HUMAN VISION IS ATTUNED TO THE DIFFUSENESS OF NATURAL LIGHT

Yaniv Morgenstern¹, Richard F. Murray², and Wilson S. Geisler³

¹ Neuroscience and Behavioral Disorders Program, Duke-National University of Singapore Graduate Medical School, 8 College Road, Singapore 169857

² Department of Psychology and Centre for Vision Research, York University, 4700 Keele Street, LAS 0009, Toronto, Ontario, Canada, M3J 1P3

³ Department of Psychology and Center for Perceptual Systems, University of Texas at Austin, 108 E. Dean Keaton, Stop A8000, Austin, Texas, U.S.A., 78712-1043

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Address correspondence to: Yaniv Morgenstern
Neuroscience and Behavioral Disorders Program
Duke-National University of Singapore Graduate Medical School
8 College Road, Singapore 169857
tel +65 6516 4386
yaniv.morgenstern@gmail.com
ABSTRACT

All images are highly ambiguous, and to perceive 3D scenes the human visual system relies on assumptions about what lighting conditions are most probable. Here we show that human observers’ assumptions about lighting diffuseness are well-matched to the diffuseness of lighting in real-world scenes. We use a novel multidirectional photometer to measure lighting in hundreds of environments, and we find that previous psychophysical estimates of the visual system’s assumptions about diffuseness fall in the same range as the diffuseness of real-world lighting. We also find that natural lighting is typically directional enough to override human observers’ assumption that light comes from above. Furthermore, we find that although human performance on some tasks is worse in diffuse light, this can be largely accounted for by intrinsic task difficulty. These findings show that what seem to be perceptual biases actually arise from vision being attuned to lighting conditions in real world scenes.
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The image of an object can vary enormously depending on the direction, diffuseness, and complexity of its illumination (Dror, Willsky, & Adelson, 2004; Figure 1). As a result, when the human visual system attempts to recover the 3D shape and surface properties of an object from retinal images, whether it succeeds often depends on whether it has accurate information about the scene’s lighting (Fleming, Dror, & Adelson, 2003). The visual system estimates lighting conditions from cues in individual scenes (Brainard & Maloney, 2011; Pont & Koenderink, 2007), but it also relies on general assumptions about what lighting conditions are most likely to occur (Metzger, 1936/2006, pp. 148-150). In a Bayesian statistical framework, these assumptions are called priors. Two central problems for understanding human visual perception are determining what the true statistical distributions of lighting conditions, shapes, and materials are in the real world, and what priors the visual system relies on to perceive 3D scenes (Kersten, Mamassian, & Yuille, 2004; Knill & Richards, 1996). Here we study these problems as they relate to lighting.

Most work on the human visual system’s assumptions about lighting has examined the light-from-above prior, the assumption that light comes from overhead (Metzger, 1936/2006; Morgenstern, Murray, & Harris, 2011; Ramachandran, 1988). An equally important property of lighting, though, is its diffuseness, the extent to which light comes mostly from a single direction, as on a sunny day, or from all directions, as on a cloudy day (Langer & Bülthoff, 2000; Tyler, 1998). Lighting diffuseness has a large effect on object appearance (Figure 1), and the assumptions that observers make about diffuseness can have a correspondingly strong influence on their perception of 3D scenes. Five recent psychophysical studies have investigated the assumptions that observers make about lighting diffuseness when estimating shape and reflectance, and found that observers
tend to assume high levels of diffuseness -- often higher than the actual diffuseness of the light in the scene being viewed (Bloj et al., 2004; Boyaci, Maloney, & Hersh, 2003; Boyaci, Doerschner, & Maloney, 2004, 2006; Schofield, Rock, & Georgeson, 2011). This suggests that observers may have a prior for highly diffuse lighting.

Figure 1. Photographs illustrating the influence of lighting direction and diffuseness on image appearance. The small plaster figure is illuminated from various directions with various levels of diffuseness. Contrast amplitude and even contrast polarity vary markedly from image to image.

A prior is adaptive when it matches the observer’s environment, but almost nothing is known about typical diffuseness levels of natural lighting. In Experiment 1 we examine the diffuseness of lighting in a wide range of real-world scenes, and we compare these measurements to previous psychophysical estimates of the assumptions that observers make about lighting diffuseness.

EXPERIMENT 1

We used a custom-built multidirectional photometer (Figure 2) to record natural lighting in several hundred diverse scenes. The photometer recorded low-resolution, omnidirectional ‘light
probes’: snapshots of the pattern of illumination incident from all directions at a point in space at a
given time (Dror et al., 2004; Mury, Pont, & Koenderink, 2007, 2009a, 2009b). We measured
lighting conditions in rural and urban environments, under sunny and cloudy conditions, and in
indoor environments.

We define a new measure of diffuseness, Lambertian contrast energy (LCE), that allows us
to describe our lighting measurements and the results of previous psychophysical studies in a
common language. Let $E(\theta, \phi)$ be the illuminance pattern over the surface of a unit sphere
illuminated by a light probe, described in spherical coordinates where $\theta$ is the declination from the
north pole and $\phi$ is the azimuth. We define the LCE of the light probe to be the coefficient of
variation of the illuminance over the sphere, i.e., its standard deviation divided by its mean:

$$
\lambda = \left( \frac{1}{4\pi} \int_0^{2\pi} \int_0^\pi \left( \frac{E(\theta, \phi) - \bar{E}}{\bar{E}} \right)^2 \sin \theta d\phi d\theta \right)^{1/2}
$$

Here $\bar{E}$ is the mean illuminance over the sphere. Under diffuse light, illuminance is largely
constant across surface orientations, whereas under directional light the illuminance depends on the
orientation of a surface relative to the dominant light sources. LCE is a measure of this variation of
illuminance across orientations, and hence of diffuseness. LCE ranges from 0 for a completely
uniform, ambient light source to 1.29 for a distant point light source (Morgenstern, 2011).

We compared the LCE of natural lighting measurements with the LCE of the diffuseness
levels assumed by human observers, as measured in previous psychophysical studies.
METHOD

Measurements of natural illumination

We used a multidirectional photometer that recovers light probes up to their second order spherical harmonics, which is the component of lighting that is relevant to illumination of convex Lambertian objects (Ramamoorthi & Hanrahan, 2001; Basri & Jacobs, 2003). The device is a 20 cm diameter aluminum sphere equipped with 64 evenly spaced photodiodes (UDT Sensors, Inc., model PIN-10AP) that are filtered to have the same spectral sensitivity as human observers under photopic viewing conditions. A laptop computer records the activation of each photodiode. For further information on the photometer, see Morgenstern (2011).

Measurements were made at York University between 12:00 pm and 1:30 pm, from August to October 2010. Each measurement site was chosen so that previous sites could not be seen. The photometer sat on a microphone stand, 122 cm above the ground. We kept it 30 cm away from objects, except in rural, forested areas where this was not always possible. We made 570
measurements in several environments, listed in the legend to Figure 3. All measurements are available online as supplemental information.

We calculated the LCE of each light probe measurement. Ramamoorthi and Hanrahan (2001) and Basri and Jacobs (2003) show how to find the illuminance pattern $E(\theta,\phi)$ over a sphere illuminated by a light probe.

### Data from psychophysical studies

To describe actual lighting conditions and the lighting conditions assumed by human observers, previous psychophysical studies used the notion of a point-plus-ambient (PA) illuminant (Phong, 1975). A PA illuminant consists of a distant point source and an ambient source, and under such lighting the illuminance on a surface patch is

$$ E(\alpha) = \begin{cases} 
E_p \cos(\alpha) + E_A & \alpha < 90^\circ \\
E_A & \alpha \geq 90^\circ 
\end{cases} $$(2)

Here $\alpha$ is the angle of the surface normal relative to the point source direction, $E_p$ is the maximum illuminance from the point source, and $E_A$ is the illuminance from the ambient source.

Morgenstern (2011, pp. 141-143) shows that the LCE of a PA light source is

$$ \lambda = \begin{cases} 
\frac{\sqrt{5/48}}{(E_A / E_p) + 0.25} & E_p > 0 \\
0 & E_p = 0 
\end{cases} $$(3)

In the supplemental information we explain how we recovered the ratios $E_A / E_p$ from the previous psychophysical studies. We used equation (3) to convert these ratios to LCE.
RESULTS AND DISCUSSION

Figure 3a shows the LCE of our lighting measurements. Each environment’s histogram is scaled to peak at one. Figure 3a also shows two reference values: the dashed vertical line at the right shows the LCE of a distant point light source, and the dashed vertical line near the middle shows the LCE of the default lighting in OpenGL, a typical example of illumination in computer-generated scenes. The histograms show that natural light is more diffuse than one might have expected. The light probes mostly fall in the bottom half of the range of physically possible LCE values, and only the most directly illuminated environments are as direct as default OpenGL lighting. (We use “direct” to mean the opposite of “diffuse”.) The lowest LCE’s come from indoor environments, and the highest come from forested environments on sunny days, where the sun is sometimes visible through openings in the canopy. The vertical blue line in Figure 3a shows the mean LCE over all measurements, but this value is only a rough measure of central tendency, since it depends on the relative number of measurements in the different environments. Supplemental Table S1 gives the means and standard deviations of the LCE in individual environments.

Figure 3b shows the assumptions about diffuseness that guided observers’ behavior in previous psychophysical studies. Bloj et al. (2004) and Boyaci et al. (2003, 2004, 2006) inferred observers’ assumptions about diffuseness from biases in lightness and color constancy tasks, and Schofield et al. (2011) used a shape perception task.

The lighting in Bloj et al.’s scenes mostly had LCE values above those of most natural environments. Their observers behaved as if the lighting was much more diffuse than this, though, with LCE values closer to the middle of the LCE distribution for natural lighting, as would occur if their lighting estimates were guided by a prior that matched natural environments.
Figure 3. Comparison of LCE values from natural lighting and psychophysical performance.

(a) Histograms of the LCE of natural lighting in several environments, each scaled to peak at one. The dashed vertical lines show the LCE of a light source matched to Morgenstern et al.’s ‘weak cue’ condition, the LCE of default OpenGL lighting (a distant point source and an ambient source, with the point source five times as strong as the ambient), and the LCE of a distant point light source. The thick vertical blue line shows the mean LCE over all environments. (b)

Psychophysical estimates of observers’ assumptions about diffuseness. Small vertical blue lines show the LCE assumptions of individual observers. Blue dots show averages across observers. The thick vertical blue line shows the mean LCE over all of Bloj et al.’s and Schofield et al.’s observers. Red lines show the LCE of the actual illuminants in the experiments. Schofield et al. ran their experiments in the dark and with a highly ambiguous sine wave stimulus, so we do not show a red line indicating the LCE value for their lighting.
Schofield et al.’s observers also assumed diffuseness levels that were consistent with the levels we found in natural lighting. Schofield et al.’s method of inferring diffuseness priors was different from Bloj et al.’s (based on shape judgments instead of lightness judgments), so their data provide an independent test of observers’ assumptions about lighting. Furthermore, Schofield et al.’s measurements are the most direct indicators of the visual system’s prior on diffuseness, as their experiments were run in the dark and their stimulus was simply a sine wave grating, which is highly ambiguous with regard to lighting and 3D shape; Bloj et al.’s and Boyaci et al.’s scenes were more complex and contained cues to lighting diffuseness that may have affected observers’ estimates of the lighting conditions. Supplemental Figure S1 shows LCE values based on a refinement of Schofield et al.’s model; the LCE values are somewhat lower, but still well within the range of natural lighting.

Boyaci et al. obtained rather different results. The lighting in Boyaci et al.’s scenes had LCE values that were more typical of natural environments (except Boyaci et al.’s (2006) experiment 2), but their observers seem to have assumed that lighting was highly diffuse, and in fact much more diffuse than almost any realistic lighting condition. (In the supplemental information we discuss the four unusually high LCE values from Boyaci et al. (2004), which we believe to be artifacts.) However, there are good reasons to think that their results are biased towards high estimates of diffuseness (i.e., low LCE). Boyaci et al.’s observers’ lightness constancy was poor; their lightness matches were partway between matching the luminance of image patches on the computer screen and matching the reflectance of the surface patches they depicted, with a strong bias towards matching luminance (e.g., Boyaci et al. (2003), Figure 8). The ‘equivalent illuminant’ model that Boyaci et al. used to infer observers’ diffuseness assumptions
attributes such failures of lightness constancy to assumptions of high diffuseness. However, there are many reasons why lightness constancy can fail, besides observers assuming unrealistically high levels of diffuseness. Unlike Bloj et al.’s scenes, Boyaci et al.’s scenes were computer generated, and if observers did not see them as completely realistic then they may have been biased towards matching screen luminance instead of matching the depicted surface reflectance. Supporting this view, Lee and Brainard (2012) found that a computer-generated replication of Gilchrist’s (1977) paper-based lightness perception experiments led to much weaker constancy. Furthermore, failures of lightness constancy occur when observers judge lightness in scenes that have dark backgrounds, small frameworks, and low articulation (Gilchrist, 2006, p. 276), which are all factors consistent with weak lightness constancy in Boyaci et al.’s experiments. Thus Boyaci et al.’s estimates of observers’ assumptions about diffuseness were probably biased, and we do not see them as persuasive evidence against a diffuseness prior that matches natural lighting.

To summarize, all five psychophysical studies suggest that human observers have a prior on lighting diffuseness, and Bloj et al.’s and Schofield et al.’s results indicate that observers’ priors fall in the same range as our measurements of the diffuseness of real-world lighting. Observers showed a wide range of assumptions about lighting diffuseness, but this is consistent with studies of the light-from-above prior, which have also found large individual differences in assumed lighting directions (Adams, 2007).

Our measurements show that the average of observers’ diffuseness assumptions is in line with the average diffuseness of natural lighting. This leaves open the question of how strong observers’ diffuseness prior is, i.e., how narrow the prior is as a statistical distribution, and whether it usually overrides diffuseness cues in individual scenes. One the one hand, the large individual differences in observers’ diffuseness assumptions, as well as the wide range of diffuseness in
natural lighting, suggest that the prior may be weak. On the other hand, the fact that Bloj et al.’s stimuli provided observers with cues to diffuseness and yet observers’ diffuseness estimates consistently had lower LCE than the actual lighting suggests that the prior may be strong. Further studies will be needed to settle this question.

**EXPERIMENT 2**

If human vision is tuned to the relatively high diffuseness levels of natural lighting, then what are we to make of findings that human observers perform some tasks poorly under diffuse lighting? For example, Pont and Koenderink (2007) found that observers are much worse at estimating the dominant lighting direction under diffuse lighting than under direct lighting. Furthermore, it is well known that the image of a Lambertian sphere rendered under completely diffuse lighting is simply a uniform disk, and does not appear spherical at all. One possibility suggested by the latter example is that diffuse lighting makes some tasks intrinsically harder, in the sense that diffusely lit scenes simply provide less task-relevant information to the observer. If so, then poor performance under diffuse lighting might be explained by the reduction in task-relevant information, and could be consistent with the idea that human vision is optimized for diffuse lighting. To test this possibility, we designed a lighting direction discrimination task in which we measured the performance of both human observers and an ideal observer that makes optimal use of the stimulus information, achieving the best possible performance (Geisler, 1989). We measured lighting direction discrimination thresholds $\Delta \alpha$ for human and ideal observers under four levels of lighting diffuseness. We calculated human observers’ efficiency, the squared ratio of ideal and human thresholds (Tanner & Birdsall, 1958):

$$\eta = \left( \frac{\Delta \alpha_{\text{ideal}}}{\Delta \alpha_{\text{human}}} \right)^2$$

(4)
Efficiency is 1.0 for a human observer who has the same threshold as the ideal observer, and less for an observer who has a higher threshold. Efficiency corrects for intrinsic task difficulty, so it gives an effective way of comparing performance across diffuseness conditions.

METHOD

Participants. The first author and four naïve observers (paid $10/hour) from York University participated. All observers reported normal or corrected-to-normal vision, and their ages ranged from 20 to 31 years old. All observers ran in both the slant task and the tilt task.

Figure 4. Typical stimuli in the lighting direction discrimination experiment, illuminated from slant 60° and tilt 30°. The LCE values are those used in the experiment, namely (a) 0.65, (b) 0.35, (c) 0.18, and (d) 0.08.

Stimuli. The stimuli were OpenGL renderings of a hemispherical polyhedron composed of 152 Lambertian triangles (Figure 4). The polyhedron subtended 9 degrees of visual angle. The
simulated lighting consisted of a distant point source with direction \( \hat{p} \) and maximum illuminance \( E_p \), and an ambient source with illuminance \( E_A \). The luminance of each triangular patch with reflectance \( \rho \) and surface normal \( \hat{n} \) was determined by the Lambertian shading model:

\[
l = \frac{\rho}{\pi} (E_p \max(\hat{p} \cdot \hat{n}, 0) + E_A)
\]

(5)

Here \( \max(x, y) \) is the larger of \( x \) and \( y \), and \( \cdot \) is the vector dot product.

The reflectances of the triangles making up the polyhedron were drawn independently for each new stimulus from a truncated normal distribution \( \phi_{tr}(x, \mu, \sigma) \) with mean 0.6 and standard deviation 0.2. The distribution was truncated at two standard deviations from the mean, so reflectance spanned the interval [0.2, 1.0].

Stimuli were shown on a CRT monitor (Dell E770s, 15”, resolution 1024 x 768, pixel size 0.305 mm, frame rate 85 Hz) in a dark room at a viewing distance of 57 cm. The colour lookup table of the computer’s video card linearized the relationship between RGB values in video memory and luminance on the monitor. A simulated surface patch with the mean reflectance value (0.60) had luminance 110 cd/m\(^2\) when directly facing the virtual point light source.

**Procedure.** We describe lighting directions in terms of slant and tilt. Slant is the angle relative to a line perpendicular to the computer monitor, so a slant of 0° is directly towards the viewer and 90° is in the plane of the monitor. We define tilt such that 0° is upwards and positive angles are clockwise.

In the slant discrimination task, observers discriminated between two lighting directions with different slants. Each observer participated in four 10-15 minute blocks of 300 trials over one or two days. In different blocks, the ambient-to-total light ratio \( E_A / (E_p + E_A) \) of the illuminant was set to 0.20, 0.40, 0.60, or 0.80, corresponding to LCE values of 0.65, 0.35, 0.18, and 0.08,
respectively. The maximum simulated illuminance $E_p + E_a$ was held constant at 576 lux. Blocks were run in random order.

Each trial began with a blank screen for 500 ms, followed by the first stimulus for 500 ms, another blank screen for 500 ms, the second stimulus for 500 ms, and finally a blank screen until the observer responded. One stimulus interval showed a hemisphere illuminated from slant $60^\circ + \Delta \theta$ and tilt $0^\circ$, and the other showed a hemisphere illuminated from slant $60^\circ - \Delta \theta$ and tilt $0^\circ$. The two slant directions were randomly assigned to the two stimulus intervals. The observer pressed a key to indicate which interval had a lighting direction closer to the line of sight. The task was not trivial, because reflectances were assigned randomly in each new stimulus, so the luminance variations that provided information about lighting direction were partly masked by luminance variations caused by random assignment of reflectances. After an incorrect response, the observer heard a beep. The next trial began immediately. The perturbation angle $\Delta \theta$ varied over trials according to interleaved staircases converging on 71% and 79% correct performance (Wetherill & Levitt, 1965). The blank screens and the stimulus background were shown at the monitor’s lowest luminance, which was less than 0.1 cd/m$^2$. We made a maximum-likelihood fit of a Weibull psychometric function to proportion correct as a function of the angle between the two lighting directions, and we took the angle corresponding to 75% correct performance as the observer’s threshold.

The tilt discrimination task was the same as the slant task, except that the two stimulus intervals showed polyhedral hemispheres illuminated from tilts $\pm \Delta \phi$ and slant $60^\circ$. Observers indicated which stimulus had lighting from a more clockwise direction. We measured the difference between lighting angles that gave 75% percent correct performance.

*Ideal observer analysis.* We simulated the performance of an ideal observer on the slant
and tilt discrimination tasks, at the same four diffuseness levels seen by human observers, and found the ideal observer’s 75% thresholds. In the supplemental information we give a mathematical description of the ideal observer and we provide the code for our ideal observer simulations. Ideal observer analysis has mostly been applied to 2D problems in spatial vision, and to our knowledge this ideal observer is novel in that it incorporates a 3D imaging model, illustrating how ideal observers can be used to understand perception of lighting, and potentially also 3D shape and reflectance.

RESULTS AND DISCUSSION

In Figure 5, panels (a) and (b) show thresholds as a function of lighting diffuseness. In both tasks, thresholds were higher at higher levels of diffuseness. In the slant task, a linear regression of threshold against LCE had slope -60.8, with a bootstrapped 95% confidence interval of (-119.0, -46.7). In the tilt task, the regression had slope -75.4 with confidence interval (-85.7, -64.8). This result is consistent with Pont and Koenderink’s (2007) finding that observers are less accurate at estimating the direction of diffuse lighting than of direct lighting. For two observers the slant task was so difficult at the highest diffuseness level that thresholds could not be measured, so green and light blue data points are missing from the leftmost cluster of thresholds.

The black squares in the same panels show the ideal observer’s thresholds, which follow a similar pattern to human thresholds even though they are an order of magnitude lower. This suggests that much of the variation in human performance across diffuseness levels is due to the intrinsic difficulty of the tasks. Panels (c) and (d) show human efficiency as a function of lighting diffuseness, and support this interpretation. Compared to thresholds, efficiency is almost constant across diffuseness levels, and if anything is higher at high diffuseness levels. In the slant task, a
linear regression of efficiency against LCE had slope -0.022 with a bootstrapped 95% confidence interval of (-0.038, -0.012). In the tilt task, the regression had slope -0.002 with confidence interval (-0.013, 0.012). Thus the fact that human performance is much better with directly illuminated scenes does not mean that vision is optimized for direct illumination. Observers’ performance simply reflects the fact that directly illuminated scenes provide more task-relevant information.

Figure 5. Thresholds and efficiency in the lighting direction discrimination experiment. Each colour corresponds to a different observer. Error bars represent 95% confidence intervals, obtained by parametric bootstrapping. The black squares in the top two panels show the ideal observer’s thresholds. All observers viewed lighting conditions with the same four LCE values, but we have jittered the data points horizontally so that they do not overlap.
We did not find observers to be consistently more efficient under diffuseness levels typical of natural lighting, as one might expect if they have a realistic prior for diffuseness. However, the many polygon faces in our stimuli, covering a hemisphere of orientations, provide a great deal of information about the lighting direction and diffuseness in the scene. We confirmed this using ideal observer simulations: ideal thresholds for direction discrimination are just the order of a few degrees, and ideal thresholds for diffuseness discrimination are on the order of 0.01 LCE units. Thus any prior assumptions about diffuseness may have been overridden by the precise lighting information conveyed by these stimuli. Similar experiments with less informative stimuli, such as polyhedra with fewer faces, may reveal larger differences in efficiency across diffuseness conditions. A related point is that the diffuseness levels we tested were all within the range of natural lighting. An interesting task for future studies is to test whether efficiency is lower for unnaturally direct or diffuse lighting.

GENERAL DISCUSSION

Previous studies have also measured light probes in order to examine the statistical structure of natural lighting (Dror et al., 2004; Mury et al., 2007, 2009a, 2009b). The contribution of our experiments has been to collect a large number of light probes in diverse environments, and to characterize the diffuseness of the lighting in these scenes. Dror et al. used Debevec’s (1998) and Teller et al.’s (2003) high-resolution light probes to examine the statistics of natural lighting. Debevec measured a small number of high-resolution light probes, and Dror et al. used just nine light probes of this type. Teller et al.’s light probes covered only about half of the sphere of possible directions, so they cannot be used to measure diffuseness. Mury et al. used a multidirectional photometer similar to our own (and developed independently), but they examined a
smaller number of light probes in a limited range of environments, and did not examine diffuseness. Morgenstern et al. (2011) showed that the light-from-above prior is weak, in the sense that it is easily overridden by lighting direction cues such as shading and shadows. Does this mean that natural lighting usually overrides the light-from-above prior, so that this well-known prior is actually unimportant in everyday perception? Our diffuseness measurements also provide an answer to this question.

Morgenstern et al. created a lighting condition (their ‘weak cue’ condition) that is matched to the light-from-above prior: lighting conditions that provide stronger lighting direction cues than this matched condition override the prior, and lighting conditions that provide weaker cues do not. The dashed vertical line at the left of Figure 3a shows the LCE of a lighting condition that provides lighting direction cues as strong as those in Morgenstern et al.’s matched lighting. (See supplemental information for details of this calculation.) Almost all our natural lighting measurements had much higher LCE’s than this, so they almost certainly provided stronger lighting direction cues. The strength of lighting direction cues also depends on whether there are 3D shapes in the scene that generate shading and shadow cues, of course, but few scenes are completely devoid of such shapes, and Morgenstern et al.’s equivalent illuminant is so far below the natural LCE distribution that observers will rarely encounter light that approaches this level of diffuseness. We conclude that the light-from-above prior is unimportant in everyday perception.

The Bayesian view of vision has been influential, but it has often been difficult to compare the psychophysically determined assumptions that guide perception with independently measured statistical distributions that characterize the real world. Fortunately there has been much work recently on characterizing perceptually important properties of real-world scenes (Attewell & Baddeley, 2007; Dror et al., 2004; Mury et al., 2007, 2009a, 2009b; Potetz & Lee, 2003). The case
of natural lighting shows how we can advance our understanding of the human visual system by comparing its performance to properties of the world whose ambiguous signals it must use to create accurate and reliable percepts.
REFERENCES


Calculating Lambertian contrast energy from previous studies

Bloj et al. (2004) show plots where diffuseness is given by data points’ radial positions (their Figures 5 to 10). The radial position is $\nu = 1 / (F_A + 1)$ (their equation (7)). $F_A$ is the ratio of the illuminance $E_A$ from ambient light, to the illuminance $I_D \sin(\phi_D) / d^2$ from a point source of luminous intensity $I_D$ at distance $d$ and elevation $\phi_D$: $F_A = d^2 E_A / I_D \sin(\phi_D)$ (unnumbered equation below their equation (6)). The illuminance that a surface would receive directly facing the illuminant is $E_P = I_D / d^2$, so $E_A / E_P = F_A \sin(\phi_D)$. In Bloj et al., $\phi_D = 30^\circ$. We read $\nu$ from their plots using data capture software, and calculated $E_A / E_P = F_A \sin(30^\circ) = ((1 / \nu) - 1) \sin(30^\circ)$. Equation (3) converts $E_A / E_P$ to LCE.

Boyaci et al. (2003) report the ratio $\hat{\pi} = E_p / (E_p + E_A)$ that explains each observer’s behavior (their Table 1). $E_A / E_P = (1 / \hat{\pi}) - 1$, and equation (3) converts $E_A / E_P$ to LCE.

Boyaci et al. (2004) report ratios $\Delta = E_A / E_P$, and equation (3) converts this to LCE.

Boyaci et al. (2006) show plots where the radial coordinate is $\hat{\pi} = E_p / (E_p + E_A)$, which can be converted to LCE the same way as Boyaci et al.’s (2003) $\hat{\pi}$.

Schofield et al. fit their equation (5) to observers’ shape judgements, and reported diffuseness parameters $\gamma$ in their Table 1. The first term in their equation (5), in parentheses following $(1 - \gamma)$, approximates the luminance pattern of a sinusoidal surface under a point source that would create a luminance of $1 - \gamma$ on a surface facing it directly. The second term, following $\gamma$, approximates the luminance pattern of a sinusoidal surface under an ambient source that creates a maximum luminance of $0.5\gamma$. Thus $E_A / E_P = 0.5\gamma / (1 - \gamma)$, and equation
Note on Boyaci et al. (2004). The wide range of LCE values for Boyaci et al. (2004) in our Figure 3 reflects their Table 2, where $\Delta = \frac{E_A}{E_P}$ was highly variable. Large differences in $\Delta$ do not always reflect clear differences in behaviour. Consider their observer BH, who had $\Delta = 1.39$ for light from the left and $\Delta = 0.12$ for light from the right (their Table 2). These correspond to LCE values of 0.20 and 0.87, respectively. Their Figure 11 shows observers’ chromaticity settings, and BH’s settings were not drastically different for lighting from left and right. Similar comments apply to RG. Furthermore, their Figure 10 suggests that MM’s chromaticity settings varied less with patch orientation than MD’s, and yet their Table 2 attributes more direct illumination assumptions to MM. Thus their estimates of $\Delta$ may have had a large variance.

Ideal observer analysis of lighting direction discrimination

The ideal observer knew the polyhedron’s 152 normal vectors, the reflectance distribution, and the two lighting directions on each trial, $\tilde{p}_1$ and $\tilde{p}_2$. The stimulus was two sets of 152 luminances, $L_i = \{l_{ij}\}_{j=1}^{152}$, $i = 1, 2$, from two stimulus intervals. The posterior probabilities that the lighting directions were shown in order ($\tilde{p}_1, \tilde{p}_2$) or ($\tilde{p}_2, \tilde{p}_1$) are

\begin{align}
P(\tilde{p}_1, \tilde{p}_2 | L_1, L_2) &= \frac{P(L_1, L_2 | \tilde{p}_1, \tilde{p}_2) P(\tilde{p}_1, \tilde{p}_2)}{P(L_1, L_2)} \quad (S1) \\
P(\tilde{p}_2, \tilde{p}_1 | L_1, L_2) &= \frac{P(L_1, L_2 | \tilde{p}_2, \tilde{p}_1) P(\tilde{p}_2, \tilde{p}_1)}{P(L_1, L_2)} \quad (S2)
\end{align}

The ideal observer finds the probability ratio

\begin{align}
\frac{P(\tilde{p}_1, \tilde{p}_2 | L_1, L_2)}{P(\tilde{p}_2, \tilde{p}_1 | L_1, L_2)} \quad (S3)
\end{align}
The two lighting orders are equally probable, so equation (S3) is equivalent to the likelihood ratio

$$\frac{P(L_1, L_2 \mid \bar{p}_1, \bar{p}_2)}{P(L_1, L_2 \mid \bar{p}_2, \bar{p}_1)}$$  \hspace{1cm} (S4)

Given a fixed lighting order, luminances $l_{ij}$ of different patches are independent, so the numerator in equation (S4) is

$$P(L_1, L_2 \mid \bar{p}_1, \bar{p}_2) = P(L_1 \mid \bar{p}_1)P(L_2 \mid \bar{p}_2)$$  \hspace{1cm} (S5)

$$= \prod_{j=1}^{152} P(l_{1j} \mid \bar{p}_1) \prod_{j=1}^{152} P(l_{2j} \mid \bar{p}_2)$$  \hspace{1cm} (S6)

Equation (5) shows that the distribution of each luminance $l_{ij}$ is a rescaling of the reflectance distribution with constant of proportionality $c_{ij} = (E_p \max(\bar{p}_k \cdot \bar{n}_j, 0) + E_A) / \pi$. If stimulus interval $i$ has lighting direction $\bar{p}_k$, the probability density of $l_{ij}$ is $c_{ij}^{-1} \phi_n(c_{ij}^{-1} l_{ij}, \mu, \sigma)$, where $\phi_n(x, \mu, \sigma)$ is the truncated normal distribution of reflectances. Equation (S6) becomes

$$= \prod_{j=1}^{152} c_{1j}^{-1} \phi_n(c_{1j}^{-1} l_{1j}, \mu, \sigma) \prod_{j=1}^{152} c_{2j}^{-1} \phi_n(c_{2j}^{-1} l_{2j}, \mu, \sigma)$$  \hspace{1cm} (S7)

The likelihood of the observed luminances under the opposite lighting order is

$$P(L_1, L_2 \mid \bar{p}_2, \bar{p}_1) = \prod_{j=1}^{152} c_{2j}^{-1} \phi_n(c_{2j}^{-1} l_{1j}, \mu, \sigma) \prod_{j=1}^{152} c_{1j}^{-1} \phi_n(c_{1j}^{-1} l_{2j}, \mu, \sigma)$$  \hspace{1cm} (S8)

The ideal observer calculates the likelihoods of the luminances under the two lighting orders using equations (S7) and (S8), and chooses the order that generates the higher likelihood.

Using simulations we found the ideal observer’s 75% thresholds in the slant and tilt discrimination tasks, under the four diffuseness levels seen by human observers.
Morgenstern et al.’s (2011) ‘weak cue’ lighting condition was about as strong as the light-from-above prior in terms of its influence on observers’ lighting direction estimates. We cannot simply calculate the LCE of this illuminant and compare it to natural lighting, though. In their strong cue condition, the light was a point source in the direction of the viewer, and a stronger source slightly forward of the frontoparallel plane. In their weak cue condition, they switched the two sources, so that most light came from the viewing direction. Thus lighting in the two conditions had the same LCE, and the weak condition provided weak cues only because the stronger source was accidentally aligned with the viewing direction.

We circumvented this problem by finding the PA illuminant that provides lighting cues that are equally informative, to an ideal observer, as the weak cue condition. First we measured ideal performance at discriminating between lighting directions 10° apart, in Morgenstern et al.’s weak cue scenes covered in pixelwise white Gaussian noise. (This ideal observer is simply a template matcher.) We averaged ideal performance across 36 such tasks, with lighting directions 0° vs. 10°, 10° vs. 20°, etc. Second, we measured ideal performance at the same task, but with a PA illuminant. The point source varied across the same directions as in the first simulation. A point-to-ambient ratio $E_A / E_p = 5.54$ gave the same ideal performance as in the first task. Equation (3) converts this to an LCE of $\lambda = 0.056$, shown by the dashed line in Figure 3.
Supplemental Figure S1. This figure is the same as Figure 3, except for the data for Schofield et al.; see Supplemental Table S2 for details. The revised LCE values from Schofield et al. are still in the range of natural lighting, although slightly lower than the corresponding values in Figure 3.
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**Supplemental Table S1.** Summary statistics of LCE values shown in Figures 3 and S1.
Supplemental Table S2. Andrew Schofield (personal communication) suggested that equation (S1) approximates the luminance profile of a sinusoidal surface better than Schofield et al.’s equation (5).

\[
L \approx (1 - \gamma) \left[ \cos \left( \frac{\pi}{2} - e \right) - 0.12 \sin(x) \cos \left( \frac{\pi}{2} - \phi + \lambda \right) \sin \left( \frac{\pi}{2} - e \right) \right. \\
- \cos \left( \frac{\pi}{2} - e \right) 0.12 \sin^2(x)/2 \left. \right] + \gamma \left( 0.5 - 0.067(1 - \cos(x)) + 0.041(1 + \cos(2x)) \left\lfloor -0.99 \cos(x) \right\rfloor \right) 
\]

Here the variables are the same as in Schofield et al.’s equation (5), and \( \left\lfloor x \right\rfloor \) is \( x \) rounded to the next higher integer. Andrew Schofield provided us with the values in the table, obtained by fitting equation (S1) to Schofield et al.’s data instead of Schofield et al.’s equation (5).

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