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Variability in constancy of the perceived surface reflectance across different illumination statistics

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ABSTRACT

In contrast to the classical findings of lightness constancy, recent psychophysical studies show the strong dependency of the perceived reflectance of a surface on the structure of the natural illumination. The present study examined this inconstancy for systematic variations in the light field and an image-based explanation for it. Observers matched the specular and diffuse reflectance of a three-dimensional object in a complex scene under a fixed light field to that in the scene under different light fields with variable mean, contrast, and gamma. For the both specular and diffuse components, the matched reflectance was relatively constant against changes in the mean illuminance but varied extensively with changes in the contrast and gamma of the light field. We found that the matching data were well predicted by the similarity of the subband histograms of the images. The results support the notion that early spatial filtering can provide a unified account of both the constancy in the perceived surface reflectance against mean illuminance and the inconstancy for higher-order illumination statistics.

1. Introduction

It has long been suggested that humans perceive the constant lightness of matte and flat surfaces against variations in the intensity of illumination (Adelson, 1999; Brainard & Maloney, 2011; Gilchrist, 2006; Land & McCann, 1971; Wallach, 1948). A number of studies have demonstrated that humans can estimate, although imperfectly, constant and veridical lightness not only when a patch is embedded in a simplified background (e.g., Adelson, 1999; Arend & Goldstein, 1987; Wallach, 1948), but also when it is naturally located in realistic three-dimensional scenes with a particular orientation with respect to the direction of the light source (Bloj, Kersten, & Hurlbert, 1999; Boyaci, Maloney, & Hersh, 2003; Brainard, 1998; Brainard & Maloney, 2011; Doerschner, Boyaci, & Maloney, 2007; Gilchrist, 1977; Gilchrist & Radonjic, 2010; Knill & Kersten, 1991). Several studies have extended the findings to non-flat objects (Gilchrist & Jacobsen, 1984; Robilotto & Zaidi, 2004). This lightness (and color) constancy has been considered primary support for the notion that the visual system virtually discounts illumination when estimating the reflectance property of a surface (Brainard, 1998; Gilchrist, 2006; Maloney & Yang, 2003).

On the other hand, recent psychophysical evidence shows that the perceived glossiness of a non-flat object can depend substantially on the structure of the global illumination; i.e., the light field (Doerschner, Boyaci, & Maloney, 2010; Dror, Willsky, & Adelson, 2004; Fleming, Dror, & Adelson, 2003; Olkkonen & Brainard, 2010; Pont & te Pas, 2006). While the perceived glossiness of a sphere is relatively constant across several natural light fields (Fleming, Dror, & Adelson, 2003), it can vary substantially with the structure of the light field (Doerschner, Boyaci, & Maloney, 2010; Fleming, Dror, & Adelson, 2003; Olkkonen & Brainard, 2010; Pont & te Pas, 2006). In an extreme case, a glossy natural object appears matte under diffuse light fields (Pont & te Pas, 2006). This glossiness inconstancy does not favor the idea of veridical reflectance reconstruction.

The nature of the discrepancy between the lightness constancy and the glossiness inconstancy is not very clear. Lightness constancy has been shown mostly for matte and flat, or near-flat, 'patches' while glossiness inconstancy has been shown for glossy and shaped surfaces. Very recently, Olkkonen and Brainard (2010) investigated both perceived diffuse and specular reflectances in an integrated situation, and showed that human reflectance matching of a sphere is independent of the light field for the diffuse component, but not for the specular component. On the other hand, demonstrations by Pont and te Pas (2006) indicate that both the apparent gloss and lightness of complex shaped objects are strongly affected by the type of light field.

The present study examined both the perceived diffuse and specular reflectances of a complex shaped object in a naturalistic scene under light fields whose intensity statistics were systematically varied. Observers were asked to match the reflectance of the target object under a fixed light field to that under light fields with

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different mean, contrast, and gamma. We found that the matched specular and diffuse reflectances were both relatively constant across changes in the mean illuminance, but differed considerably depending on the contrast and gamma of the light field. The replacement of the background image with those under low contrast/gamma light fields had virtually no effect on the matching. Thus, neither the perceived lightness nor the glossiness is constant against variations in the structure of the light field except for the mean illuminance.

These results appeared to indicate the limitations of the visual system in estimation of the constant surface reflectance against variations of illumination. This led us to consider the possibility that the visual system estimate the reflectance by utilizing simple image features, which can be extracted via early spatial filtering. Several psychophysical findings support this idea by showing that the apparent glossiness and lightness of a natural surface can be predicted from the luminance histogram of the surface image (Nishida & Shinya, 1998) or by its moment statistics, such as contrast and skewness (Ho, Landy, & Maloney, 2008; Motoyoshi et al., 2007; Sharan et al., 2008). However, later studies challenge this idea by showing the failure of such predictions (Anderson & Kim, 2009; Kim & Anderson, 2010; Kim, Marlow, & Anderson, 2011; Marlow, Kim, & Anderson, 2011; Olkkonen & Brainard, 2010; Wijntjes & Pont, 2010). Taking advantage of the present stimulus display in which a target with a more complex shape is located in a richer context than in the previous studies, we tested whether the matching data are predictable in terms of the image statistics of the target surface. We found that the matching data were surprisingly well predicted by the similarity in the image subband histograms (but not the pixel luminance histogram) for the reference and the test; the correlation coefficient between the predicted and observed data was higher than 0.95. This suggests that image statistics as derived by early spatial filtering can give a simple and unified account of both the reflectance constancy for the mean illuminance and the inconstancy for the other illumination statistics.

2. Psychophysical experiment

2.1. Methods

Experiments were conducted with completed consent forms and permission from the NTT CS Labs Ethical Committee.

2.1.1. Observers

Eleven naive observers and one of the authors (IM) participated. All had normal or corrected-to-normal vision. Some of them participated in the test under all light field conditions, and others participated in the test under some of the conditions. The naive observers were neither researchers nor students and were naive to the purpose of the study.

2.1.2. Apparatus

Visual stimuli were presented on a 21 in. CRT (SONY GDMF500R, 160 Hz, 800 × 600 pixels) controlled by a graphics card (CRS ViSage). The image (512 × 512 pixels) was displayed in the center of the monitor. A black-flocked board was placed in front of the CRT. The observers viewed the stimulus from 2 m away through a square hole in the center of the board. The measurements were performed in a room whose walls and ceiling were painted in black. The visual field outside the stimulus image was kept almost completely dark.

2.1.3. Stimuli

The visual stimulus was a room containing many objects, including a table, a cabinet, a chair, and sculptures (Fig. 1). The image subtended 7.3 × 7.3° (512 × 512 pixels). There were two versions of the room. One was the test stimulus set under variable light fields (left image of Fig. 1), and the other was the reference stimulus under a fixed light field (right image in Fig. 1). In each of the two stimuli, there was a target object, a sculpture of angel, which was located on the table in the center of the room. The reflectance of the target object in the reference stimulus could be adjusted to match that of the target object in the test room. The target objects in the two rooms faced in different directions to minimize the possibility that the observers would match the local image intensity.

All images were generated using commercial computer graphics software (NewTek LightWave 9.6). We used this software since it allowed us to arrange many objects easily in the scene. The 3D geometry data of objects, including those of the target, were taken from a commercial database (Evermotion Inc.). Some of the objects, such as the floor, wall, and sphere, were modeled using the software. All the objects were assumed to be opaque and have a variety of reflectance properties. The target object had eight levels of diffuse (D) and specular (S) reflectance as follows: $(D, S) = (0.25, 0)$, $(0.79, 0)$, $(0.16, 0.01)$, $(0.44, 0.03)$, $(0.05, 0.07)$, $(0.09, 0.29)$, $(0, 0.13)$, $(0, 0.71)$. The diffuse reflection was Lambertian. The model of specular reflection used in the software is proprietary, as in our previous study (Motoyoshi, 2010), but our analysis showed that it is approximated by Phong's reflection model (Phong, 1975) with a specular exponent coefficient (n) of 900. To improve the reality and familiarity of the scene, most of the objects (but not the target) were texture-mapped with bitmap images supplied by the database. The objects were arranged in the room as naturally as possible. The whole scene was rendered under a particular global light field as described later. In the rendering, interreflections between surfaces were computed eight times. Interreflections higher than the ninth order were not considered, as they produced almost no visible change in the image.

The diffuse and specular reflectance of the target object in the reference stimulus (Fig. 1, right) was independently variable by 20 levels. Some examples of the levels are shown in Fig. 2. The diffuse reflectance was varied according to $\log D = -2 + 0.104 \times i$ ($i = 0, 1, \ldots, 19$), and the specular reflectance according to $\log S = -4 + 0.21 \times i$ ($i = 0, 1, \ldots, 19$). We chose these functions so that the difference in the appearance would be similar across each step. Since the step size was relatively large, there was a possibility that adjustments involved some thresholding effects across different levels of the reference stimuli. However, the observers rarely chose the same reference stimulus as the final match in different trials. The reference stimuli were rendered individually for each reflectance level ($20 \times 20 = 400$) since the image of the objects around the target differed slightly due to interreflections.

The resulting RGB image (HDR format) was converted into a gray scale using the conventional NTSC formula. We utilized the 14-bit look-up table of the graphics card to display the stimuli with smooth shading and vivid highlights. The pixel intensity of each gray-scale image was powered by 1/3 and drawn on VRAM so that the intensity histogram would be closer to Gaussian. The image was then powered by 3.0 using the 14-bit look-up table to return to the linear luminance image on the CRT. For several images containing the target object with very high specular reflectance, pixels that exceeded the maximum value (136 cd/m^2 on the CRT) were clipped. Although our stimuli were not real objects since they were computer generated and shown on the CRT monitor, our observers reported that they looked like very realistic achromatic images.

2.1.4. Light fields

The scene in the test stimulus was illuminated by one of nine different light fields. Fig. 3 shows examples of the light fields (light-probe images) and several target objects under those light field conditions. In the original condition shown in Fig. 3a, the

Fig. 1. The test stimulus (left) and the reference stimulus (right) used in the experiment. The target object is the angel sculpture in the center. The observer adjusted the diffuse and specular reflectance of the target object in the reference stimulus. The light field of the reference stimulus was fixed while that of the test stimulus was varied (low-contrast light field here).

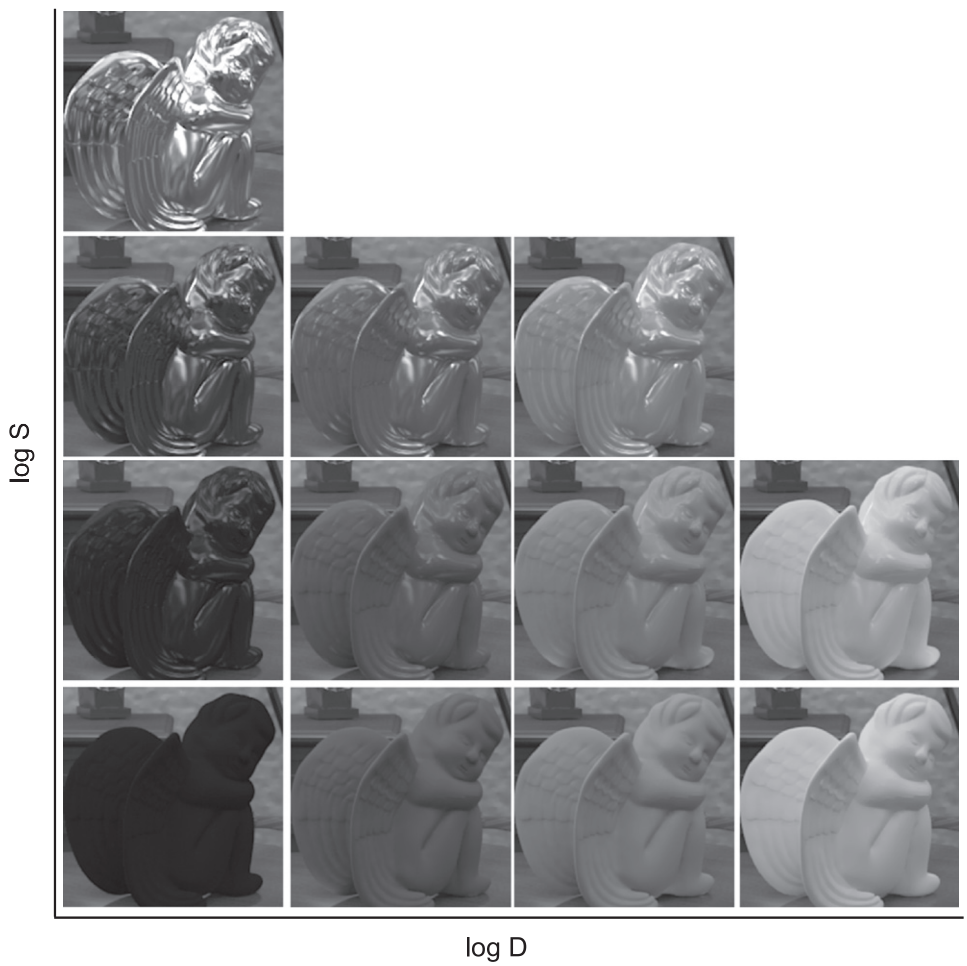

Fig. 2. Examples of reference objects arranged in the $\log D$–$\log S$ space.

room was illuminated by the light field from Debevec (1998) (RNL, Eucalyptus). Although this light field is of the outdoor while the illuminated scene is of the indoor room, it is shown that such a conflict in rendering does not strongly affect the reflectance judgment (Fleming, Dror, & Adelson, 2003).

The original light field was manipulated in three ways. First, the mean intensity was reduced by 0.5 and 0.25 (Fig. 3b). This is similar to dimming the lights in the room. Second, the contrast was reduced by 0.25 and 0.05 (Fig. 3c). This is similar to placing objects in a hazy environment. Third, the gamma was decreased by employing powers of 0.5 and 0.06 (Fig. 3d) while the contrast was kept at half (0.5×) its original value. Pixels with negative values were clipped to zero (3% for gamma of 0.5% and 6% for gamma of 0.06). Reducing gamma resulted in less bright sunlight and dark

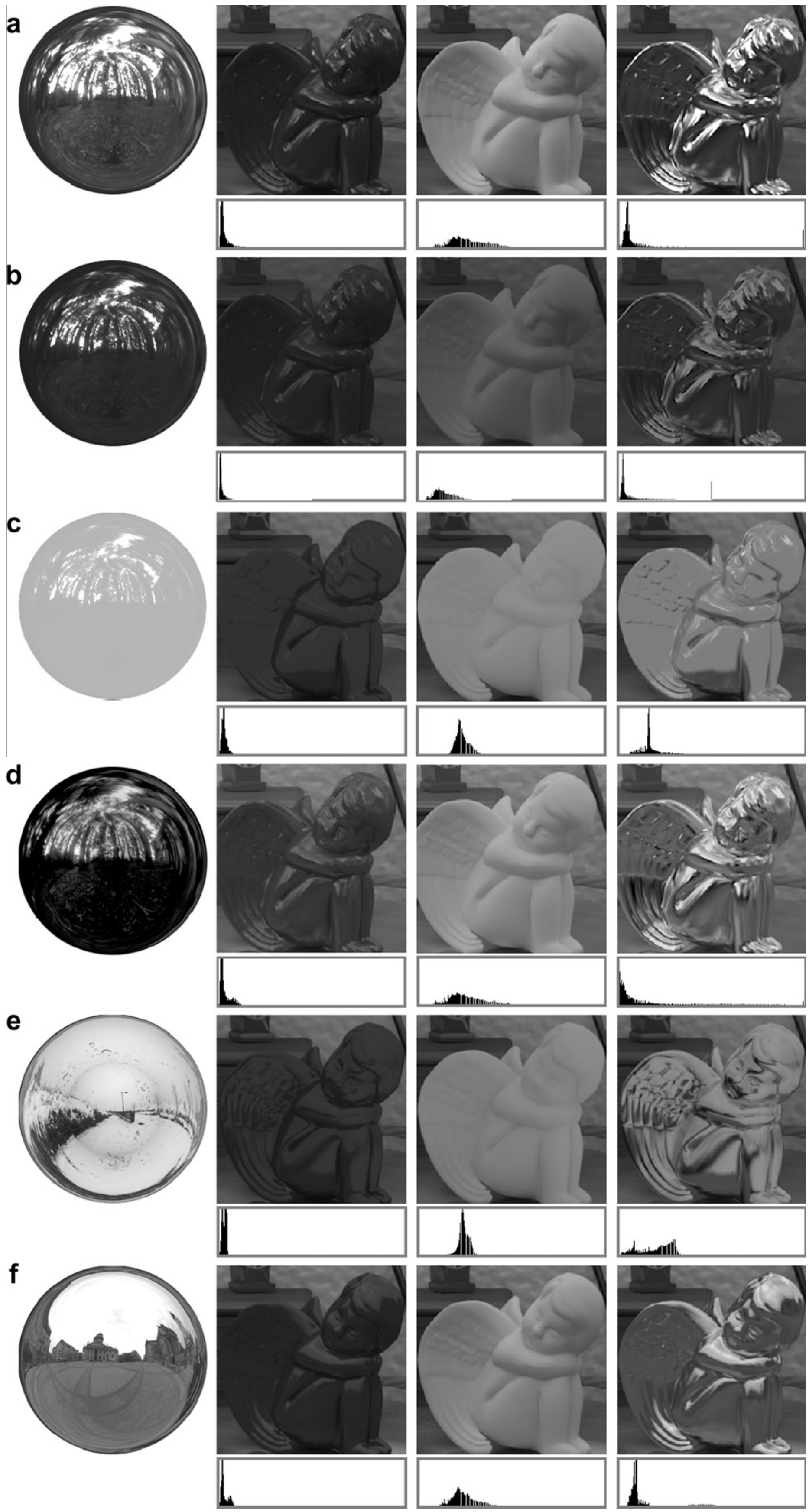

Fig. 3. Examples of test objects under different light fields. (a) Original light field (same as that for the reference stimulus). (b) Low mean intensity. (c) Low contrast. (d) Low gamma. (e) Snowy scene. (f) Cloudy scene. The luminance histogram is shown below each image.

shadows. These manipulations of the light field did not greatly affect the sharpness of specular patterns on the surface image. This allowed the observers to match the test and reference objects easily by adjusting only the diffuse and specular reflectance in our experimental procedure. In addition to these three conditions, we also employed the natural light fields of a snowy scene (Fig. 3e) and of a street under a cloudy sky (Fig. 3f). The light-probe image of the snowy scene was provided by our colleague, and that of the cloudy scene was taken from a commercial database (Sachform, Inc.). For these two light fields, some observers reported a slight difficulty in matching. Except for the conditions of different mean illuminance (Fig. 3b), the absolute intensity of the light field was adjusted so that the mean luminance of the stimulus image, excluding the target object, was virtually equal to that of the room under the original light field in Fig. 3a ($\sim$14 cd/m^2).

2.1.5. Procedure

We measured the apparent diffuse and specular reflectance using a two-dimensional matching method. The observers freely viewed the stimulus from a distance of 2 m. The test and reference stimuli were presented on a CRT at different temporal intervals. This encouraged the observers to perceive the two stimuli in different illumination contexts, outside of which they were kept in darkness. This required memory, although not of a very long duration (c.f., Jin & Shevell, 1996). In each trial, the test stimulus of a given condition appeared gradually from the darkness ($\sim$0.03 cd/m^2) in a cosine manner with a wavelength of 2 s. The observers were allowed to view it as long as they wanted. When the observer pressed a key ('5' on the keyboard), the test stimulus gradually disappeared into darkness, followed by a blank of 1 s, and then the reference stimulus gradually appeared. Using four keys on the keyboard, the observers adjusted the diffuse and specular reflectance, by loading and displaying the corresponding reference stimulus, so that the surface quality of the reference object appeared as close as possible to that of the test object. They were instructed to judge the surface material but not the brightness or contrast of the image. When the observer pressed the key ('5') again, the reference stimulus gradually disappeared and the test appeared. The observers could repeat this adjustment and review process as many times as they wanted. If the observer judged that the adjusted surface property of the reference object was close enough to that of the test object, they pressed a key ('0') to decide the final matching data. At least three matching data were collected for each condition, and the mean values of logs D and S were regarded as the matching data of that observer. All the naive observers could perform this task easily and comfortably despite the lack of previous experience in such tasks. The adjustment method is known to be accompanied by slight biases in matching (Doerschner, Boyaci, & Maloney, 2010), but the present study only considered large variations in the data across the light fields. In the analysis of the data, matched $\log S$ lower than -3.0 was clipped to -3.0 since the images in that range were almost indistinguishable from each other.

2.1.6. Effect of background

To directly assess the effect of the surrounds context on the perceived reflectance, we also examined how the perceived reflectance of the test object under a standard light field is affected when the background image is replaced by an image of a scene under different light fields. If the visual system considers the surrounding information even slightly, the test object will appear different when embedded in a different background.

The test stimulus was the composed image of the target object under a standard light field (Fig. 4a) and the background room under various light fields (Fig. 4b and c). The light field in the background was standard, low contrast (0.05$\times$), or low gamma (^0.06, contrast was 0.05$\times$). The interreflections to the target from the objects in the background were not considered, but no observer reported that the target image was pasted over the background. For each background condition, we measured the perceived reflectance of the target object with eight different reflectances. We did not test the effect of the background under different mean illuminance levels because the effect had been revealed indirectly by the constancy against the mean illuminance (Fig. 5a). The others were the same as in the main experiment. Five observers participated in the experiment.

2.2. Results

Fig. 5 shows the matched diffuse ($\log D$) and specular ($\log S$) reflectance under various light field conditions. Panels in Fig. 5a–c show the results when the mean (a), contrast (b), and gamma (c) of the same light field were manipulated, respectively. The data for the target object with the same reflectance are connected by lines. In Fig. 5a and b, the filled circles show the data for the original light field, and the open squares and triangles show the results for light fields with a reduced mean (a) and contrast (b). In Fig. 5c, the open circles show data for a light field with a low contrast (0.5), and the open squares and triangles show results for the reduced gamma. Fig. 5d shows results obtained with different natural light fields; the open squares indicate the snowy scene and the open triangles indicate the cloudy scene.

The data show that the matched reflectance tends to vary in different ways with the light field parameters. Unsurprisingly, the matched reflectance tends to vary little with the mean illuminance, except with the test object with high specular reflectance (Fig. 5a). However, the matched reflectance varies greatly with the contrast of the light field (Fig. 5b). As the contrast of the light field decreases, the glossy surface tends to appear matte and/or whitish. This is particularly profound for objects with very high specular and low diffuse reflectances (top left in the plot). These objects, which look metallic under a standard light field, appear light gray in a low-contrast light field; the matched diffuse reflectance increases by $\sim$1.0 log unit, and the matched specular reflectance decreases by $\sim$0.5 log unit. The objects with high specular and high diffuse reflectance (center right in the plot), which appear glossy gray in the standard light field, appear almost matte in the low-contrast light field; the matched specular reflectance decreases greatly. The effect of the gamma is somewhat complicated (Fig. 5c). It should be noted that under these conditions, the light fields were all set to have a low (0.5) contrast. As the gamma of the light field decreases, objects that look glossy and light tend to appear slightly less glossy (right in the plot), while objects that look glossy gray, appear to revert to metallic (top left in the plot). The results obtained for the less directional light fields (snowy scene and cloudy scene) are qualitatively similar to those obtained for the low-contrast light fields (Fig. 5d).

2.2.1. Effect of background

The matching data for the replaced backgrounds are shown in Fig. 5. The filled circles show the results for the background of the standard light field. The open circles and triangles show the results for the backgrounds of low contrast and low gamma, respectively. The data show that the perceived reflectance of the target object is almost totally unaffected by the differences in the background image. This suggests that the observers only consider information within the image region of the target object, at least in our stimuli. It should be noted again that the background under different mean illuminance levels had a profound effect on the responses as indirectly shown by the constancy against the mean illuminance (Fig. 5a).

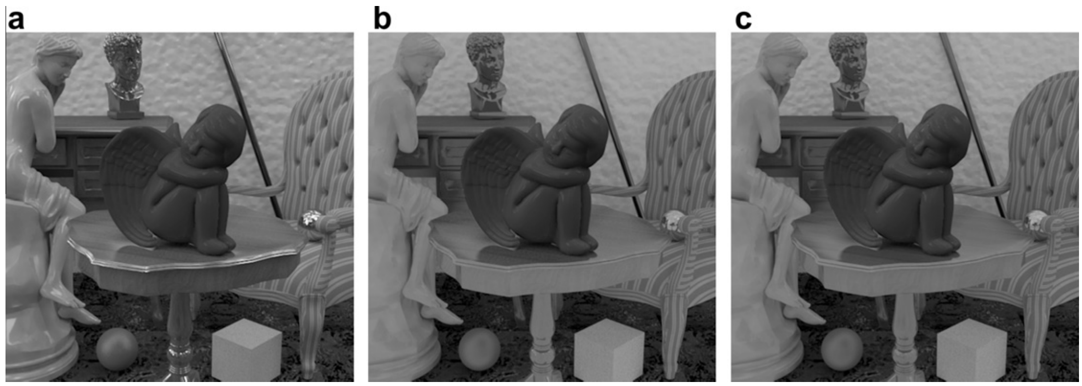

Fig. 4. Stimuli with the replaced backgrounds. (a) Test object under a standard light field. (b) Test object embedded in the background scene under a low-contrast light field.

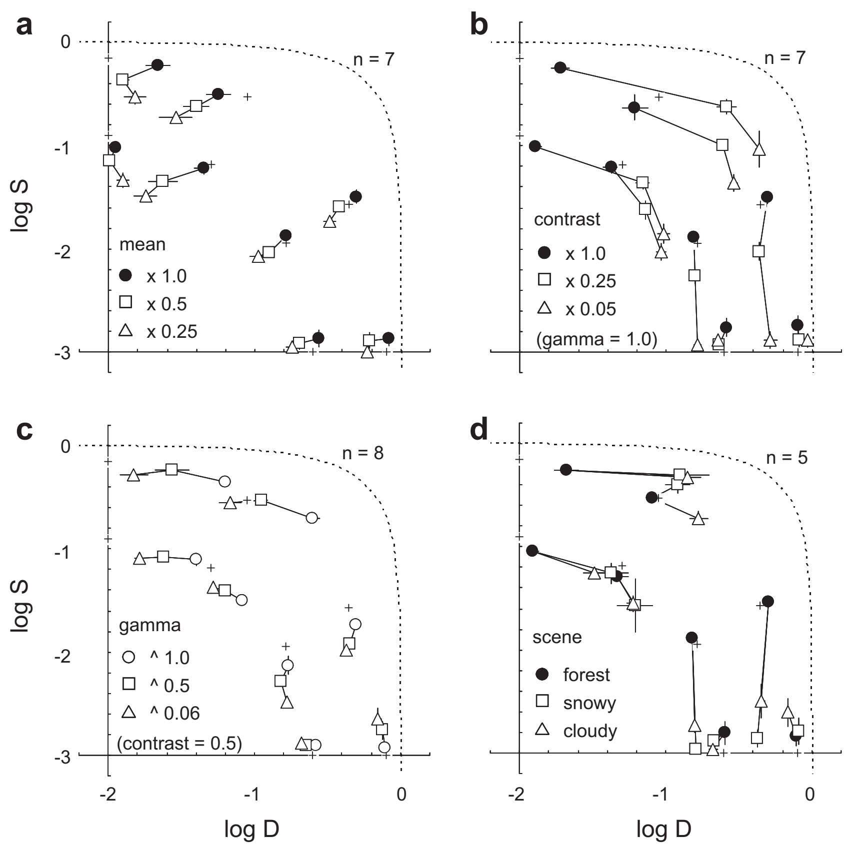

Fig. 5. Experimental results. The matched reflectance of the test objects under light fields of (a) variable mean, (b) contrast, (c) gamma, and (d) scenes. The filled circles show the data for the test object under the same (original) light field as the reference objects, and the open symbols show the data under different light fields. Small crosses represent the physical reflectance of the test object. Dashed curves are the traces of $S + D = 1$. Error bars represent ±1 SEM across observers.

3. Prediction by image statistics

3.1. Histogram similarity

Based on a method similar to that used by Nishida and Shinya (1998), we tested whether the matching data could be predicted in terms of the similarity in the histogram statistics.

3.1.1. Methods

Each image was decomposed into subband images of eight different spatial scales (1,2,4,...256 c/image; 0.14–35 c/deg) by using bandpass filters with a bandwidth of 1 octave. We used the subband image instead of the pixel luminance image because the visual system has no access to pixel luminance, but analyzes the image in a spatial-frequency selective manner. Our previous study has also shown that the subband histogram provides a better prediction than the pixel histogram (Motoyoshi, Nishizawa, & Uchikawa, 2007). Fig. 7 shows examples of the filtered image at different spatial scales. The filtered outputs at low-spatial frequencies seem to be related to whether the mean intensity of the target region is relatively higher (on) or lower (off) than that of the background. The outputs in high spatial frequency bands seem to be related to the edgy structures of the objects, textures, and the presence of highlights. As it consists of band-pass filters, the model completely discounted the mean luminance of the scene, which varied with the mean illuminance of the light field.

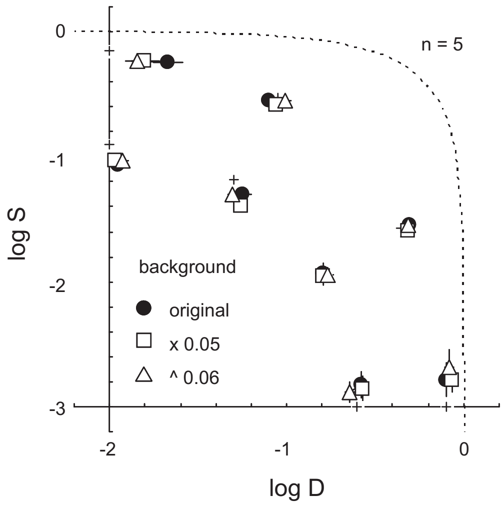

Fig. 6. Effect of the background. The matching data are shown for the background under the original (filled circles), low-contrast (open squares), and low-gamma (open triangles) light fields. Error bars show ±1 SEM across observers.

For each subband, the histogram was calculated within the region of the target object (512 levels, bin = 0.016, 256 corresponds zero of the wavelet coefficient). We obtained the subband histograms for the test object and for the reference object and took the difference (d) between them as follows:

$$d = \sum_{f=1}^{8} \sum_{i=0}^{511} |p_{test}(i,f) - p_{ref}(i,f)| \tag{1}$$

where $p(i,f)$ is the probability of the ith pixel value in the subband image of the fth spatial scale (1–8). Among the reference stimuli used in the experiment, we found those that gave the two smallest d values and took the mean of their reflectance ($\log D$ and $\log S$) as the predicted matching data.

3.1.2. Results

The predicted matching data are shown in Fig. 8. They capture the basic tendencies observed under all experimental conditions: constancy against the mean illuminance (Fig. 8a), dependency on the contrast and gamma of the light field (b, c, and d), and the absence of the effect of the background (e). As shown in Fig. 8f, the predicted reflectance was surprisingly well correlated with the observed data ($r = 0.96$ for $\log D$, $r = 0.96$ for $\log S$). The average distance between the observed and predicted data was 0.25 in the $\log D$–$\log S$ space.

3.2. Moment statistics

In a similar manner, we additionally examined whether the matching data could be predicted from the summarized moment statistics of the subband image.

3.2.1. Methods

We calculated the first- to fourth-order moments (mean, s.d., skewness, and kurtosis) of the subband histograms and took the weighted sum of the difference in each moment between the test and reference (dm):

$$dm = \sum_{j=1}^{4} \left[w_j \cdot \sum_{f=1}^{8} |M_{test}(j,f) - M_{ref}(j,f)| \right] \tag{2}$$

where $M(j,f)$ is the jth order moment in the subband image (within the target region) of the fth spatial scale (1–8), and w_j is the weight, which represents the contribution of the difference in each moment. The reference stimuli that gave the two smallest dm values were determined, and the mean of their reflectance was adopted as the predicted matching data. The parameter w_j was optimized via a simplex algorithm so that the predicted data were as close as possible to the observed data in the $\log D$–$\log S$ space.

3.2.2. Results

We found that the moments statistics can also predict the matching data to some degree ($r = 0.94$ for $\log D$, $r = 0.77$ for $\log S$) with the optimized weight, w_j (5.1 for mean, 3.1 for s.d., 0.2 for skewness, and -0.03 for kurtosis).

4. Discussion

The present study examined the perceived reflectance of a 3D object located in a highly complex scene under various light fields. The results showed that the perceived reflectance (both lightness and glossiness) is relatively constant against changes in the mean illuminance but dependent on changes in the contrast and gamma of the light field.

A number of studies have demonstrated the constancy in the perceived diffuse reflectance (lightness) of matte-flat surfaces against changes in the mean illuminance (Adelson, 1999; Brainard, 1998; Gilchrist, 2006; Land & McCann, 1971; Wallach, 1948). The present results indicate that this law is also relevant, although imperfectly, for objects with complex 3D shapes and also for the perceived specular reflectance (glossiness). On the other hand, the results show that the higher-order parameters of the light field strongly affect not only the apparent glossiness (Doerschner, Boyaci, & Maloney, 2010; Fleming, Dror, & Adelson, 2003), but also the lightness, even with rich contextual information in the background. This is consistent with observations with real objects (Pont & te Pas, 2006), but partially inconsistent with results that showed the lightness (and color) constancy of flat patches and spheres against the illumination structure (Brainard & Maloney, 2011; Doerschner, Boyaci, & Maloney, 2007; Olkkonen & Brainard, 2010). This discrepancy may originate from the complexity of the shape of the target object; e.g., shadings around concaves that were present in our target and in many real objects, but not in flat patches and spheres. The other factor is that we tested target objects with a wider range of reflectances (from matte to almost metallic) than the previous study (Olkkonen & Brainard, 2010). We also manipulated the light field, and used two specific natural light fields; snowy and cloudy scenes. There remains a possibility that these light fields were unusual with respect to typical illumination statistics in natural environments.

The huge errors in judgments may highlight an essential limitation of the perceptual constancy of surface quality across variations in illumination. The successful prediction of such errors by the image subband histogram further supports the idea that the reflectance judgments depend on simple image statistics (Ho, Landy, & Maloney, 2008; Motoyoshi et al., 2007; Nishida & Shinya, 1998; Sharan et al., 2008). A particularly important finding in the present study is that the subband histogram can account not only for the inconstancy for the higher-order structure of light field but also for the constancy against the mean illuminance. The constancy against the mean illuminance is simple to predict from the fact that subband filtering discounts the mean luminance of the display, which varied with the mean illuminance. While the current model predicted perfect constancy (Fig. 8a) since it completely discounted the mean luminance, human data showed imperfect constancy (Fig. 5a) possibly because the observers incorporated, or did not fully adapt to, the luminance of the display. It has been claimed that many lightness and brightness phenomena can be well

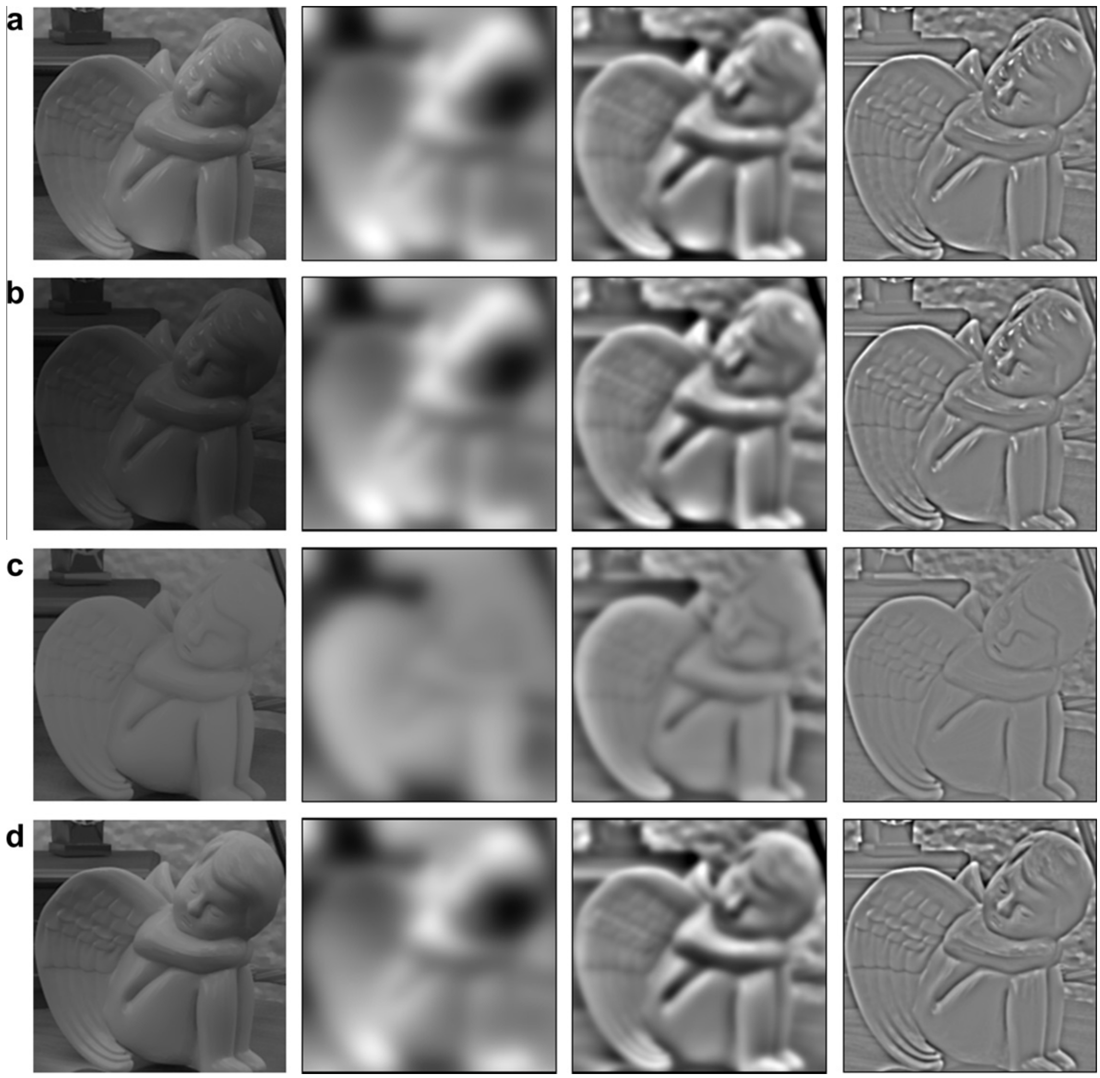

Fig. 7. Example subband images of the test object under four illumination conditions: (a) original, (b) low mean (0.5×), (c) low contrast (0.05×), and (d) low gamma (^0.06). The leftmost column shows the pixel luminance image, and the others show subband images of 0.6, 2.2, and 8.7 c/deg, respectively.

described in terms of the outputs of spatial filtering, which can be achieved via simple neural computations in the early visual cortex (Blakeslee, Pasieka, & McCourt, 2005; Kingdom & Moulden, 1992). Consistent with this notion, the present data suggest that the visual system employs a multi-scale analysis of the whole scene, not just of the target object, to extract important information on the lightness and glossiness of an object within it.

However, this does not mean that simple image statistics such as subband histogram are sufficient for reflectance judgment. Whereas the perceived glossiness of some natural surfaces is shown to be correlated with histogram skewness (Ho, Landy, & Maloney, 2008; Motoyoshi, Nishizawa, & Uchikawa, 2007; Motoyoshi et al., 2007; Sharan et al., 2008), there are clear examples in which a surface is perceived matte even if it had a positively skewed histogram (Anderson & Kim, 2009; Kim, Marlow, & Anderson, 2011; Marlow, Kim, & Anderson, 2011; Motoyoshi, Nishizawa, & Uchikawa, 2007; Motoyoshi et al., 2007; Wijntjes & Pont, 2010). It is also well known that the perceived lightness profoundly depends on the apparent depth of the object (e.g., Gilchrist, 1977). These findings suggest an involvement of higher-order interpretations of the object and scene, particularly those correlated with the shape and layout in 3D space (Anderson & Kim, 2009; Gilchrist, 1977; Kim, Marlow, & Anderson, 2011; Knill & Kersten, 1991; Marlow, Kim, & Anderson, 2011; Olkkonen & Brainard, 2010) although neural computation for such interpretations is unknown.

Changing the mean luminance of the background greatly altered the perceived reflectance of the target, as indirectly suggested by the constancy against changes in the mean illuminance (Fig. 5a). On the other hand, replacing the background with light fields of low contrast and low gamma had negligible effects on the judgments (Figs. 4 and 6). And both results were successfully accounted for by a subband image analysis of the whole scene (Fig. 8). It is clear that mean luminance of the background inevitably and profoundly affects the filtered outputs at low spatial frequencies within the target region, and thereby affects the judgment. When the background of the target in Fig. 7a is replaced by that under low illuminance (0.25×), for example, the mean of the low-frequency subband (0.6 c/deg) within the target region is varied from 0.16 to 1.04. On the other hand, the replaced low-contrast/gamma backgrounds (see Fig. 4) had a similar mean luminance to the original, and differed at middle and high spatial frequencies. Such information is likely to change the image statistics at around the target contours, but little inside the target region, and so had little effect on the perceived reflectances. Replacing the background of the target of Fig. 7a to that under low contrast (0.25×) alters the mean of the target-region's

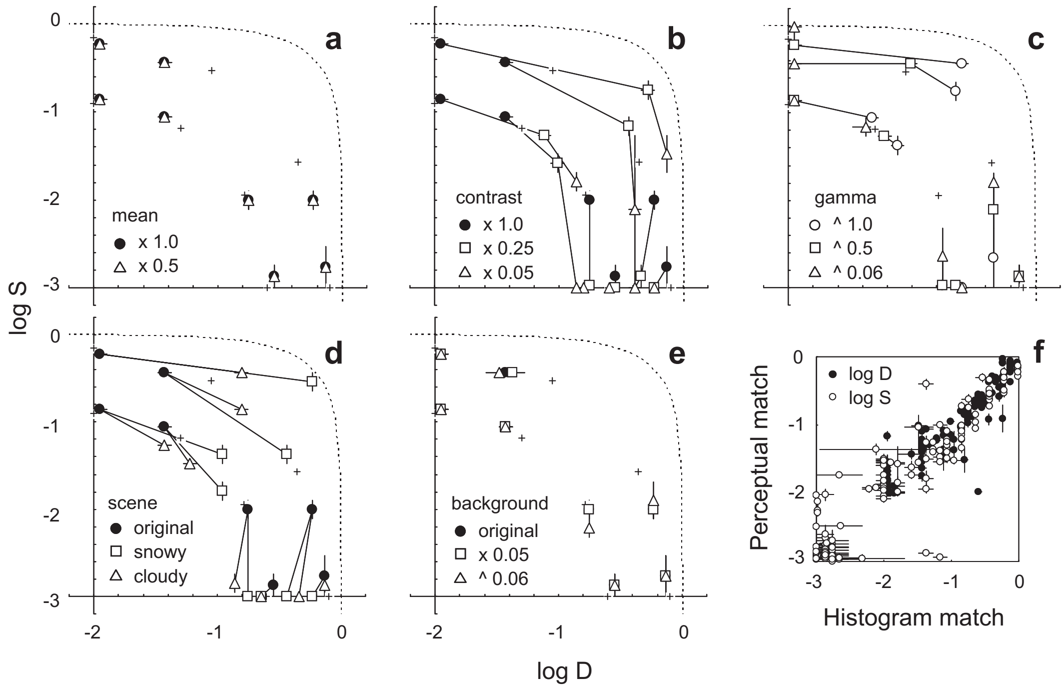

Fig. 8. Matching data predicted by the similarity in the subband histograms. (a–d) The predicted results for the main experiment. (e) The predicted results for the replaced backgrounds. Each data point shows the mean reflectance (and ±1 SEM) of the best-two reference objects whose subband histograms were the closest to those of the test object.

high-frequency subband (8.7 c/deg) from 0.016 to 0.012. However, given the previously reported effects of scene geometry on the perceived lightness and color (e.g., Boyaci, Maloney, & Hersh, 2003), it is possible that the above results and explanations depend on the type of stimuli.

The present results may appear inconsistent with the fact that we rarely perceive changes in the material of an object across indoor and outdoor situations and across sunny and cloudy days, which have very different illumination statistics. The present results may be the consequence of a lack of some important information in our stimuli. In real scenes, we may utilize a variety of other cues, such as color (Nishida et al., 2008), motion (Hartung & Kersten, 2002; Sakano & Ando, 2010), and stereo (Wendt et al., 2010), to achieve constant reflectance perception. Texture patterns, which are ubiquitous on natural surfaces, may also play an important role in segmenting highlights from the surface body (Tan & Ikeuchi, 2005; Todd, Norman, & Mingolla, 2004). However, we preliminarily observed that none of these cues greatly improved the constancy in the perceived reflectance across different light fields. Another interesting possibility is that the recognition of the material and the estimation of the reflectance are partially distinct functions constrained by different information sources. It is possible that the illumination structure only affects the latter judgment. Looking at a chair made of well-polished wood, for example, we would be able to recognize it as a wooden chair regardless of the illumination, probably from the texture that is specific to the wood, whereas we would assess how glossy it is on the basis of histogram statistics that are likely to depend on the illumination.

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