). These stimuli appear to perceptually segregate in three layers: a figure and background each with uniform reflectance, occluded by a cloud-like layer of variable opacity.

Both Albert (2007) and Anderson and Winawer (2005, 2008) believed that local contrast serves as a cue to

determine which stimulus parts are seen in plain view and which parts are occluded, although they propose a slightly different mechanism responsible for the percept. However, Poirier (2009) found an interaction between texture and luminance configuration that casts doubt on both Anderson and Winawer’s and Albert’s interpretations. This interaction is shown in Figure 2, which shows stimuli built using four luminance configurations used by Anderson and Winawer (2005), combined with either a square-wave grating (A–D) or a cloudy texture (E–H). Square-wave gratings emphasize occlusion cues and remove spatial noise and texture complexity. For the square-wave grating at high figure contrast (A–B), we interpret the occluder as white (A) or black (B), thus the circle is seen as black (A) or white (B). This is consistent with percepts at the same luminance configurations for cloudy textures [compare (A)–(B) with (E)–(F)].

In panels with low figure contrast (C–D, G–H), a different pattern emerges. For the square-wave grating, we interpret the occluder as dark gray (C) or light gray (D), thus the circle is seen as light gray (C) or dark gray (D). This is in the opposite direction as percepts at the same luminance configurations for cloudy textures [compare

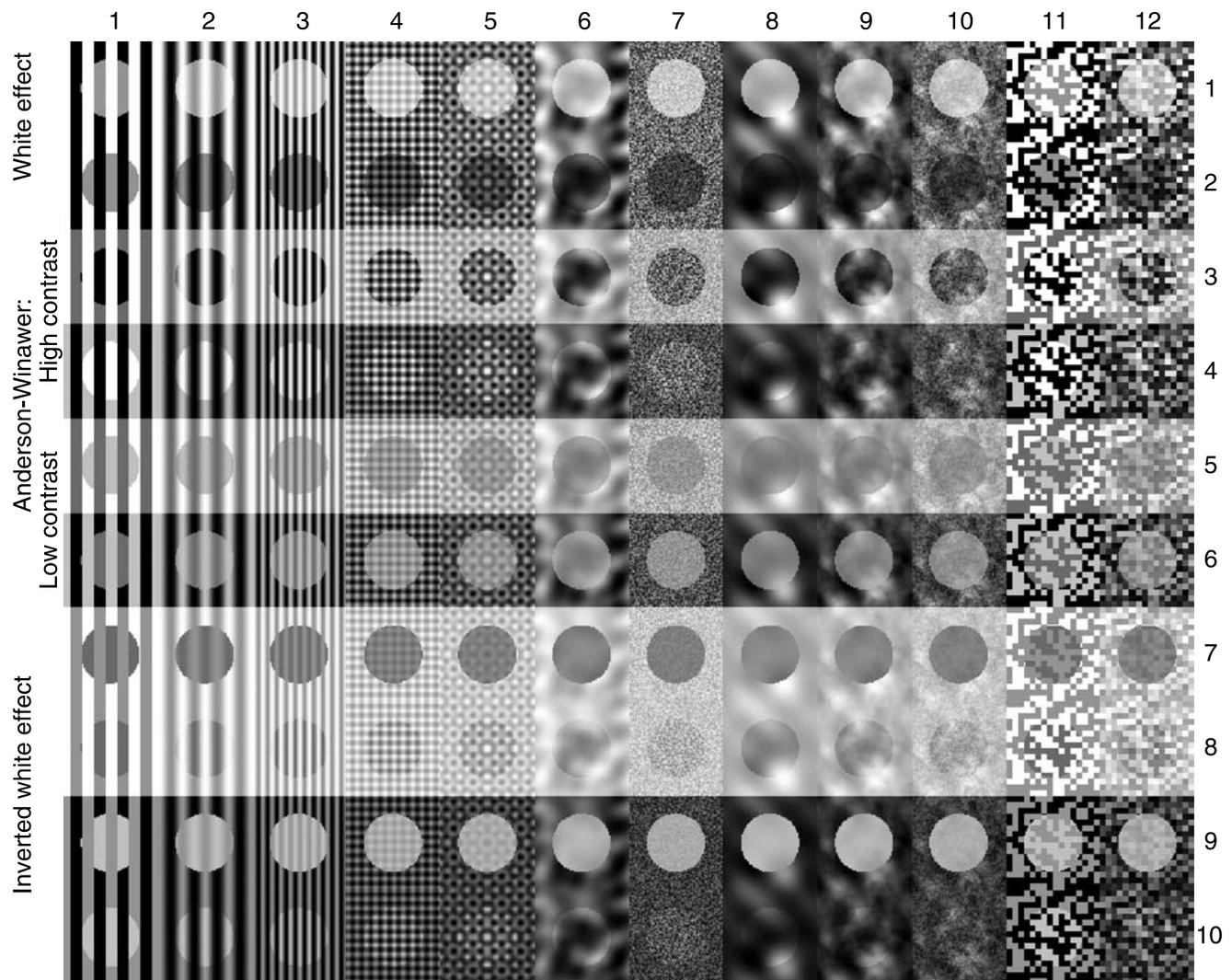


Figure 1. Perceived luminance is dependent on both the texture (constant for a given column) and the luminance configuration (constant for a given row). The textures used are: (columns 1–3) square- and sine-wave gratings, (columns 4–5) sine waves summed across several orientations, (columns 6–10) cloudy textures with different spatial frequency spectra, and (columns 11–12) random squares textures. The luminance configurations used correspond to luminance configurations used in: (rows 1–2) the White effect, (rows 7–10) the inverse White effect, and (rows 3–6) the Anderson–Winawer illusion. Of all these possible combinations of texture and luminance configurations, only a few have been used in previous experiments. Examples include the White effect (rows 1–2, columns 1 and 11), the inverse White effect (rows 7–10, column 1), and the Anderson–Winawer illusion at the higher and lower contrast ranges they tested (column 9, rows 3–4 and 5–6, respectively). Existing interactions between luminance configurations and textures suggest that different strategies may be used to estimate lightness (see Poirier, 2009 and below).

(C)–(D) with (G)–(H)]. Indeed, instead of perceiving the circle as light (G) or dark gray (H), the percept is of a dark (G) and a light (H) circle at corresponding luminance configurations. In fact, of the four stimulus pairs [i.e., (A)–(B), (C)–(D), (E)–(F), (G)–(H)], only the pair with low figure contrast and a square-wave grating (C–D) is consistently perceived with the circle on the right as darker than the circle on the left. Neither Anderson and Winawer (2005, 2008) nor Albert (2007) tested that condition, thus this important effect was missed.

Thus, to fully understand the effects involved here, it is crucial to understand possible interactions between texture and luminance configurations, which is the focus of the current study.

### White effect

The use of cloudy textures is recent in lightness perception research, and thus, there is not much data collected using them. In view of the above-mentioned

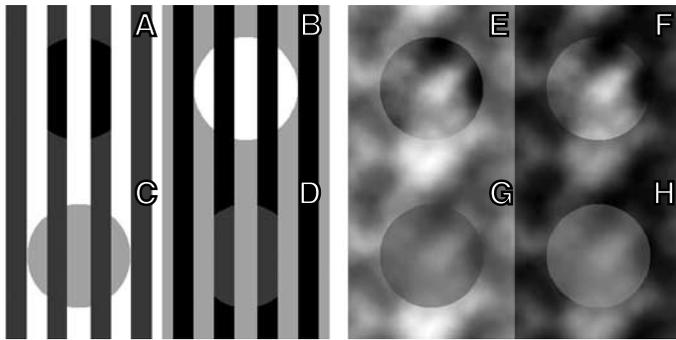


Figure 2. A demonstration that lightness depends on texture characteristics. The Anderson–Winawer luminance configuration applied to two different textures, shown for high-contrast (row 1) and low-contrast figures (row 2). For the square-wave texture (A–D), the direction of the effect clearly reverses at lower figure contrast [compare (A)–(B) with (C)–(D)]. For more complex textures (E–H), a reversal occurs especially with moving textures as used here (compare (E)–(F) with (G)–(H); see also Poirier, 2009).

effect reversal caused by this texture, it is unclear whether other luminance configurations would similarly be affected by texture characteristics.

The White (1979, 1981) effect is one such stimulus that could be affected by the strategy used to recover the figure’s luminance. In the White effect, a gray patch is perceived as darker (or lighter) whether it is placed on a white (or black) part of a square-wave grating. One common explanation is that occlusion cues place the gray patch at the same depth as the part it occludes and that its luminance is contrasted to that of parts perceived to be at the same depth. The inverse White effect uses a similar stimulus, except for using a black patch on a gray and white grating or a white patch on a gray and black grating (Ripamonti & Gerbino, 2001). If the cloudy texture removes occlusion information as claimed by Poirier (2009), then the White and/or inverse White effects could be strongly affected by such texture changes.

## Transparency

Viewing the world behind a semi-transparent surface is highly predictable. The semi-transparent surface simply reduces contrast and adds its own luminance. The semi-transparent surface can never increase or invert contrast (Anderson, 1997; Metelli, 1985; Ripamonti, Westland, & Da Pos, 2004; Singh & Anderson, 2002).

Thus, in theory, it does not matter what the semi-transparent surface “occludes,” as long as the background surface includes at least two different luminance levels to allow a reduction of contrast to be observed and enough texture information to measure texture continuity. Any textured background should support percepts of

transparency, and the perceived properties of the semi-transparent surface should not depend on texture properties of the background.

## The present study

The main goal of the current paper is to further document how textures and luminance configurations interact. We include every combination of 3 textures and 30 luminance configurations, some of which are displayed in Figure 1 (see below and Methods section for details). For each of these 90 stimuli, we measured perceived luminance, transparency, and “texturedness” (i.e., whether participants perceived the circle as having a homogenous surface or as having its own texture) of the circle. We then model biologically plausible perceptual strategies that participants may be using to resolve the percepts. The model uses a single set of parameters to account for percepts across the 90 conditions tested. Finally, by removing one strategy at a time from the model, we show which strategies are responsible for the effects in each condition.

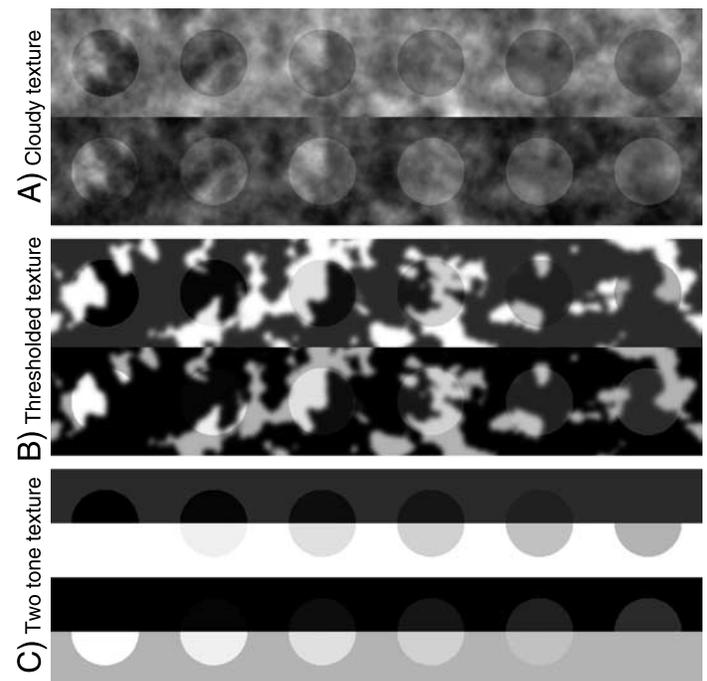


Figure 3. The Anderson–Winawer luminance configurations applied to the three different textures used in this study. Shown here are sample stimuli varied along three dimensions: (1) figure contrast varied from high-contrast (left) to low-contrast figures (right), (2) background mean luminance was lighter or darker (top or bottom row for each texture, respectively), and (3) texture was either the original cloudy texture (A), the thresholded texture (B), or the two-tone texture (C).

Condition	Details, figure contrast	$C_A$	$C_B$	$S_A$	$S_B$	Figure
Gray (homogeneous)	Light background	33.0	33.0	98.6	14.9	–
	Dark background	33.0	33.0	6.2	60.8	–
White	White occluder	98.6	33.0	98.6	6.2	1
	Black occluder	6.2	33.0	6.2	98.6	1
Inverse White	Black figure, white occluder	98.6	14.9	98.6	33.0	1
	Black figure, gray occluder	33.0	14.9	33.0	98.6	1
	White figure, black occluder	6.2	60.8	6.2	33.0	1
	White figure, gray occluder	33.0	60.8	33.0	6.2	1
Transparency	17.3%	39.0	27.5	98.6	6.2	–
	48.2%	52.9	18.5	98.6	6.2	–
	70.7%	69.3	11.9	98.6	6.2	–
	84.3%	88.2	7.5	98.6	6.2	–
Anderson–Winawer, light background	17.3%	39.0	27.5	98.6	14.9	–
	33.6%	45.7	22.7	98.6	14.9	–
	48.2%	52.9	18.5	98.6	14.9	–
	60.6%	60.8	14.9	98.6	14.9	1, 2, 3, 4
	70.7%	69.3	11.9	98.6	14.9	1, 3
	78.5%	78.4	9.4	98.6	14.9	1, 3
	84.3%	88.2	7.5	98.6	14.9	1, 3
	88.2%	98.6	6.2	98.6	14.9	1, 2, 3
Inverted contrast	Light background, 88.2%	6.2	98.6	98.6	14.9	–
	Dark background, 88.2%	98.6	6.2	6.2	60.8	–

Table 1. Luminance configurations used in the experiment (in  $\text{cd}/\text{m}^2$ ). Percent values indicate the figure's Michelson contrast when applicable, based on physical luminance ranges. Values for the Anderson–Winawer on dark background conditions are not shown; however, the same figure values were used as with the light background conditions, with the background changed to  $S_A = 6.2 \text{ cd}/\text{m}^2$  and  $S_B = 60.8 \text{ cd}/\text{m}^2$ . Background contrasts are 81.5% for the dark background, 73.7% for the light background, and 88.2% for backgrounds used in transparency conditions. Gray circles were shown on either the dark or light background. The last column (Figure) tells in which figure(s) examples of this luminance configuration can be found.

The 90 conditions are composed of every combination of the 3 textures (cloudy, thresholded cloudy, and two-tone) with 30 luminance configurations (2 gray-circles control conditions, 2 inverted-contrast-circles control conditions, 6 White and inverse White conditions, 4 transparency conditions, and 16 conditions including and extending those used by Anderson & Winawer, 2005, 2008).

This study expands on Poirier's (2009) study by (1) adding the thresholded texture, i.e., a cloudy texture with pixels either black or white to sharpen edge information (see Figure 3), (2) measuring transparency as well as up to two perceived luminances, i.e., one luminance if the circle is perceived as homogeneous or two luminances to indicate the luminance range perceived in the texture if the circle is perceived as textured, (3) including 30 luminance configurations rather than just 4 (see Table 1), and (4) providing a model of several mechanisms known to influence perceived lightness to account for the effects. Although 30 luminance configurations may seem excessive, they are important to include to validate the various measures used here, as well as to allow a measure of

relatively pure effects such that a comparison can be made when these effects are then combined.

## Summary of results

Results and model show many texture-dependent effects: (1) For solid gray and inverted-contrast control conditions, participants accurately reported the luminance (s) of the stimulus, although texture complexity increased transparency report rates and decreased the perceived lightness range. (2) Texture complexity greatly increased the White effect and increased transparency report rates for both White and inverted White luminance configurations. (3) Transparency conditions were largely unaffected by texture. (4) The Anderson–Winawer illusion showed a reversal of the direction of its effect at luminance configurations producing T-junctions, and simplifying the texture decreased the transparency report rates for those same conditions. (5) The Anderson–Winawer conditions at intermediate figure contrasts (i.e., 70.7%–84.3%) showed increased incidence of binomial

response distributions as texture was simplified, indicating bistable (or perhaps even tristable) percepts. (6) Percepts for the thresholded texture were generally in between results for the cloudy texture and for the two-tone texture. These results suggest that when textures become complex, occlusion cues become unreliable for depth segregation, thus forcing the visual system to rely on a simpler strategy.

## Methods

### Participants

Eight participants volunteered (3 males and 5 females), which included the first author, as well as university undergraduate and graduate students. Their vision was normal or corrected to normal.

### Apparatus

Testing and data collection was done on a PC (P4 3 GHz) and a calibrated CRT monitor set to a resolution of  $800 \times 600$  pixels and a refresh rate of 75 Hz. Responses were recorded via mouse button presses. Viewing distance was 68.5 cm, where the stimulus subtended a  $16^\circ \times 16^\circ$  area (not including response bars, see below).

## Procedure

### Stimuli

Three types of textures were created. The first texture was a grayscale noise with  $1/f^4$  power spectrum, henceforth named the “cloudy” texture. The second was a thresholded and slightly blurred version of the first, henceforth named the “thresholded” texture. Thresholding was at the median value, followed by blurring by a Gaussian filter to reduce aliasing (see Figures 2B and 3 for examples) using

$$G_{i,j} = e^{\frac{-(i^2+j^2)}{\sigma^2}}, \quad (1)$$

where  $\sigma = 0.1^\circ$ . The blur removed aliasing, but otherwise was not easily perceptible. The thresholded texture contains much sharper edges than the cloudy texture, thus creating clear T-junctions and X-junctions. Clear junctions are important occlusion cues to help establish depth relationships, thus the thresholded texture was expected to produce results more consistent with the occlusion theory.

The third texture was a two-tone texture, consisting of zeros in one half and ones in the other half. This third texture has the sharpest edge, as well as very simple physical characteristics. These three textures are similar to those used by Anderson and Winawer (2008).

These textures were normalized to a range of 0–1, and then the luminance range of that texture was modified independently within a circular region ( $5^\circ$  of diameter), henceforth named “center” ( $C$ ), and its surrounding region, henceforth named “surround” ( $S$ ), according to

$$C_{ij} = T_{ij}(C_A - C_B) + C_B \text{ and } S_{ij} = T_{ij}(S_A - S_B) + S_B, \quad (2)$$

where subscripts  $i$  and  $j$  indicate position on the image (omitted henceforth for simplicity), and the “luminance configuration” is defined as the constant values of  $C_A$ ,  $C_B$ ,  $S_A$ , and  $S_B$ . The luminance configuration thus defines the minimum, maximum, and range for each region (e.g., min value for center =  $\min(C_A, C_B)$ , range for center region =  $|C_A - C_B|$ ), as well as the luminance change across the center–surround boundary (from  $|C_A - S_A|$  to  $|C_B - S_B|$ ). The four constants forming the luminance configuration can be set to match luminance configurations normally used for the White effect, the inverse White effect, or the Anderson–Winawer illusion (see Table 1; sample stimuli are shown in Figures 1–4). Using this definition, any texture can be combined with any

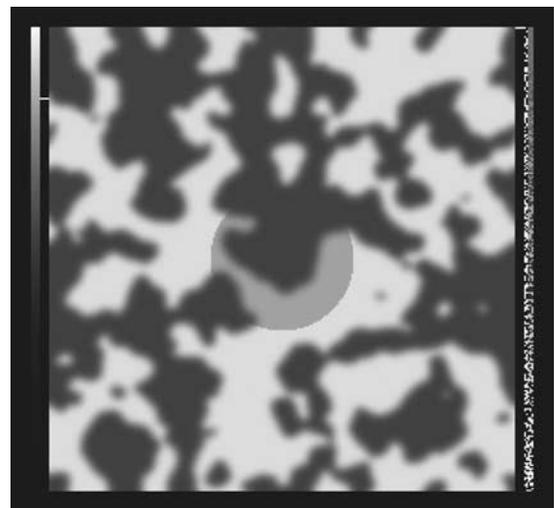


Figure 4. A sample stimulus as presented during the experiment, corresponding to the thresholded texture with one of the Anderson–Winawer luminance configurations (60.6% figure contrast, light background). The response bars on the sides are also shown. Participants indicated the perceived luminance(s) on the white-to-black bar on the left and transparency on the textured bar on the right. A small white bar indicated their responses, which participants could adjust before passing to the next stimulus. In this example, the participant reported perceiving the circle as light gray and opaque.

luminance configuration to create new stimuli. Note that changing a texture for a given luminance configuration can change the effect, thus combining a cloudy texture with the luminance configuration of the White effect may not produce the White effect. For this reason, we use the terms “texture” and “luminance configuration” to describe texture and the luminance ranges used to construct the stimulus, and the terms “effect” or “illusion” to describe the experienced perceptual biases as measured through the experiment.

The luminance configurations used here included luminance configurations used previously, i.e., in (1) the White effect, (2) the inverted White effect, (3) the Anderson–Winawer illusion, as well as (4) its gray control condition and (5) its rotation control (here, we used contrast inversion instead). We also included conditions extending the Anderson–Winawer illusion to lower figure contrast values and conditions to measure transparency percepts (i.e., parameters chosen consistent with transparency where the occluder reduces contrast, but otherwise does not produce a significant shift in physical luminance).

The cloudy and thresholded textures moved at  $2.2^\circ/\text{s}$ , at  $23.6^\circ$  upward from left motion. This reduced the risks that most pixels along the center–surround border would be confined to a range of possible values and, over time, produced a variety of edge properties. The circle remained centered in the stimulus. The two-tone texture remained motionless.

## Task

Participants were presented with a stimulus with a combination of a given luminance configuration and texture, and they were told to report perceived properties of the figure (i.e., the physical properties of the central circle) on response bars on the sides of the stimulus (see Figure 4). On the left, on a bar ranging from white to black, they indicated the perceived lightness of the figure using the mouse. If they perceived the figure to contain a texture of its own, then they indicated both the lightest and darkest parts of that texture using separate mouse buttons. On the right, on a bar ranging from opaque

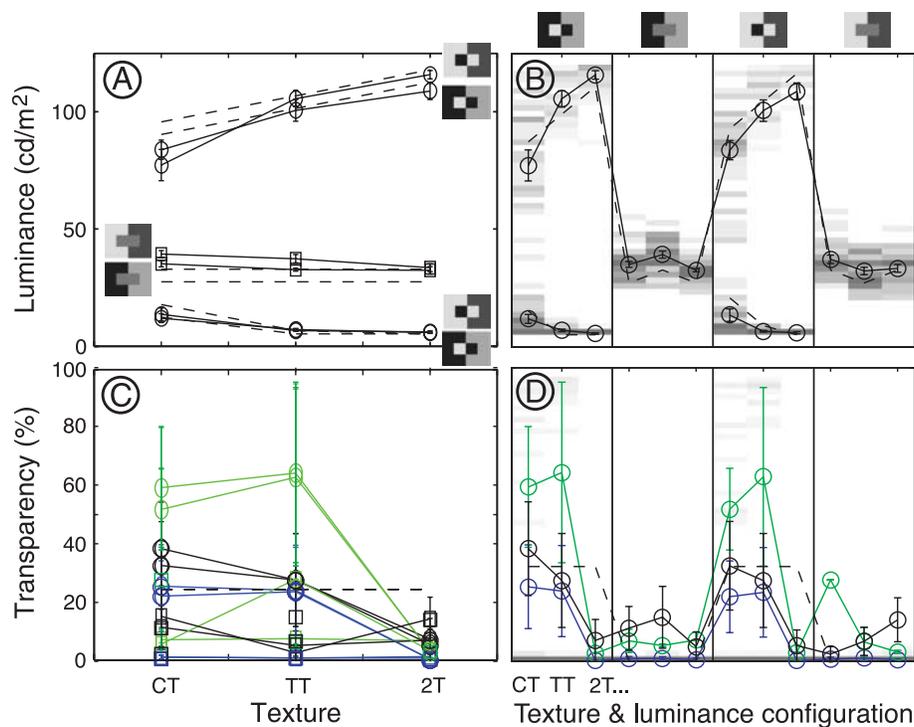


Figure 5. Luminance (A–B) and transparency estimates (C–D) for *gray and inverted-contrast conditions* for cloudy textures (CT), thresholded textures (TT), and two-tone textures (2T). Embedded pictograms depict the luminance configuration associated with the data shown. (A–B) Perceived lightness is shown in a line plot (A; symbols indicate mean and *SEM* of reported lightness, in  $\text{cd}/\text{m}^2$ ) along with simulation results (dashed lines). The same data are plotted again as a histogram (B; darker for more responses), with every condition plotted at a different X-axis position for clarity. (C–D) Transparency report rates (black) and percent perceived transparency averaged over only responses where transparency was reported (green) or over all responses (blue). Results show that: (1) responses were only bimodally distributed when contrast was inverted, showing that in all other cases participants did not report that the central region was textured, (2) reports of perceived transparency were rare ( $<20\%$  for most conditions), (3) perceived lightness was close to physical lightness, with a small bias due to surround contrast for gray circles, and (4) there was a small reduction of the perceived lightness range with increased texture complexity for the inverted conditions.

(shown as a gray area occluding the texture) to transparent (shown as the unmodified high-contrast texture), they indicated the perceived transparency of the figure (if any). Participants could adjust their responses until satisfied and press the space bar to proceed to the next trial. Participants did practice trials until they felt comfortable with the task. Each condition was repeated 5 times per participant over the course of the experiment.

## Analysis: Pre-processing

Participants could report one or two lightness judgments per trial. They were instructed to report two lightness judgments when they perceived the center as a textured object, in which case they had to report the highest and lower lightness values contained in the circle, using separate mouse buttons. They did so predominantly in inverted-contrast conditions (see [Figures 5A](#) and [5B](#)), where lightness reports were bimodally distributed. However, occasionally they only reported one lightness value in these same conditions. Moreover, participants also produced bimodal distributions of perceived lightness in some other conditions (e.g., Anderson–Winawer conditions), in which they reported that the percept alternated between several scene interpretations. That is, even though they produced a single response per trial, these responses were bimodally distributed. Because of these complications, simple averages are not always representative of actual responses or percepts of participants.

In an effort to ensure that the results presented here reflect the participants' responses, we have pre-processed the data by (1) establishing which conditions had bimodal distributions and (2) split the bimodal distributions into two distributions for separate analysis. Bimodality was assessed by eye and the threshold was also selected by eye. In all cases, the distributions are plotted alongside the data plots, including the threshold value used to separate the distributions. Thus, the reader can readily see how responses were analyzed.

## Analysis: Statistics

In most cases, reported analyses used factorial repeated-measures ANOVAs. In some rare cases, however, participants' responses were split into two categories. This happens, for example, when participants see a textured region as in the inverted-contrast conditions. This also happens when the percept could alternate between several alternatives, such as was the case in some of the Anderson–Winawer conditions using two-tone textures. The resulting responses were not always bimodal or evenly distributed between the high and low, thus the analyses had to be adapted to circumvent unequal sample sizes. We solved this problem by using between-participants factorial

ANOVAs instead in those cases. The type of analysis used can be inferred from the degrees of freedom for the error term, which is dividable by 7 for within-participants or by 11 for between-participants analyses.

Some effects receive less attention in the [Results](#) section, such as the main effect of texture on lightness perception. This is because we believe that these effects could disappear with only relatively small changes to the luminance parameters used in constructing the stimuli. Indeed, the nonlinear mapping chosen produced textures that seemed to be more continuous and provided good contrasts between center and surround. However, these parameters could have created some imbalances between darker and lighter areas of the textures, especially after perceptual nonlinearities are taken into consideration.

## Analysis: Modeling

Throughout the analysis, we refer to modeling done to explain the results. The model was developed to (1) provide a concise account of the data and (2) verify that the account proposed generates correct predictions. Moreover, a single set of parameters was used across the full data set. The details of this model are discussed after the results. However, the broad strokes of the model are introduced here.

The guiding principles were (1) include only previously documented strategies, (2) use only mechanisms that can easily extract the information from the current class of stimuli, (3) restrict effects by textures or luminance configurations only when this cannot be avoided, and (4) combine effects linearly to produce one or two measures of perceived lightness and one measure of likelihood of perceived transparency.

The model takes as input the luminance configurations, that is, the luminance values used to modulate the texture luminances in the center (i.e.,  $C_A$ ,  $C_B$ ) and surround regions ( $S_A$ ,  $S_B$ ), as well as an indicator of texture complexity ( $\beta$ ). All other properties are derived using these five values. These five parameters are easy to extract via careful examination of the stimulus or via simple algorithms, at least for the stimuli used in the present study.

The model predicts perceived lightness based on a combination of effects, including occlusion, lightness contrast, and transparency. The model does that in several steps: (1) assess which lightness effects contribute in a given condition, based on various selection rules, (2) compute a measure of bias for each eligible lightness effect, and (3) combine the biases using a weighted sum, with a single set of weights adjusted to maximize the fit with data over all 90 conditions.

The three main factors influencing perceived lightness are (1) occlusion, that is, when a part of the stimulus is perceived as occluded, only the part seen as unoccluded is

used to judge perceived lightness, (2) most likely pixel, that is, when the center region is on average lighter (or darker) than the surround region, the lightest (or darkest) pixel is used as an estimate of lightness, and (3) transparency, that is, perceived lightness is predicted by transparency rules after evaluation of opacity. The first two factors often but not always produce the same predicted lightness. In cases where the two factors produce conflicting results, we can see which factor accounts best for the results and, thus, infer the selection rules governing strategy selection.

Other effects are also included in the model. We leave the discussion of these effects to the [Modeling](#) section, because they contribute relatively little to lightness estimates, involve already-documented effects, and unnecessarily complicate the understanding of the major factors influencing lightness perception in the range of stimuli presented here.

## Results

### Control conditions

Anderson and Winawer (2005) used homogeneous gray figures and rotated texture figures as control conditions because these controls did not produce their illusion. We used the same homogeneous gray figures but replaced the rotated texture with an inverted-contrast texture, which produces the same control effect but maintains the same motion direction.

In our data, the reported average lightness in the gray control conditions is fairly close to the actual physical lightness, as was the case in Anderson and Winawer. For the inverted-contrast figure condition, participants reported seeing a textured center and reported the highest and lowest lightness of that texture, which differed drastically from each other ( $F(1,11) = 2334, p < 0.001$ ). Thus, the inverted-contrast conditions reflect both the average lightness and the lightness range perceived by participants. These results parallel those of Anderson and Winawer, except that in the inverted conditions, our participants reported both the maximum and the minimum lightness instead of only the average lightness.

Biases due to background luminance configurations or textures are relatively small but systematic. First, gray centers appear slightly lighter (or darker) when placed on darker (or lighter) surrounds ( $F(1,7) = 12.2, p = 0.01$ ), an effect that is not found in the inverted-contrast conditions ( $F(1,11) = 0.252, p > 0.62$ ). Second, in the inverted-contrast conditions, participants reported high and low lightnesses that were clearly different from each other ( $F(1,11) = 2334, p < 0.001$ ). The perceived figure lightness range is slightly increased as texture complexity decreases, i.e., participants reported a slightly larger

lightness range for the two-tone texture (least complex) than for the cloudy texture (most complex;  $F(2,22) = 16.4, p < 0.001$ ). In addition, texture had an effect on perceived luminance for both gray ( $F(2,14) = 9.57, p = 0.002$ ) and inverted-contrast controls ( $F(2,22) = 6.843, p = 0.005$ ). All other lightness effects and interactions were not statistically significant ( $ps > 0.15$ ).

Transparency report rates were very low, i.e., participants usually reported gray and inverted-contrast circles as opaque. Thus, analyses showed no effects (all  $ps > 0.21$ ), except for a texture effect for inverted-contrast conditions, where participants tended to report seeing semi-transparent circles more often as texture complexity increased ( $F(2,14) = 4.04, p = 0.041$ ).

Control conditions thus show mild texture-related changes: (1) a reduction of perceived lightness range for complex textures and (2) an increase in transparency report rates for the inverted-contrast range as texture complexity increases.

### White effect and inverted White effect

The White effect is often shown using a stimulus where the background is a black and white square grating, with 2 gray rectangular figures, one placed on the white area and another placed on the black area. Even though both gray figures have the exact same physical luminance, the one placed over the white area appears darker than the one placed over the black area (White, 1979, 1981). The Inverted White effect uses the same display, except that the stimulus is either a white figure on a gray and black background or a black figure on a white and gray background. Under inverted White conditions, the White effect persists but is reduced in strength (Ripamonti & Gerbino, 2001).

The White effect was replicated here for the two-tone texture (see [Figure 6A](#);  $F(1,7) = 7.243, p = 0.031$ ), which is similar to the square-wave texture used by White. However, texture significantly increased the effect of background ( $F(2,14) = 17.3, p = <.001$ ), where the “White” effect was greatly amplified with the cloudy and thresholded textures, with the amplification in the same direction as the White effect, which averages across textures to a significant bias on perceived lightness in the same direction as the White effect ( $F(1,7) = 85.7, p < 0.001$ ). There was also a main effect of texture ( $F(2,14) = 8.46, p = 0.004$ ).

The inverted White effect was also replicated ( $F(1,7) = 13.6, p = 0.008$ ); however, there was no amplification of the inverted White effect due to texture ( $F(2,14) < 0.21, p > 0.81$ ). For the inverted White conditions, there was also an effect of texture ( $F(2,14) = 6.37, p = 0.011$ ), of center luminance ( $F(1,7) = 148.9, p < 0.001$ ), and an interaction between texture and center luminance ( $F(2,14) = 8.5, p = 0.004$ ). All other effects were not significant (all  $F_s < 1.96$ , all  $ps > 0.2$ ).

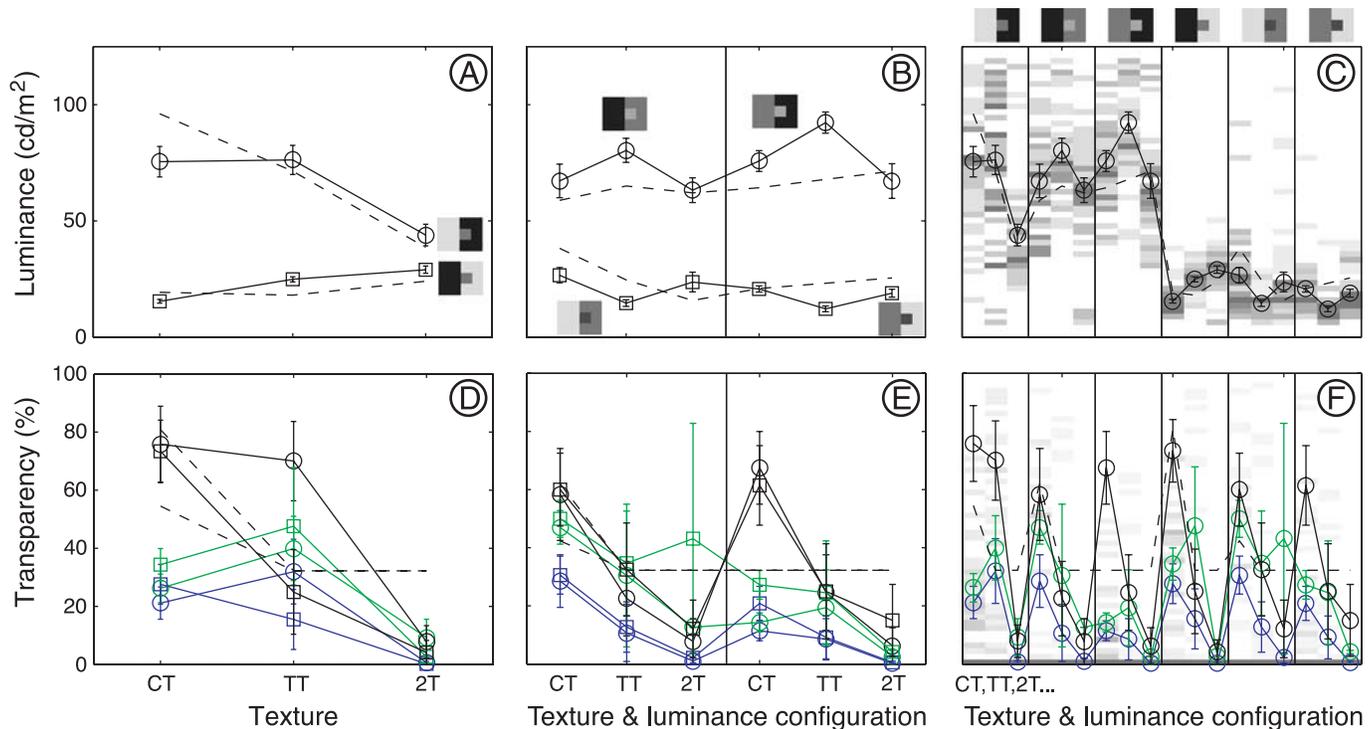


Figure 6. Luminance (A–C) and transparency estimates (D–F) for *White* (A, D) and *Inverted White* conditions (B, E) for the cloudy texture (CT), the thresholded texture (TT), and the two-tone texture (2T). The histograms for the same conditions (C, F) are also shown. Results show that: (1) texture complexity greatly increased the “White effect” in the White conditions, (2) texture complexity had no effect on perceived lightness in the Inverted White conditions, and (3) more complex textures were more likely to be perceived as transparent for both White and inverted White luminance configurations. The increased “White effect” is likely due to a change in strategy. See [Figure 5](#) for legend and the main text for details.

Transparency report rates increased with texture complexity for both the White ( $F(1,7) = 14.95, p < 0.001$ ) and inverse White effects ( $F(2,14) = 5.466, p = 0.018$ ). That is, for both luminance configurations, transparency rates were low in the two-tone texture conditions, high in the cloudy texture conditions, and moderate in the thresholded texture conditions. For the White conditions, there was also an effect of background ( $F(1,7) = 8.58, p = 0.022$ ) and an interaction between texture and background ( $F(2,14) = 9.9, p = 0.002$ ). For the inverse White conditions, none of the other effects or interactions were significant (all  $F$ s  $< 2.066$ , all  $p$ s  $> 0.194$ ).

These effects are readily understood when combined with modeling results. The amplification in the White effect with increased texture complexity co-occurs with an increase in transparency report rates. In particular, in increasingly complex textures, the “gray” area becomes effortful to isolate. Thus, participants shift from comparing the gray area (in two-tone textures) to comparing the whole central region (in cloudy textures), causing the amplification of the effect. The amplification is not seen in the Inverted White effect because, as discussed in the [Occlusion vs. MLP](#) section, both strategies produce exactly the same predicted perceived lightness within those luminance configurations. That is, a shift of strategy, if it occurs, does not produce a measurable lightness effect

in the inverted White conditions. The common increase in frequency of reported transparency with texture complexity indicates that this shift in strategy might be occurring nevertheless.

## Transparency

Metelli (1985; see also Ripamonti et al., 2004) described several conditions for perception of transparency to occur. For example, a semi-transparent surface will (1) reduce luminance range and (2) preserve contrast relationships. Thus, if a surface appears to increase contrast or change contrast relationships, it will be interpreted as something else than a semi-transparent surface. Our experiment included many conditions consistent with Metelli’s rules: the transparency conditions, as well as the Anderson–Winawer conditions except for figure contrast of 88.2% for the light background or below figure contrast of 70.7% for the dark background. The inverted-contrast control condition breaks Metelli’s rules.

In conditions that break Metelli’s rules, transparency report rate was less than 20% (e.g., both control conditions, see [Figure 5](#)). However, in conditions clearly consistent with percepts of transparency, transparency report rates were much higher ( $>60\%$  in 11 of 12

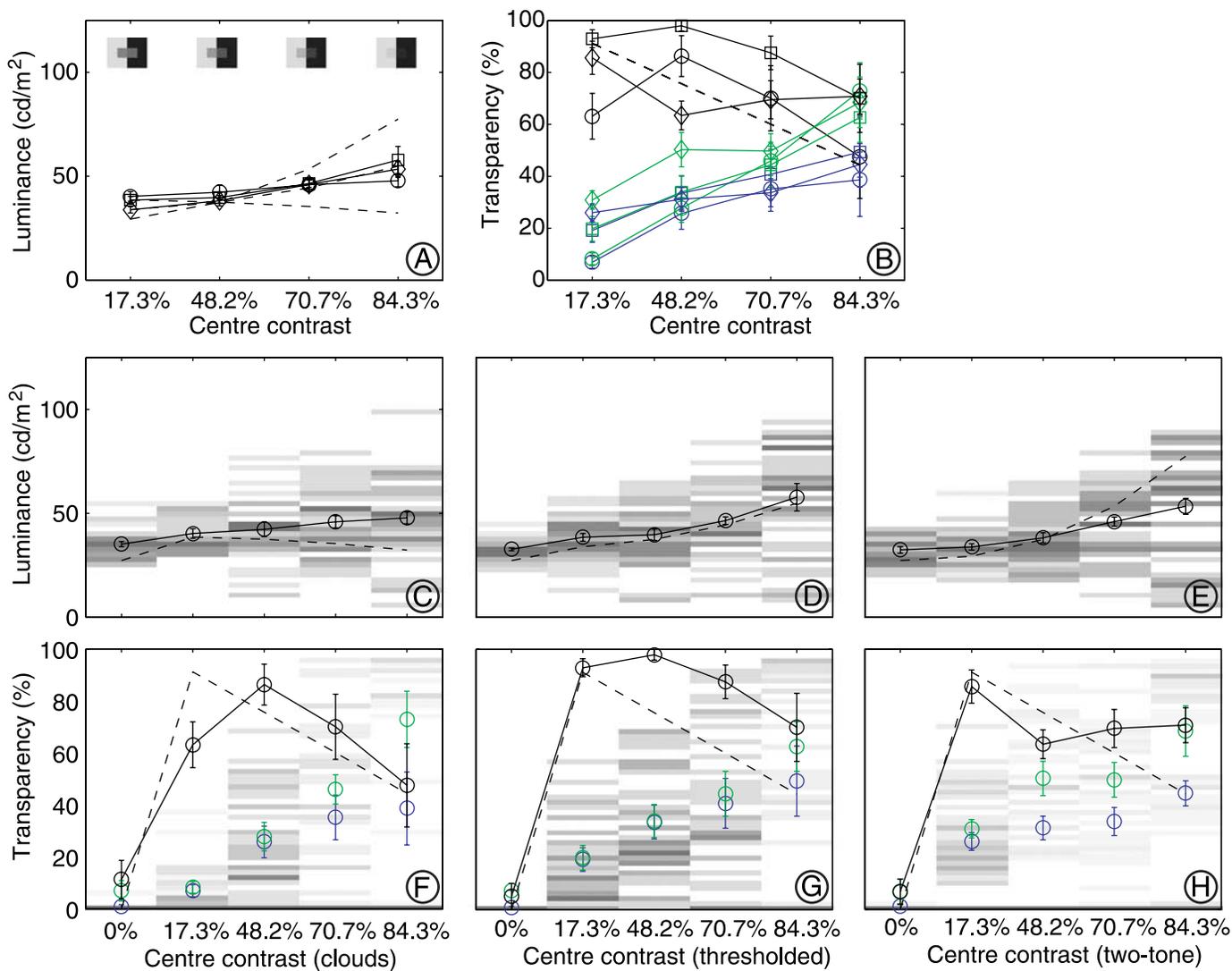


Figure 7. Luminance (A, C–E) and transparency estimates (B, F–H) for *transparency conditions* for the cloudy texture (CT; A–C, F), the thresholded texture (TT; A–B, D, G), and the two-tone texture (2T; A–B, E, H). Results show that: (1) perceived lightness is nearly invariant with texture and center contrast range, and (2) perceived transparency peaks at low levels of center contrasts, i.e., a high-contrast center is more likely to be reported as a partly occluded opaque surface. See Figure 8 that also includes transparency conditions, Figure 5 for legend, and the main text for details.

conditions in Figure 7;  $\geq 60\%$  in 18 of 18 conditions of Figure 8 with figure contrasts of 48.2% or less). Thus, Metelli’s rules at first glance appear to account for most of the reports of transparency.

For transparency conditions as well as Anderson–Winawer conditions with figure contrasts ranging from 17.3% to 48.2% (Figures 7 and 8), texture effects were not significant (including interactions; all  $F_s < 1.71$ ,  $p_s > 0.14$ ). Perceived lightness increased with figure contrast for both transparency ( $F(3,21) = 10.2$ ,  $p < 0.001$ ) and Anderson–Winawer conditions ( $F(2,14) = 11.3$ ,  $p = 0.001$ ). For Anderson–Winawer conditions, perceived lightness increased when the background was darker ( $F(1,7) = 28.4$ ,  $p = 0.001$ ), but there was no interaction

between figure and background properties ( $F(2,14) = 0.269$ ,  $p > 0.76$ ). Thus, based on perceived lightness results alone, one might be tempted to conclude that transparency is based on additive effects of figure and background luminance properties and independent of texture.

However, analysis of transparency report rates shows that Metelli’s rules are insufficient to explain transparency perception. Indeed, in the transparency conditions, transparency report rates are somewhat dependent on texture ( $F(2,14) = 3.71$ ,  $p = 0.051$ ) with the thresholded texture perceived as transparent more often. Transparency report rates decreased with figure contrast ( $F(3,21) = 3.71$ ,  $p = 0.028$ ), and there was an interaction between figure

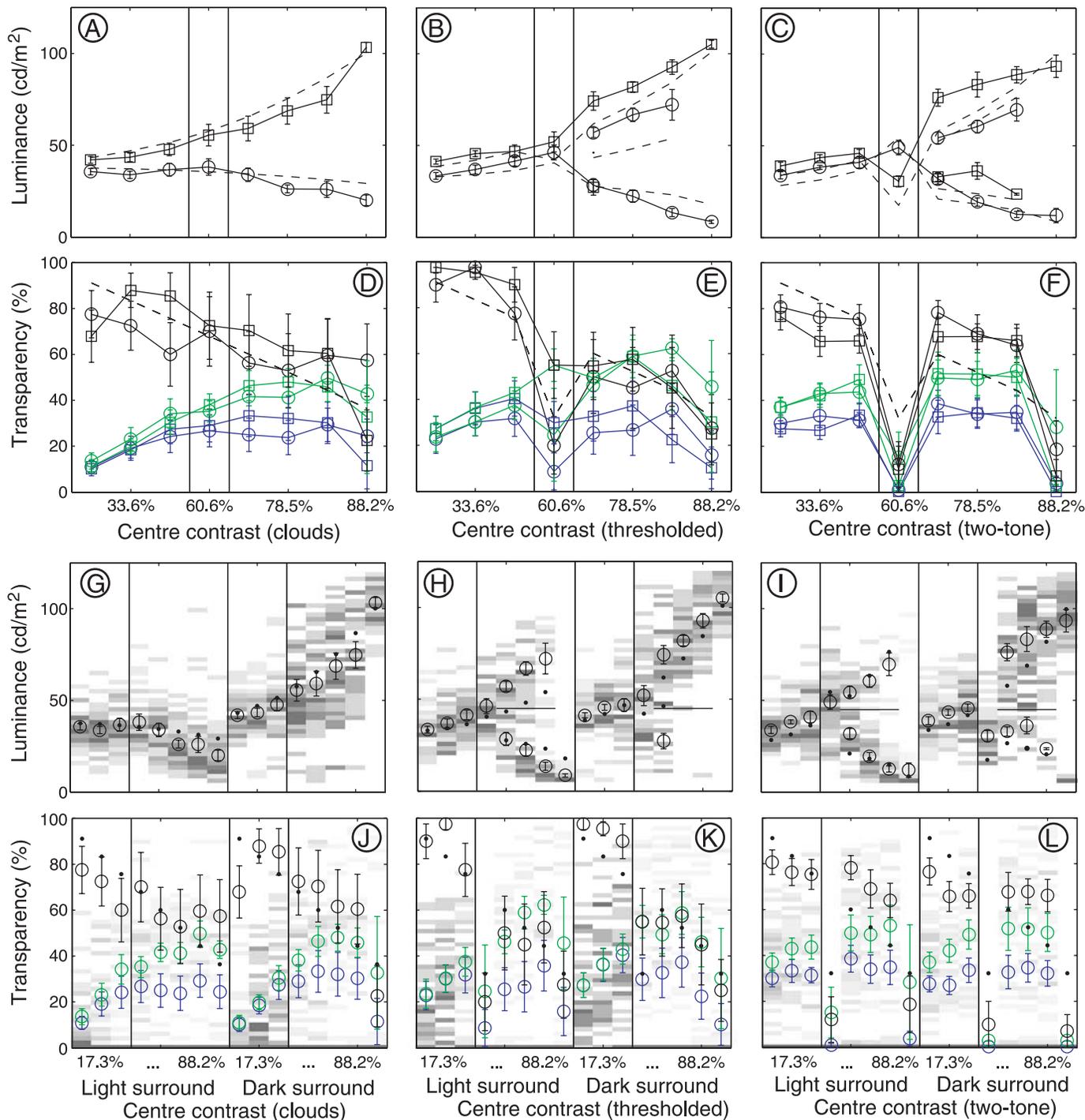


Figure 8. Luminance (A–C, G–I) and transparency estimates (D–F, J–L) for *Anderson–Winawer luminance configuration conditions* for the cloudy texture (left), the thresholded texture (middle), and the two-tone texture (right). Results show that: (1) changing the texture causes a reversal of the perceived lightness only for the 60.6% figure contrast condition (isolated by two lines in (A)–(F); see also [Figure 9B](#)), (2) changing the texture changes the rates of bimodal distributions for the 70.7%–84.3% figure contrast conditions, (3) a sudden drop of transparency report rates occur with the 60.6% and 88.2% figure contrast conditions, i.e., the only two conditions reliably producing T-junctions instead of X-junctions, and (4) the sudden drop of transparency report rates is largest for two-tone textures and absent for cloudy textures, despite both textures producing similar X- and T-junctions. See [Figure 5](#) for legend and the main text for details.

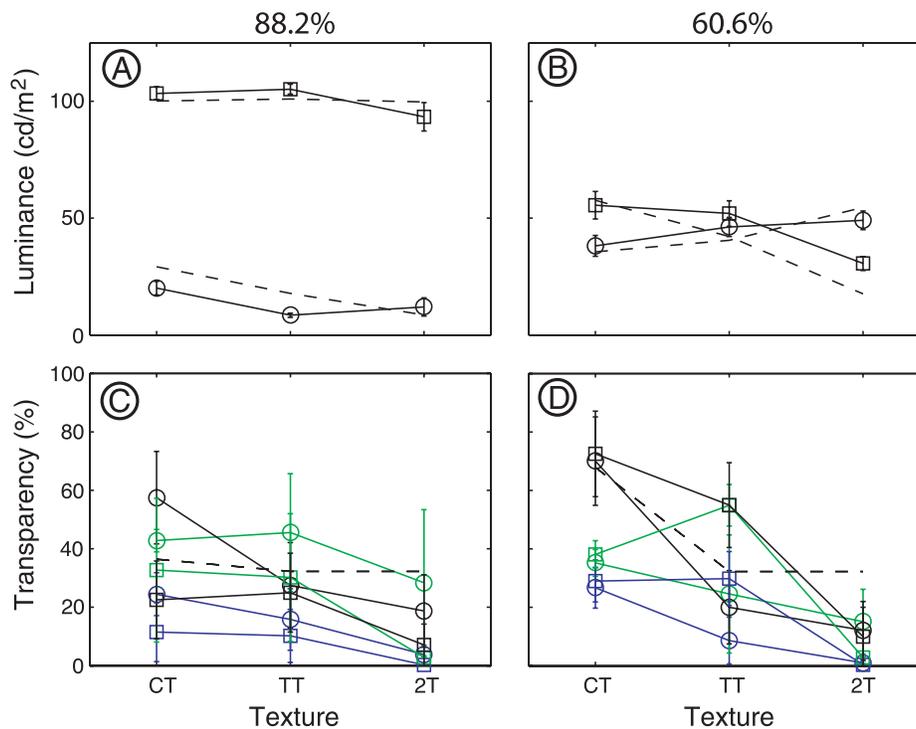


Figure 9. Luminance (A–B) and transparency estimates (C–D) for *Anderson–Winawer luminance configuration conditions* for the cloudy texture (CT), the thresholded texture (TT), and the two-tone texture (2T), for the high-contrast center (88.2%; A, C) and medium-contrast center conditions (60.6%; B, D). Results show that: (1) perceived lightness is texture invariant for the 88.2% condition, (2) perceived lightness reverses as texture complexity decreases for the 60.6% condition, and (3) simplifying the texture reduces the transparency report rates for both conditions. These results replicate the findings of Poirier (2009), suggesting a strategy shift (see [Modeling](#) section for details). Moreover, the common texture-dependent change in transparency report rates suggests that the same strategy shift occurs in both luminance configurations. See [Figure 5](#) for legend and the main text for details.

contrast and texture ( $F(6,42) = 3.02, p = 0.015$ ). Texture effects on perceived transparency rates are unexplained by Metelli’s rules and differ from the texture complexity effects generally seen with other luminance configurations within this study.

In the limited 17.3%–48.2% figure contrast range of the *Anderson–Winawer* conditions, background luminance was not significant overall ( $F(1,7) = 1.045, p > 0.34$ ), although it did interact with texture ( $F(2,14) = 6.285, p = 0.011$ ), and the interaction between figure contrast and background luminance was nearly significant ( $F(2,14) = 3.677, p = 0.052$ ). All other effects and interactions were not significant (all  $F_s < 1.411$ , all  $p_s > 0.25$ ).

Overall, for both transparency and *Anderson–Winawer* conditions, the effects of background, figure contrast, and texture were relatively small compared to effects found with other luminance configurations (e.g., White, *Anderson–Winawer*).

### Anderson–Winawer conditions

We replicated Anderson and Winawer’s (2005, 2008) experiment, in which the surround texture could be light

or dark, and figure contrast varied from high to medium contrasts (see [Figures 8](#) and [9](#)).

We added an additional 3 levels of figure contrast at the low-contrast end (see [Figure 8](#)). Because the results of these conditions are consistent with those of transparency conditions, they were discussed in greater detail separately in the previous section. However, we include a summary in the current section as well to understand the full progression and the uniqueness of the 60.6% figure contrast condition.

Anderson and Winawer’s results are replicated when using a cloudy texture similar to the one they used. Overall, perceived lightness was near the center’s lightest (or darkest) pixel when the center was lighter (or darker) than the background, thus showing a robust background effect ( $F(1,7) = 89.8, p < 0.001$ ). However, except for a lack of interaction between texture and background luminance ( $F(2,14) = 0.583, p > 0.57$ ), all effects and interactions of figure contrast, background luminance, and texture were significant (all  $F_s > 3.9$ , all  $p_s < 0.044$ ). Similarly, transparency reports included several complex effects. Except for no main effects of texture or background contrast ( $F_s < 0.45, p_s > 0.52$ ), all effects and interactions of figure contrast, background luminance, and

texture were significant (all  $F_s > 2.15$ , all  $p_s < 0.015$ ). Reports of transparency follow one of two trends depending on texture: (1) they gradually reduce as figure contrast increases for the cloudy texture, or (2) they gradually reduce except for two pronounced dips at specific figure contrasts (i.e., 60.6% and 88.2% figure contrasts) for the two-tone texture. Reports of transparency for the thresholded texture are a mixture (average) of the two trends, with the dips not as pronounced. These two unique conditions are those producing T-junctions. It therefore makes sense to use these two conditions as separators, to decompose the data set into a set of restricted analyses.

To clarify these effects, figure contrast conditions were decomposed in three subsets: (1) 17.3%–48.2%, analyzed in detail in the [Transparency](#) section, (2) the two special conditions that produce T-junctions, i.e., 60.6% and 88.2%, and (3) the conditions with intermediate figure contrasts, i.e., 70.7%–84.3%. In other words, three separate analyses were conducted, corresponding to figure contrasts (1) below conditions producing T-junctions, (2) only including conditions producing T-junctions, or (3) between conditions producing T-junctions.

The figure contrast range below 60.6% was analyzed above (see [Transparency](#) section above), and the main findings were (1) perceived lightness is based on additive effects of figure and background luminance properties and independent of texture at least in this limited figure contrast range, (2) transparency report rates were mainly independent of figure contrast, background luminance, and texture over the range studied, and (3) these effects were relatively small.

The 60.6% and 88.2% figure contrast conditions are the only two conditions associated with a sudden drop of reported transparency for the two-tone texture (see [Figure 8F](#)). All effects and interactions between texture, contrast, and background were significant when only sampling at these two figure contrasts (all  $F_s > 6.6$ , all  $p_s < 0.008$ ), except the interaction between texture and background ( $F(2,14) = 1.125$ ,  $p = 0.35$ ). In particular, the three-way interaction was significant ( $F(2,14) = 6.7$ ,  $p = 0.009$ ). At the 60.6% figure contrast, thresholding the texture removes the background effect (see [Figure 8B](#)), and further simplifying it into a two-tone texture reverses the background effect ( $F(2,14) = 21.3$ ,  $p < 0.001$ ; see [Figure 8C](#) compared to [Figure 8A](#); see also [Figure 9B](#); this reversal of the effect was originally shown by Poirier, 2009). At 88.2% figure contrast, changing the texture does not produce a reversal effect ( $F(2,14) = 2.06$ ,  $p = 0.164$ ; see [Figure 9A](#)), despite the transparency report rate dropping suddenly for the two-tone texture (see [Figures 8F](#) and [9C](#)). Thus, it seems that both of these conditions are associated with a percept that is different from those at other figure contrasts, a perceptual difference that is readily measured via transparency reports, yet can only be shown via lightness measurements for the 60.6% figure contrast condition.

The intermediate figure contrasts (i.e., 70.7%–84.3% figure contrast conditions) produced stimuli that were interpreted least reliably. Indeed, these conditions were associated with an increased occurrence of bimodality in luminance reports, especially for the two-tone texture but also, to some extent, for the thresholded texture as well. These intermediate contrasts are characterized by a figure luminance range that exceeds the background luminance range in one direction only. That is, some center pixels are either brighter or darker than all surround pixels, depending on background properties. Unlike the 60.6% and 88.2% figure contrasts, the luminance of the center and surround textures do not match where they are at their maximum or minimum (i.e.,  $C_A \neq S_A$  and  $C_B \neq S_B$ ). The resulting stimuli are difficult for participants to classify reliably. Indeed, according to subjective reports after data collection, the same stimulus could be perceived as a light moon or as a dark moon, and the percept could switch during a trial. Such bimodal responses are more common for simpler textures. The ambiguity arises because, for these stimuli, it is unclear whether the occluder itself is light or dark. This ambiguity translates into an ambiguity regarding the moon's lightness. After averaging the low and high responses (when data were bimodal), there were significant effects of texture ( $F(2,14) = 7.321$ ,  $p = 0.007$ ) and figure contrast ( $F(1,14) = 47.104$ ,  $p = < 0.001$ ), as well as significant interactions of these two factors with background luminance ( $F(4,28) = 3.433$ ,  $p = 0.021$  and  $F(2,14) = 28.369$ ,  $p < 0.001$ , respectively). Other effects were not significant ( $F_s < 1.76$ ,  $p_s > 0.165$ ). These effects are difficult to interpret in light of bimodal distributions. Transparency rates were independent of these factors and their interactions (all  $F_s < 1.6$ ,  $p_s > 0.2$ ). Note that stimuli at figure contrasts of 70.7% to 84.3% are more difficult to classify for the light background than for the dark background, at least for the thresholded texture. This is because the dark background has a lower contrast than the light background, thus the figure contrast can more easily exceed it. Once the figure contrast exceeds the background contrast, transparency is no longer a consistent interpretation.

## Modeling

The main challenge to theories of luminance perception is to account for lightness illusions, given that they are differentially affected by manipulations of luminance, stimulus configuration, aspect ratio, size, etc. (see Blakeslee & McCourt, 2004; Ripamonti & Gerbino, 2001; Spehar, Clifford, & Agostini, 2002). This is especially true when considering the novel stimuli introduced by Anderson and Winawer (2005, 2008; see also Anderson & Khang, 2010), which would be difficult to model by many existing

lightness models. This problem is exacerbated by the fact that some of these effects are dependent on texture characteristics, as demonstrated here and by Poirier (2009).

The model included below is a concise description of the current data set using documented effects. We first describe how the percentage of perceived transparency was modeled and then describe how perceived luminance was modeled.

## Common parameters

Some parameters influence percepts in many strategies; thus, they will be discussed first. These parameters are texture continuity ( $\alpha$ ) and texture complexity ( $\beta$ ).

Texture continuity ( $\alpha$ ) serves as a cue for surface segmentation and edge assignment and is defined as 1 if the luminance values on each side of the center-surround edge are strongly positively correlated or 0 otherwise. In our stimuli, this simplification is sufficient:

$$\alpha = \begin{cases} 1 & \text{if } (C_A - C_B)(S_A - S_B) > 0 \\ 0 & \text{otherwise} \end{cases}, \quad (3)$$

where a texture is perceived as discontinuous (i.e.,  $\alpha = 0$ ) when luminance variations on either side of the edge are negatively correlated together or if either the center or surround region is not textured. Given that our stimuli are either strongly positively correlated (in most cases), uncorrelated (gray control), or strongly negatively correlated (contrast-inverted), this definition is sufficient for the class of stimuli used here. This definition could be extended to include a variety of cues that signal discontinuities (e.g., changes in texture, binocular depth, color, motion) and could be improved further for general use by determining how much correlation is necessary for texture continuity to be perceived.

Texture complexity ( $\beta$ ) serves as an indicator of how “perceptually complex” a texture is. For the purposes of the current paper, the following simplification is sufficient:

$$\beta = \begin{cases} 1 & \text{for cloudy} \\ 0.5 & \text{for thresholded.} \\ 0 & \text{for two-tone} \end{cases}. \quad (4)$$

This equation provides an approximation of how difficult information such as T-junctions or X-junctions are to retrieve from stimuli such as those used in the current paper.

If the central area of a stimulus had its luminance range contained within the range of luminances of the surround

area, then the resulting stimulus was consistent with Metelli’s rule of reduced contrast. These conditions are captured by the semi-transparency indicator ( $\gamma$ ):

$$\gamma = \begin{cases} 1 & \text{if } (\max(C) < \max(S)) \text{ and } (\min(C) > \min(S)) \\ 0 & \text{otherwise} \end{cases}. \quad (5)$$

## Percent transparency

Here, we model the frequency of transparency percepts, not the degree of transparency perceived. Thus, whether a stimulus is reported as almost opaque or almost completely transparent does not matter in this measure, as long as it is not reported as completely opaque.

Cloudy textures provide the simplest case, for which percent reports of transparency ( $T\%$ ) were well described as: (1) almost always opaque ( $T\% \approx 0$ ) if the center region is a homogeneous gray region (i.e.,  $C_A = C_B$ ), (2) usually opaque ( $T\% \approx T_{\min}$ ) if the texture in the center region appears discontinuous with the texture in the surround region, as is the case when contrast is inverted (i.e.,  $\alpha = 0$ ), or (3) with frequency of “opaque” responses dependent on the contrast of the center region in all other cases, where a higher contrast center region is less likely to be perceived as transparent. These influences can be summarized as

$$T\% = 0 \quad \text{if } C_A = C_B, \quad \text{otherwise}, \quad (6)$$

$$T\% = T_{\min} + (T_{\max} - T_{\min})\alpha \left(1 - \frac{|C_A - C_B|}{L_{\text{white}}}\right), \quad (7)$$

where  $T_{\min}$  and  $T_{\max}$  are free parameters describing the range of transparency percent reports, and  $L_{\text{white}}$  is a constant equal to the maximum luminance presented during the experiment. The maximum luminance was always present in the stimuli at least in the response bars.

Two-tone textures follow the same general pattern but with some notable differences: The stimuli used in the White, inverted White, and both the high- and medium-contrast figure versions of the Anderson–Winawer were rarely reported as transparent, much less than predicted by Equations 6–7. The common aspect of all these conditions is that they produced T-junctions rather than X-junctions and, thus, provided salient occlusion cues. This is captured by modifying Equation 7 by adding a term that captures the presence of T-junctions:

$$T\% = T_{\min} + (T_{\max} - T_{\min})\alpha \left(1 - \frac{|C_A - C_B|}{L_{\text{white}}}\right) (1 - T_{\text{junctions}}), \quad (8)$$

Influence	Restrictions	Free parameter	Equations
Percent transparency ( $T\%$ )	$(C_A \neq C_B)$	$T_{\min}, T_{\max}$	6–9
Average luminance ( $L_0$ )	None	None	10
Contrast enhancement ( $L'_{CE}$ )	None	$\omega_{CE}$	11
Texture discontinuity ( $L'_{INV}$ )	$1 - \alpha$	$\omega_{range}, \omega_{INV}$	12
Atmospheric darkening ( $L'_{AD}$ )	$\alpha(1 - \beta)(C_A \neq C_B)$	$\omega_{AD}$	13
Occluder removal ( $L'_{Occ.}$ and $L'_{Occ\_opp}$ )	$\alpha\beta(1 - \gamma)$	$\omega_{Occ.}$	14–19
Most likely pixel ( $L'_{MLP}$ )	$\alpha(1 - \beta)(1 - \gamma)$	$\omega_{MLP}$	20–21

Table 2. List of the sources of influence on perceived luminance used in the current model. “Restrictions” show which conditions must be met for the influence to be effective. The influence is absent if these restrictions result in a value of false or “0.” “Free parameter” indicates the free parameter(s) used in the data fit. “Equations” point to the equations involved in estimating the strength and presence of the influence. These influences are then summed in Equation 22. The percent transparency reports, which indicates the likelihood that a circle was reported as being semi-transparent, is also shown. Many factors are dependent on texture continuity ( $\alpha$ ), texture complexity ( $\beta$ ), and/or contrast ranges consistent with semi-transparency ( $\gamma$ ). See text for details.

where

$$T_{\text{junctions}} = (C_A = S_A) \text{ or } (C_B = S_B), \quad (9)$$

that is, transparency reports were the same as with the cloudy textures, except for stimuli that contained a T-junction, in which case transparency was rarely reported (i.e., with a T-junction present, the term  $(1 - T_{\text{junctions}})$  equals 0, thus  $T\% = T_{\min}$ ). Transparency reports for the thresholded textures follow the same pattern as that of the two-tone texture and is thus captured by Equation 8.

## Perceived luminance

The simplest estimate of surface lightness is its *average luminance*, i.e.,

$$L'_0 = \bar{C} = (C_A + C_B)/2, \quad (10)$$

which is valid in the absence of any contributions from corrective mechanisms, segregation mechanisms, or other influences. We used midpoint luminance instead of average for simplicity, which does not affect significantly the predictions for the stimuli presented here because luminance distributions were not systematically skewed.

The more important factors influencing lightness reports in the above stimulus conditions are due to the interpretation of the stimulus, i.e., is it a transparent surface above a textured background, an opaque surface behind a variable-opacity occluder, or a circle with a texture of its own? The factors involved in stimulus interpretation are discussed below. All influences on lightness discussed below are expressed as deviations to the average luminance ( $L'_0$ ). If a formula below returns a value of 0, it means that this factor has no influence on the perceived luminance in the given condition. Table 2 provides a list

of influences on perceived luminance included in the present model.

## Contrast enhancement

Lightness is affected by *contrast enhancement* mechanisms ( $L'_{CE}$ ):

$$L'_{CE} = \bar{C} - \bar{S} = (C_A + C_B)/2 - (S_A + S_B)/2, \quad (11)$$

where luminance biases are dependent on the average luminance in center and surround regions. The resulting effect is an amplification of the average difference between the center and its surround. This bias would still operate if stimulus details were not resolvable (e.g., if sufficient blur was applied). Its effect is present in all stimuli and does not depend on texture characteristics.

## Inverted contrast

Contrast inversion disrupts texture continuity and, thus, has a large effect on stimulus interpretation. Contrast inversion (or texture rotation) introduces cues that are inconsistent with the interpretation of homogeneously colored occluders. Indeed, for a homogeneous figure over a homogeneous background, the luminance difference at the edge is constant. Introducing an occluder of constant luminance but variable opacity modulates the amount of that difference *but not its sign*. For example, if clouds cover a light moon over a dark sky, then no part of the moon can be darker than an adjacent part of the sky, independently of how opaque the clouds are locally and independently of whether the clouds are themselves light, gray, or dark. Contrast inversion (or texture rotation) create the possibility that the center-surround difference

could increase in certain places and decrease in other places.

Thus, a common control condition used to break transparency or segregation cues is to introduce sign changes at the center–surround edge, either via rotating the texture (e.g., Anderson & Winawer, 2005) or via a texture polarity change as done here. Indeed, reversing the polarity of the figure region or rotating the texture contained within it breaks the Anderson–Winawer illusion, causing us to see a textured figure over a textured background, with no occluders or percept of transparency. To describe this variable, we use the term “texture continuity,” which is captured by the variable  $\alpha$  (see Equation 3).

When a texture discontinuity is perceived, participants perceive the texture contained within the central region as belonging to the figure and report the lightest and darkest parts of it ( $L'_{INV}$ ) according to

$$L'_{INV} = \pm(1 - \alpha) \frac{|C_A - C_B|}{2} (1 - \omega_{range}(1 - \beta)), \quad (12)$$

that is, when contrast inversion is perceived (i.e.,  $\alpha = 0$ , thus  $1 - \alpha = 1$ ), lightness reports are made above and below the mean center lightness, of amplitude equal to half the center’s lightness range, with a small amplitude modulation effect ( $\omega_{range}$ ) due to texture complexity ( $\beta$ ). The modulation effect observed is a decrease of the effect as texture complexity increases, for which the simplest plausible explanation is that participants have a reduced ability to perceive the true luminance range contained in complex textures. This parallels a general reduced ability to recover occlusion information in complex textures. It also offers a plausible explanation for the amplitude differences observed between the two strategies (see [Discounting the occluder](#) and [Most likely pixel \(MLP\)](#) sections below).

## Atmospheric darkening

*Atmospheric darkening* ( $L'_{AD}$ ) is defined as the physical reduction in light intensity when it passes through any semi-transparent medium. Perceptual compensation for this effect has not been investigated before. Anderson and Winawer (2005, 2008) reported an unexplained bias, and Poirier (2009) proposed that this bias was consistent with atmospheric darkening. He further argued that this bias was inconsistent with incomplete lightness constancy as the bias is in the wrong direction in some conditions (see Poirier, 2009).

In our model, atmospheric darkening is perceptually compensated for when certain conditions are satisfied, i.e., (1) the center is textured (i.e.,  $C_A \neq C_B$ ), (2) the texture is continuous (i.e.,  $\alpha = 1$ ; see Equation 3), and (3) the texture is complex, thus it does not provide good segmentation

cues ( $\beta = 0$  or 0.5; see Equation 13), all of which can be represented as

$$L'_{AD} = \begin{cases} 0 & \text{if } C_A = C_B \\ \alpha(1-\beta) & \text{otherwise} \end{cases}, \quad (13)$$

that is,  $L'_{AD}$  equals one if all of these conditions are satisfied (or 0.5 for the thresholded texture), in which case there is a perceptual compensation for atmospheric darkening. This compensation biases lightness reports toward lighter values, regardless of whether the figure is lighter or darker than the background. With the thresholded texture,  $L'_{AD}$  equals 0.5; thus, we assume that with a texture that has some segmentation cues, the perceptual compensation for atmospheric darkening will be partial.

Although the amount of atmospheric darkening depends on the amount of transparency in real-world conditions, it is currently not known if the same is true of perceptual atmospheric darkening compensation. As the current model does not predict the amount of transparency (rather it predicts the likelihood that transparency of any magnitude is reported), and as there is no data specific to atmospheric darkening compensation in the literature, we opted for a constant amount of atmospheric darkening compensation when it occurs, for simplicity. Further research on atmospheric darkening could help improve this part of the model. The impact of atmospheric darkening is relatively small compared to other components of the model, thus small inaccuracies should not impact the fit for other components of the model.

## Discounting the occluder

The stimulus is often perceived as variable-opacity clouds over a homogeneous circular figure (moon), itself over a homogeneous background (sky). However, recovering the figure’s physical characteristics such as its luminance and transparency is not trivial. Poirier (2009) presented two strategies reviewed below that can be used to discount the occluder, and in some specific conditions, he showed that the two strategies produce opposite predictions. By comparing the data and predictions in those specific conditions, he identified which of the two strategies was used in which condition. The strategy selected was dependent on occlusion cues, which was dependent on texture complexity ( $\beta$ , Equations 4, 19, and 21). We replicated his results and expanded both data and model to an extra texture (i.e., thresholded clouds) and to various contrast levels.

The first strategy named “discounting the occluder” is to infer the occluder’s physical characteristics and then discount those characteristics to estimate the figure’s physical characteristics. This is what “occlusion” usually refers to in the literature. The second strategy named

“most likely pixel” (detailed later) is to infer the figure’s physical characteristics by directly comparing the center and surround regions, without estimating occluder characteristics.

Discounting the occluder requires an understanding of how the luminance of the figure and background changes as it passes through a semi-transparent occluder. According to Metelli’s (1985; see also Ripamonti et al., 2004) transparency rules, a homogeneous transparent circle above a textured background will produce a stimulus satisfying the following relationships:

$$C_A = S_A\varphi + \text{Occ.}(1 - \varphi) \text{ and } C_B = S_B\varphi + \text{Occ.}(1 - \varphi), \quad (14)$$

where ( $S_A$ ,  $S_B$ ) are the surround luminance values, ( $C_A$ ,  $C_B$ ) are the center luminance values,  $\varphi$  is the figure’s opacity, and “Occ.” is the occluder’s luminance. Center and surround luminance values are easily extracted from the stimulus, thus only  $\varphi$  and Occ. need to be estimated. This system of two equations with two unknowns is easily solved, as the two functions intersect with

$$\text{Occ.} = \frac{S_A C_B - C_A S_B}{C_B - C_A - S_B + S_A}, \quad (15)$$

providing an estimate of occluder luminance (Occ.) from which occluder transparency can be estimated. Even if the image does not contain a point where  $\text{Occ.} = C_i = S_i$ , Occ. can be estimated by extrapolation. The occluder’s transparency can be measured as

$$\varphi_A = \frac{C_A - \text{Occ.}}{S_A - \text{Occ.}} \text{ or } \varphi_B = \frac{C_B - \text{Occ.}}{S_B - \text{Occ.}}, \quad (16)$$

where both formulas will provide the local transparency at points A and B, respectively. Note that the occluder’s transparency is variable over the image for most luminance configurations, i.e.,  $\varphi_A \neq \varphi_B$  for most luminance configurations. The value of Occ. was used to determine the perceived luminance of the center. The occluder’s transparency was not calculated or used further.

Perceived luminance of the center was defined as the luminance contained in the center region that contrasted most with the occluder’s luminance (Occ.):

$$F'_{\text{Occ.}} = \begin{cases} C_A - \bar{C} & \text{if } |C_A - \text{Occ.}| > |C_B - \text{Occ.}| \\ C_B - \bar{C} & \text{otherwise} \end{cases}, \quad (17)$$

where  $F'_{\text{Occ.}}$  is the expected deviation from average luminance when this strategy is used. Note that the average luminance is removed here but re-added later

(as  $L'_0$ , Equations 10 and 22). This strategy is accurate if detailed luminance information is available on either side of the edge and includes a range of occluder opacities.

However, participants did not always correctly use this strategy. In our experiment, in several conditions, no part of the cloud reached the estimated occluder luminance; hence, no part of the cloud could be interpreted correctly as fully opaque (e.g., figure contrast from 70.7% to 84.3%). In those conditions, participants often showed a lightness bias in the opposite direction to  $F_{\text{Occ.}}$ , that is, they would report  $C_A$  instead of  $C_B$  or vice versa. It could be that in these cases, it becomes difficult to perceptually estimate the occluder luminance (Occ.), and thus, both alternatives become possible. This is indeed consistent with subjective reports, where many participants reported that the moon was bistable, i.e., switching between a light moon behind dark clouds and a dark moon behind light clouds. Our model included this by allowing the opposite prediction in Equation 17 but only in cases where  $C_A \neq S_A$  and  $C_B \neq S_B$ . This can be summarized as

$$F'_{\text{Occ.opp}} = \begin{cases} \bar{C} - F'_{\text{Occ.}} & \text{if } (C_A \neq S_A) \text{ and } (C_B \neq S_B) \\ \text{n./a.} & \text{otherwise} \end{cases}, \quad (18)$$

where no value is given if either  $C_A = S_A$  or  $C_B = S_B$ . The occluder removal strategy was modeled as being effective when the following conditions were met: (1) the texture was continuous, (2) the texture provided good segmentation cues, and (3) the circle was not perceived as a semi-transparent surface. These conditions are included in the calculation of the luminance bias:

$$L'_{\text{Occ.}} = \alpha\beta(1 - \gamma)F'_{\text{Occ.}} \text{ and } L'_{\text{Occ.opp}} = \alpha\beta(1 - \gamma)F'_{\text{Occ.opp}}. \quad (19)$$

This strategy gave lightness modulations that were half-strength when the texture was the thresholded cloudy texture.

## Most likely pixel (MLP)

In some cases, the figure is partly occluded by a variable-opacity occluder, but unlike described above (see Discounting the occluder section), the occlusion cues are insufficient to allow our perceptual system to segregate the surfaces. In this case, a simpler strategy is adopted.

Partially opaque occluders may reduce contrast but do not change luminance relationships. For example, the light moon over a dark sky remains light over dark independent of clouds’ lightness or opacity. Therefore, although the occluder can change the contrast, it cannot change the moon–sky polarity.

A strategy that takes advantage of this relationship is to select the lightest (or darkest) point of the center as being that of the figure if the center is on average lighter (or darker) than the background, e.g.,

$$F'_{\text{MLP}} = \begin{cases} \max(C_A, C_B) - \bar{C} & \text{if } \bar{C} > \bar{S} \\ \min(C_A, C_B) - \bar{C} & \text{otherwise} \end{cases}, \quad (20)$$

which does not require that the occluder be segregated or that precise point-by-point correspondence between figure and background luminance values be established. We called this strategy the “most likely pixel” (MLP) because in effect, the strategy selects the pixel that is most likely to be descriptive of the moon, given the impoverished information. For this strategy to work, we only need average luminance of center and surround regions as well as their luminance ranges.

However, participants did not always use this strategy. Much like the occluder removal strategy, the MLP strategy was modeled as being effective when the following conditions were met: (1) the texture was continuous, (2) the texture was not perceived as a semi-transparent surface, and (3) unlike the occluder removal strategy, the stimulus had to provide *poor* segmentation cues. These conditions are included in the calculation of the luminance bias:

$$L'_{\text{MLP}} = \alpha(1 - \beta)(1 - \gamma)F'_{\text{MLP}}. \quad (21)$$

Note that because the occluder removal strategy is effective with good segmentation cues, and the MLP strategy is effective with poor segmentation cues, they are usually mutually exclusive. The exception is for the thresholded texture, where both strategies contribute half of their effects. It is unclear whether this is perceptual averaging or a result of averaging in the data analysis.

## Occlusion vs. MLP

The two strategies discussed above (see [Discounting the occluder](#) and [Most likely pixel \(MLP\)](#) sections above) correctly recover figure luminance for various stimuli, including the Anderson–Winawer (2005, 2008) stimuli where figure contrast is high (see [Results](#) section). However, these strategies make different predictions for stimuli where the center is darker (or lighter) than the surround, yet the predicted occluder corresponds to the darker (or lighter parts) of the display (based on whether  $C_A \approx S_A$  or  $C_B \approx S_B$ ). This situation occurs in the Anderson–Winawer luminance configurations with figure contrast of 60.6%.

For example, [Figures 2C](#) and [2G](#) show two stimuli where the luminance ranges within the center and surround are

confined to 14.9–60.8 cd/m<sup>2</sup> and 14.9–98.6 cd/m<sup>2</sup>, respectively, that is, the center region is on average darker than the surround region. The occlusion strategy (i.e., [Equations 14–19](#)) recovers 60.8 cd/m<sup>2</sup> as figure luminance (i.e., the *lightest* point) because it estimates the occluder at 14.9 cd/m<sup>2</sup> (the luminance common to center and surround). In contrast, the most likely pixel strategy (i.e., [Equations 20](#) and [21](#)) recovers 14.9 cd/m<sup>2</sup> as figure luminance (i.e., the *darkest* point) because on average the center region is darker than the surround region. Therefore, this particular luminance configuration can serve as a diagnostic tool to establish which of the two strategies is used, as demonstrated previously (Poirier, 2009). The strategy used depends on texture properties.

## Prediction

Lightness ( $L'$ ) is given as the average luminance of the surface plus a weighted sum of the various luminance biases:

$$L' = L'_0 + \omega_{\text{CE}}L'_{\text{CE}} + \omega_{\text{INV}}L'_{\text{INV}} + \omega_{\text{AD}}L'_{\text{AD}} + \omega_{\text{Occ}}L'_{\text{Occ}} + \omega_{\text{MLP}}L'_{\text{MLP}}, \quad (22)$$

where  $\omega_{\text{CE}}$ ,  $\omega_{\text{INV}}$ ,  $\omega_{\text{AD}}$ ,  $\omega_{\text{Occ}}$ , and  $\omega_{\text{MLP}}$  are weights regulating the size of biases induced by the various influences on perceived luminance.

These five weights ( $\omega_{\text{CE}}$ ,  $\omega_{\text{INV}}$ ,  $\omega_{\text{AD}}$ ,  $\omega_{\text{Occ}}$ , and  $\omega_{\text{MLP}}$ ; [Equation 22](#)) and three model parameters (i.e.,  $\omega_{\text{range}}$ ,  $T_{\text{min}}$ , and  $T_{\text{max}}$ , from [Equations 6](#), [7](#), and [11](#)) were adjusted by gradient descent to minimize squared error between predictions and data, for both perceived luminance(s) and percent transparency reports. Data were well fit by the weights  $\omega_{\text{CE}} = 0.23$ ,  $\omega_{\text{INV}} = 1.33$ ,  $\omega_{\text{AD}} = 11.5$ ,  $\omega_{\text{Occ}} = 1.30$ ,  $\omega_{\text{MLP}} = 0.972$ ,  $\omega_{\text{range}} = 0.364$ ,  $T_{\text{min}} = 24.3\%$ , and  $T_{\text{max}} = 95.3\%$ .

The best-fit model indicates that (1) transparency reports vary between 24.3% ( $T_{\text{min}}$ ) and 95.3% ( $T_{\text{max}}$ ), (2) the luminance bias due to contrast enhancement is  $\pm 23\%$  ( $0.5\omega_{\text{INV}}$ ) of the difference between the average center and surround luminances ( $\omega_{\text{CE}}$ ), (3) the luminance bias present in stimuli with inverted contrasts is  $\pm 66.5\%$  of the figure luminance range for two-tone texture and drops to  $\pm 42.3\%$  for the cloudy texture (i.e., drops by 36.4% from 66.5%;  $\omega_{\text{range}}$ ), (4) compensation for atmospheric darkening adds 11.5 cd/m<sup>2</sup>, (5) the occluder strategy biases luminance by  $\pm 65.0\%$  ( $0.5\omega_{\text{Occ}}$ ) of the luminance range of the center, (6) and the “most likely pixel” strategy biases luminance by  $\pm 48.6\%$  ( $0.5\omega_{\text{MLP}}$ ) of the luminance range of the center.

Note that the reduction of the effect size from the occluder strategy ( $\pm 65.0\%$  for the simple texture) to the most likely pixel strategy ( $\pm 48.6\%$  for the complex texture) is very similar to that observed in inverted

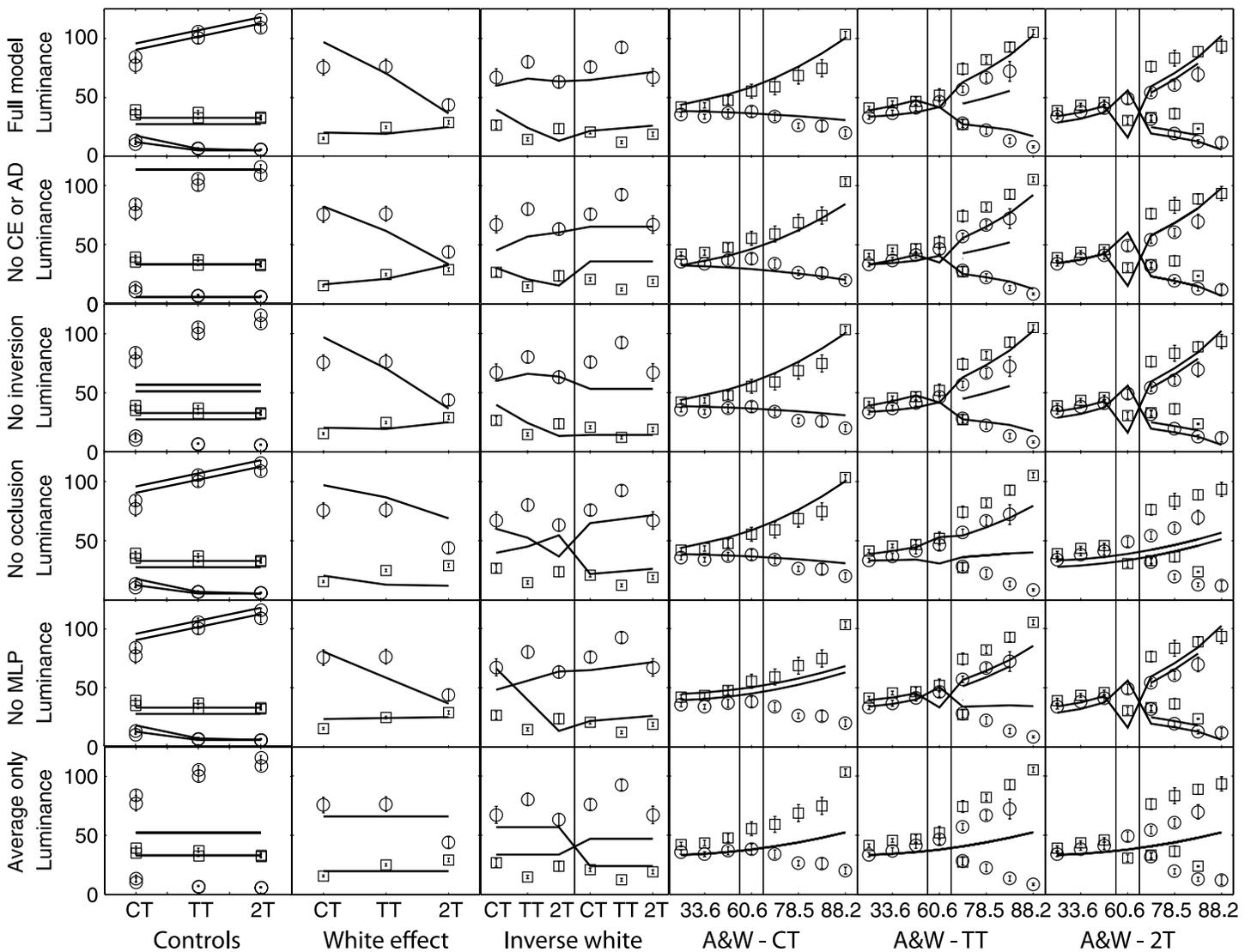


Figure 10. Luminance estimates for all conditions above except transparency conditions, and model predictions. Each row presents the model either in full (row 1), without any components (last row), or with various components excluded (rows 2–5). Model parameters were not re-adjusted when components were removed, to show the contribution of components to the final solution. Removed components are (2) contrast enhancement and atmospheric darkening, (3) inversion, (4) discounting the occluder, and (5) most likely pixel. Transparency conditions not shown. See text for details.

contrast (from  $\pm 66.5\%$  to  $\pm 42.3\%$ ). This similarity suggests that the inability to correctly recover the full luminance range in complex textures observed in the inverted-contrast conditions may well be what is causing the reduced effect size observed in Anderson–Winawer luminance configuration conditions.

The model replicates the main observations made above, namely, (1) a different pattern of lightness emerges for textures that do or do not provide visible segmentation cues, i.e., cloudy textures support the MLP strategy, whereas two-tone textures support the occluder removal strategy, (2) the White effect is much stronger with complex stimuli, reflecting mainly a different solution for segmentation mechanisms (i.e., the occluder is segmented in simple textures, whereas the occluder is

interpreted as semi-opaque but cannot be segmented for complex textures, resulting in the use of the MLP strategy), and (3) the Anderson–Winawer illusion changes direction in one specific condition for simple textures, which is due again to a different solution for segmentation mechanisms than found at higher contrasts or for complex textures.

Figure 10 breaks down the contributions to lightness of different model components. The main contribution comes from the two strategies discussed above (i.e., occluder removal and MLP; see Equations 14–19 and 20–21, respectively; see Figure 10, rows 4 and 5 for models without occlusion or MLP, respectively and Figure 10, rows 2 and 3 for models with occlusion and MLP but without other factors), which when added to the average

luminance within the figure area (Figure 10, row 6) accounts for most of the variability (except for inverted-contrast conditions). Most notably, the Anderson–Winawer conditions require both strategies so that results across textures can be accounted for. Together, contrast enhancement and compensation for atmospheric darkening (Figure 10, row 2) only add a small but systematic lightness bias in most conditions.

Contrast enhancement contributes very little to lightness overall (Figure 10, compare row 2 with row 1); however, it is the only effect that adds a bias in all of the conditions presented here. It is the only bias measurable with phase-reversed (e.g., Figure 10, column 1, top and bottom lines in graph), rotated, or untextured gray figures (e.g., Figure 10, column 1, middle lines in graph). Contrast enhancement also noticeably biases lightness in both the White effect (e.g., Figure 10, column 2) and the inverse White effect (e.g., Figure 10, column 3). Note, however, that contrast enhancement adds to the existing segmentation-induced bias in the White effect, whereas it subtracts from it in the inverse White effect. This could explain why effects of surround average luminance manipulations are easier to measure in the inverse White effect than in the White effect (e.g., Ripamonti & Gerbino, 2001).

## Discussion

### Summary

It is clear that models of luminance perception will need to take into account Anderson and Winawer's (2005, 2008) data, as well as the interaction of texture and luminance configuration as shown here (see also Poirier, 2009).

Our data show that texture changes can have drastic effects on scene interpretation, thus on perceived lightness and/or transparency report rates. In our study, increasing texture complexity (1) decreased perceived lightness range and increased transparency report rates in the inverted-contrast conditions, (2) greatly increased the White effect possibly due to a shift in strategy, as well as increased transparency report rates within the same conditions, (3) changed the direction of the Anderson–Winawer effect at the 60.6% figure contrast and removed the drops in transparency report rates at the 60.6% and 88.2% figure contrast conditions, and (4) reduced the incidence of binomial distributions in the 70.7% to 84.3% Anderson–Winawer conditions.

In addition to the effects above paralleling lightness effects, transparency report rates was a useful complementary measure, showing texture-related effects even though perceived lightness remained relatively unaffected in the following conditions: (1) the inverse White

conditions, (2) the transparency conditions, and (3) the Anderson–Winawer conditions at 88.2% figure contrast.

### Model summary

We presented here a mathematical model where different lightness biases are summed. Some of these biases are effective only if given conditions are met (e.g., texture continuity or the availability of salient segmentation cues), whereas other biases are always in effect. For a variety of textures, the model predicts the White effect, the inverted White effect, and the Anderson–Winawer effect, and their interactions with different textures.

In the model proposed here, figure lightness is a sum of the following biases or mechanisms: (1) texture discontinuity detection, (2) the occluder removal mechanism that interprets certain surfaces as occluders and removes them from further analysis (or at least, removes them from interfering with analyses of the moon's luminance), (3) the most likely pixel (MLP) mechanism that factors out average effects of semi-transparent occluders, (4) contrast enhancement mechanism that increases luminance differences possibly using simple center–surround mechanisms (thus, the effect depends on the geometry of the stimulus, e.g., Anstis, 2005; Gilchrist, 1977; Ripamonti & Gerbino, 2001), and (5) atmospheric darkening mechanism that increases lightness of any surface behind a semi-transparent occluder.

The idea that different effects on lightness are additive is not a novel one. For example, Ripamonti and Gerbino (2001; see also Anstis, 2005) suggested that assimilation and contrast effects were additive and that the inverted White effect could be explained as a special condition where one of the two effects did not contribute to lightness. Even though the present model differs from their account on several points (e.g., the choice of mechanisms contributing to the effect and the necessary conditions for each mechanism to contribute), both accounts suggest that multiple biases combine to produce the illusions. More research is needed to establish which lightness biases contribute how much to lightness and in what conditions. Mathematical analyses such as the one reported here could help in this endeavor, especially when data are collected on a wider range of stimuli.

We suggest here that lightness is dependent on texture characteristics because textures differ in the amount, quality, and visibility of segmentation cues. Reducing the visibility of these segmentation cues forces a simpler interpretation of the different surfaces. Gratings of low spatial frequency, especially square-wave gratings, offer many cues for segmentation (e.g., T-functions, smooth surfaces), thus figure, background, and occluder assignments are simple and reflectance properties of the different surfaces can be recovered fairly independently of each other (Equations 14–19). Interestingly, random checkerboard

textures such as shown in Figure 1 (see also Stuart's rings: Anstis, 2005) do not seem to reduce the visibility of segmentation cues, as long as the check size is large enough, as perceived lightness for those two textures seem to mirror each other across luminance configurations.

The model presented here is meant to describe possible causes of the effects observed here. It is unclear at present what modifications will be needed to account for naturalistic stimuli, geometric manipulations, cues to scene interpretation, etc. However, we have provided a common methodological and theoretical framework through which the investigation of luminance perception can be pursued with surfaces and textures interchangeably, across a wide range of luminance configurations.

## Seeing T-junctions

The results and model suggest the presence of two main strategies that underlie stimulus interpretation: (1) discounting the occluder and (2) the most likely pixel (MLP) strategies. All other contributions to stimulus interpretation seem small by comparison. It is difficult to identify which of these two strategies underlies scene interpretation using perceived lightness alone, as in some conditions, both strategies produce similar predictions. Transparency report rates is a more reliable indicator of strategy use. The cloudy texture is linked to *higher* transparency report rates and to higher concordance with the *MLP* strategy, even at luminance configurations that produce “blurred” T-junctions. In contrast, the two-tone texture is linked to *lower* transparency report rates and to higher concordance with the *occluder-based* strategy, especially at luminance configurations that produce T-junctions.

The presence or absence of the sudden dips in transparency report rates at 60.6% and 88.2% figure contrasts in the Anderson–Winawer conditions suggests a change of strategy in the interpretation of these stimuli. Indeed, for the two-tone texture at those specific figure contrasts, one side of the center has exactly the same luminance as the background on the same side (i.e., either  $C_A = S_A$  or  $C_B = S_B$ ), thus satisfying the conditions for occlusion to be perceived (i.e., presence of a T-junction). At other contrasts, X-junctions indicate transparency. However, it appears that texture complexity “masks” these junctions, thus removing the dips. Indeed, although “blurred” versions of these T-junctions can be found in stimuli constructed using the cloudy textures, these do not reduce the transparency report rates.

It is not the specific values of 60.6% or 88.2% figure contrast that produce this effect; rather, the effect occurs because T-junctions occur in conditions where  $C_A = S_A$  or  $C_B = S_B$ . It would be trivial to adjust background luminance ranges to produce T-junctions at any figure contrast level. These T-junctions are easy to find in two-tone textures but more effortful to find in either thresholded

textures or cloudy textures. Results with thresholded textures suggest that T-junctions are sufficient to support occlusion perception, yet can be difficult to use reliably for that purpose in complex textures at intermediate figure contrasts (i.e., 70.7% to 84.3%).

## Acknowledgments

This research was supported by a CIHR grant awarded to Martin Arguin, Frédéric Gosselin, and Dan Bub. Portions of this paper were presented at VSS 2008 (Naples, Florida).

Commercial relationships: none.

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