Reflecting on a room of one reflectance

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We present a numerical analysis of rendered pairs of rooms, in which the spectral power distribution of the illuminant in one room matched the surface reflectance function in the other room, and vice versa. We ask whether distinction between the rooms is possible and on what cues this discrimination is based. Using accurately rendered three-dimensional (3D) scenes, we found that room pairs can be distinguished based on indirect illumination, as suggested by A. L. Gilchrist and A. Jacobsen (1984). In a simulated color constancy scenario, we show that indirect illumination plays a pivotal role as areas of indirect illumination undergo a smaller appearance change than areas of direct illumination. Our study confirms that indirect illumination can play a critical role in surface color recovery and shows how computer rendering programs, which model the light–object interaction according to the laws of physics, are valuable tools that can be used to analyze and explore what image information is available to the visual system from 3D scenes.

Keywords: indirect illumination, interreflection, surface color perception, rendering, color constancy

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Introduction

Imagine two rooms, each containing the same set of objects in identical spatial layout and each room illuminated by a light source. Within a room, objects share the same color and the setup of the rooms is such that the relative spectral power distribution of the illuminant in one room matches the surface reflectance function in the other, and vice versa. Can observers discriminate between rooms, and if so on what cues is this distinction based?

In most textbooks on color perception (Brainard, Kraft, & Longère, 2003, p. 308; Brown, 2003, p. 250; MacLeod & Golz, 2003, p. 207; Palmer, 1999, p. 124; Wandell, 1995, p. 293; Wyszecki & Stiles, 2000, p. 143), the color signal $C(\lambda)$ reaching the eye is described as the product of the illumination $I(\lambda)$ and the surface reflectance function $S(\lambda)$ of the viewed surface (Equation 1)

$$C(\lambda) = I(\lambda) \cdot S(\lambda). \tag{1}$$

However, when swapping the illumination $I(\lambda)$ with the surface reflectance function $S(\lambda)$, as in our proposed rooms, the color signal $C(\lambda)$ in Equation 1 would remain the same. Based on Equation 1, the visual system would not be able to distinguish between the two rooms. The description of a color signal with Equation 1 is correct when we want to describe a single flat, matte surface receiving direct illumination only and presented frontoparallel to the observer, for example, when simulating paper swatches in computer monitor-based experiments (Amano & Foster, 2004; Arend & Reeves, 1986; Bäuml, 1994, 1999a, 1999b; Brainard & Wandell, 1992; Bramwell & Hurlbert, 1996; Craven & Foster, 1992; Foster, Amano, & Nascimento, 2000, 2001; Golz & MacLeod, 2002; Nascimento & Foster, 2001; Nieves, García-Beltrán, & Romero, 2000; Rinner & Gegenfurtner, 2002; Smithson & Zaidi, 2004). But the real world contains three-dimensional (3D) objects whose surfaces reflect light many times, therefore combining direct and indirect illumination (indirect illumination describes the same phenomenon as mutual illumination). Researchers have used real 3D scenes (Bloj, Kersten, & Hurlbert, 1999; Brainard, 1998; Brainard, Brunt, & Speigle, 1997; Gilchrist, 1977; Gilchrist & Jacobsen, 1984; Kraft & Brainard, 1999; Ripamonti et al., 2004), and in particular Gilchrist (1977) and Bloj et al. (1999) demonstrated how important geometrical layout is for lightness (achromatic) and color perception, respectively. To mathematically describe the full light–surface interactions in a 3D scene can be rather complicated, and that is the reason why researchers tend to work with flat scenes receiving direct illumination only. An extensive discussion of the principal differences between flat and shape worlds is available from Maloney (1999, 2003) and Maloney and Yang (2003).

In 1984, a setup, seemingly similar to our proposed experiment, was studied by Gilchrist and Jacobsen (1984). They showed observers two real rooms in the following conditions: (1) a white room illuminated by a bright white light; (2) a black room illuminated by the same bright

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white light; and (3) a white room illuminated by a dim white light. It is important to note that even in the case of Conditions 2 and 3, no attempt was made to spectrally match the reflectance functions and relative spectral power distributions of light sources and that every point in the room under Condition 2 had a higher luminance value than the corresponding point under Condition 3. In reporting the procedures and the results from Gilchrist and Jacobsen, we will follow the terminology used by others (Adelson, 1993; Arend & Goldstein, 1987; Bloj & Hurlbert, 2002), which makes clear the distinction between lightness (apparent reflectance) and brightness (apparent luminance). In their Experiment 1, Gilchrist and Jacobsen tested all three of the above conditions and all participants reported that all objects in each room appeared the same lightness.[1] The median of lightness matches for each condition were as follows: Munsell paper 9 for the bright white room, 5.5 for the bright black room, and 7.5 for the dim white room, indicating a certain degree of lightness constancy as the bright black room had higher luminance values than the dim white room. Gilchrist and Jacobsen also report observers' brightness (Experiment 1) and lightness matches (Experiment 2) for eight different locations but only in the case of the bright white room (maximum luminance 3,151 cd/m^2) and the bright black room (maximum luminance 7.9 cd/m^2), not in the case of the dim white room.[2] Their results confirm that under these conditions, with real 3D objects and when indirect illumination is present, the human visual system has access to fairly accurate representations of both surface reflectance and illumination distribution in a scene. However, their study does not answer the question we pose in the beginning of this article.

To setup our spectrally matched room pairs in the real world, we would face practical problems that make it very difficult to exactly equate the surface reflectance function and the spectral power distribution of the light source. Instead, we use computer-simulated 3D scenes, in which the light–object interaction is modeled according to the laws of physics. This helps us overcome both the limitations of setting up real 3D scenes and the idealization of flat scenes under only direct illumination implicit in Equation 1.

In principle, the 3D computer simulation approach has been used before (Boyaci, Doerschner, & Maloney, 2004; Boyaci, Maloney, & Hersh, 2003; Delahunt & Brainard, 2004a, 2004b; Doerschner, Boyaci, & Maloney, 2004; Fleming, Dror, & Adelson, 2003; Fleming, Torralba, & Adelson, 2004; Yang & Maloney, 2001; Yang & Shevell, 2003), but the main thrust of previous studies was to generate stimuli for psychophysical research and not to analyze and compare the stimuli generated per se. Our simulations using multiple light bounces, high-resolution surface reflectance functions, and spectral power distributions provide pixel-wise physically accurate luminance and chromaticity values (Ruppertsberg & Bloj, 2006). The output from these simulations can include values that are beyond the display capabilities of a normal computer monitor because luminance values are too high or chromaticity/luminance combinations fall outside the gamut of the monitor.[3] Alternatives for displaying the resulting images include the use of tone mapping techniques that compress the desired into the available luminance range (which means that the physically true luminance values are not displayed) or the use of high dynamic range displays (Seetzen et al., 2004). The first type of manipulation is likely to introduce artifacts, and the perceptual validity of different tone mapping algorithms is an open research question (for example, see Ledda, Chalmers, Troscianko, & Seetzen, 2005). Currently, high dynamic range displays are not suitable for psychophysical experiments as there are still unresolved issues in displaying a colorimetrically calibrated image. Further, the backlight LED component has a far lower spatial resolution than the LCD layer, which would again lead to the display of nonphysically accurate images (Ruppertsberg, Bloj, Banterle, & Chalmers, 2007). Because of the above reasons, we will pursue a third approach and use the physically accurate rendering outputs for numerical analysis.

In this study, we analyzed pairs of rooms, in which the spectral power distribution of the illuminant in one room matched the surface reflectance function in the other room, and vice versa. We refer to such a pair of rooms as a "room pair." The question was whether distinction between the rooms was possible and on what cues this discrimination was based. We compare simulation results of an achromatic room pair and show that it is the indirect illumination that allows distinction between the room pair, which emphasizes the importance of studying shape worlds rather than flat worlds. These findings are then extended to chromatic room pairs. When applying the analysis to a color constancy scenario, we find that areas of indirect illumination undergo a smaller appearance change than areas of direct illumination. These results confirm Funt, Drew, and Ho (1991) and highlight the contribution of indirect illumination to stable color perception.

Methods

All scenes in this study were modeled using RADIANCE (Ward, 1994), a physical rendering software package that simulates the interaction of light and objects. We have previously shown that RADIANCE can accurately model the light–object interaction when a spectral rendering method is used (Ruppertsberg & Bloj, 2006). We modeled a room with three walls and a floor containing a sphere, a cone, and a box. The room was illuminated from the top left by a spotlight at 15° (for the geometrical description of the objects, the illuminant, and the scene composition, see Appendix A). The material and the light files are available as Supplementary data (for more details on how to render the scenes, see Ruppertsberg & Bloj, in press). All surfaces were modeled to have Lambertian surface properties; all material colors were described by surface reflectance functions, and the colors of the illuminant were described by spectral power distributions. The surface reflectance functions of colored materials and the modeled light source (a low voltage spotlight: Altman MR 16 Micro Ellipse, with a 75-W, 36° reflector) were based on measurements taken in our laboratory. We used a spectral rendering method with 81 wavebands from 380 to 780 nm, whose output is a hyperspectral image that can be converted to a three-layered *XYZ* image by applying color-matching functions (Ruppertsberg & Bloj, in press). For total illumination images, we used five light bounces and zero light bounces for the direct illumination-only images. Five light bounces is a sensible compromise between accuracy and speed. For simple geometrical scenes similar to the one used in this study, we have not found a significant difference between renderings with 2 and 50 bounces. To compute indirect illumination images, we subtracted the *XYZ* values of the direct illumination-only image from the *XYZ* values of the total illumination image, which is identical to subtracting the corresponding hyperspectral images from each other. Equation 2 outlines this for the *X* tristimulus value; $t(\lambda)$ is the spectrum of a pixel of the total illumination image and $d(\lambda)$ is the spectrum of a pixel of the direct illumination only image, $x(\lambda)$ is the corresponding matching function

$$\begin{aligned} X_t &= \int_{\lambda=380}^{780} t(\lambda)\cdot\overline{x}(\lambda)\partial\lambda \\ X_d &= \int_{\lambda=380}^{780} d(\lambda)\cdot\overline{x}(\lambda)\partial\lambda \\ X_t - X_d &= \int_{\lambda=380}^{780} t(\lambda)\cdot\overline{x}(\lambda)\partial\lambda - \int_{\lambda=380}^{780} d(\lambda)\cdot\overline{x}(\lambda)\partial\lambda\,. \\ &= \int_{\lambda=380}^{780} t(\lambda)\cdot\overline{x}(\lambda)\partial\lambda - d(\lambda)\cdot\overline{x}(\lambda)\partial\lambda \\ &= \int_{\lambda=380}^{780} (t(\lambda)-d(\lambda))\cdot\overline{x}(\lambda)\partial\lambda \end{aligned} \tag{2}$$

Results

Achromatic rooms

We start by simulating an achromatic room pair where the white room had an albedo value of 84% and the black room had an albedo value of 4.6%. Each room was illuminated by a light source that had the relative percentage intensity of the albedo in the other room. The actual mean luminance values were 1,503 cd/m^2 for the white room and 738 cd/m^2 for the black room (the maximum luminance values for the two rooms were 4,073 and 3,408 cd/m^2). These values are outside the luminance range of a standard computer monitor, which makes it impossible to display the image without resorting to the alternatives described in the Introduction section.

Figure 1A shows the tone mapped RGB images of the two rooms. Here and in all other figures, we converted the *XYZ* image to RGB using a generic monitor calibration matrix,

$$M = [0.0257 \quad -0.0117 \quad -0.0040; \quad -0.0102 \quad 0.0198 \quad 0.0004; \quad 0.0007 \quad -0.0025 \quad 0.0117], \tag{3}$$

and then scaled the values to an interval between 0 and 1. This was achieved by determining the minimum value across all three RGB channels in the image, and if this value was negative, the absolute value was added to all RGB values in the image. This ensured that no RGB values were negative. We then determined the maximum value across all three RGB channels in the image and divided all RGB values by this common factor. In all figures, the color of the box icon stands for the reflectance of all objects in the scene and the color of the bulb icon stands for the color of the illuminant.

The difference in appearance between the white room and the black room is clearly visible even in these tone mapped images (Figure 1A).

In their study, Gilchrist and Jacobsen (1984) computed luminance contrast based on measured luminance levels across a single scan line through their rooms. They found that both white rooms had a lower luminance contrast (i.e., shallower gradients) than the black room, which is due to the fact that white surfaces reflect more light than black ones. The same can be seen in Figure 1B where we show luminance profiles from three different horizontal scan lines (SL91, SL111, and SL136) for each room: The black room has steeper gradients and therefore the calculated luminance contrast for each scan line (Contrast = $(Lum_{max} - Lum_{min}) / (Lum_{max} + Lum_{min})$) is higher than that in the white room. Note that the contrast in the black room varies less than that in the white room across the three scan lines.

Although the measurement and analysis of the illumination pattern in a real 3D scene is difficult, the rendered image allows analysis on a pixel resolution. We used a color difference measure[4] and computed delta *E* values (CIELUV; Wyszecki & Stiles, 2000) for each pixel pair of the black and the white room. The tristimulus values for the white point for all calculations were *XYZ* = [100, 100, 100]. Figure 1C shows the resulting delta *E* image for the white and the black room pair where different delta *E* values are color-coded. Areas in blue signify little difference (delta $E \leq 10$) and areas in yellow and orange ($90 \leq$ delta $E \leq 190$) and red signify large differences (delta $E > 190$). The illuminant is shining down from the front left corner and therefore the top of the sphere, the left-hand side of the cone, the top of the box, and the floor receive mostly direct illumination. But these areas are blue in the

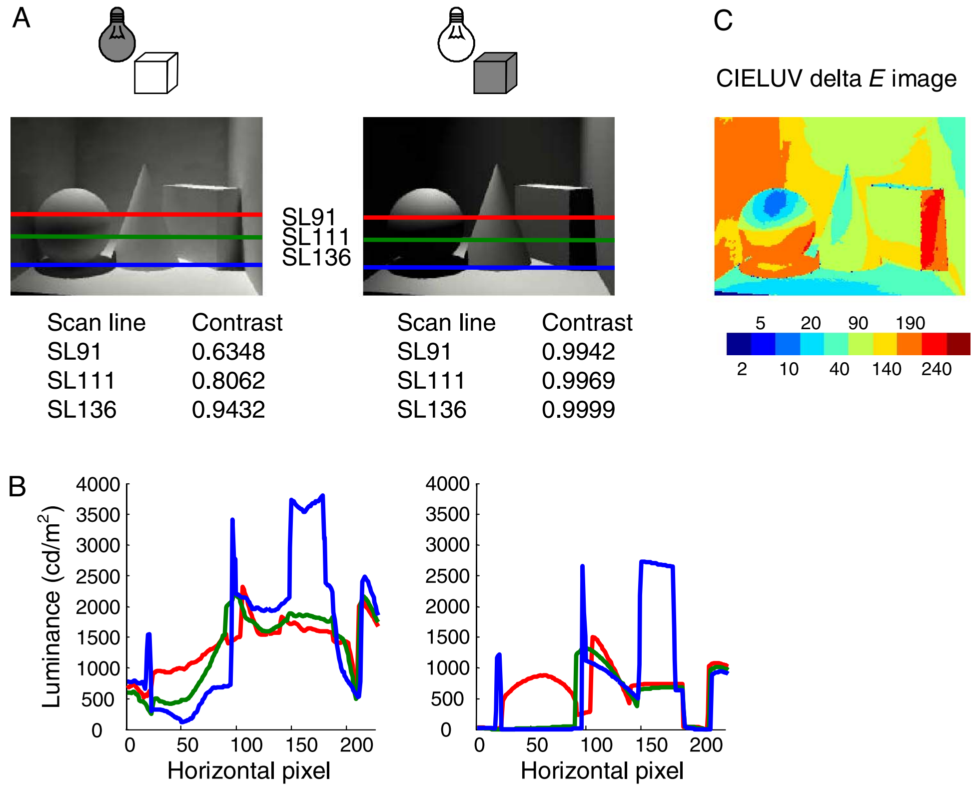

Figure 1. (A) Tone mapped RGB images for the white (left) and the black room (right). (B) Three scan lines for the above rooms. (C) Delta *E* image for the black/white room pair (for more details, see text).

delta *E* image, indicating little difference between the white and the black room. Areas that show up in red and orange (signifying larger differences) are the lower half of the sphere, the shadow of the sphere, the left wall, and the wall of the box facing the right wall. All these areas receive indirect illumination. According to standard practice, delta *E* values larger than 2 are considered to be perceptually significant. Apart from the absolute interpretation of delta *E* values, it is informative to consider its relative interpretation: The amount of area that is blue (direct illumination areas) is much smaller than the amount of area that is red or orange (indirect illumination areas).

Direct and indirect illumination images

Although contrast was a potential cue for observers, Gilchrist and Jacobsen (1984) also suggested that the indirect illumination in the two rooms could act as a cue for distinguishing rooms. They proposed that the image that reaches our eye, that is, the total illumination image, could be split into two hypothetical components, the direct and the indirect illumination image. The direct illumination image accounts for all the light that comes from the light source with a single reflection off a surface into the eye, whereas the indirect illumination image accounts for all the light that has been reflected off at least one other surface. Gilchrist and Jacobsen continue, “If such a scission could be done for the white room and the black room it would be seen that the direct [illumination] image of the white room is identical in form (but brighter than, owing to the higher reflectance of white) the direct image of the black room.… The white room has an indirect [illumination] image that is much brighter and, we believe, different from the indirect [illumination] image of the black room” (p. 17).

Obviously, such a scission is hypothetical in the real world but can be accomplished with computer graphics. We rendered a direct illumination-only image for each of our rooms (see the Methods section) and subtracted this from the total illumination image to obtain the indirect illumination image (tone mapped versions of which are shown in Figure 2). Although the total illumination images are different, the direct illumination images are actually identical (the difference between them is zero), and the indirect illumination images are the reason for the different appearance of the total illumination images. This is corroborated by the mean luminance values of each image. The mean luminance value for both direct illumination images was 716 cd/m^2, whereas for the indirect illumination images it was 786 cd/m^2 for the white room and only 22 cd/m^2 for the black room.

What happens in chromatic rooms?

We simulated two further scenarios, one achromatic/chromatic room pair and one chromatic room pair. Figure 3

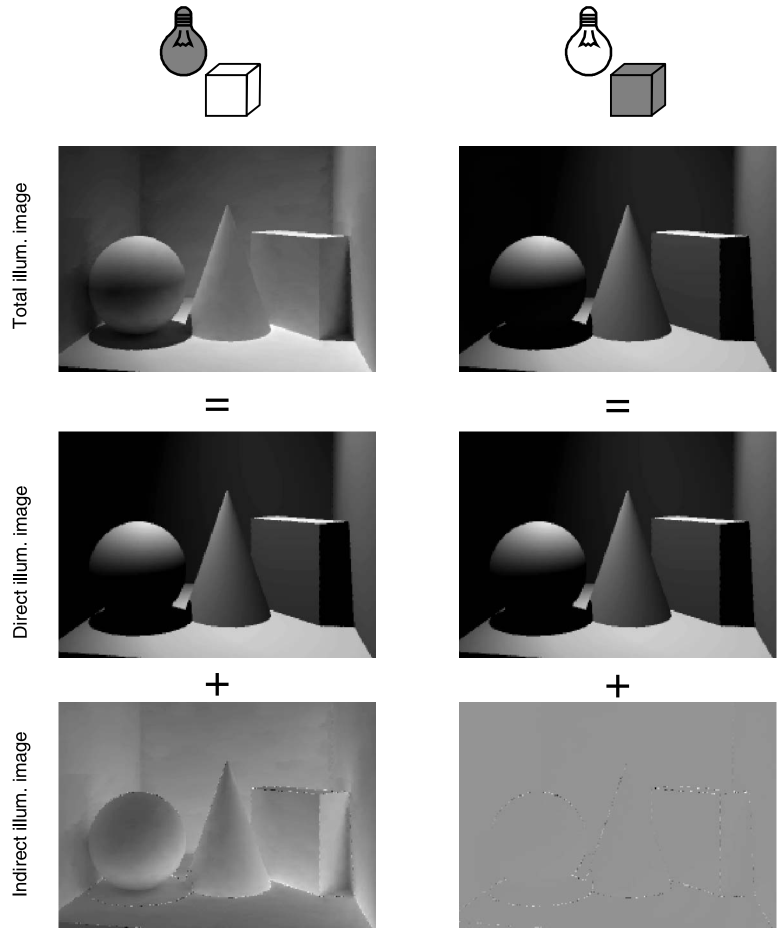

Figure 2. Total, direct, and indirect illumination tone mapped images for the white and the black room (for more details, see text). Due to tone mapping for visualization purposes, the indirect illumination image of the black room (bottom right) appears grey rather than dark.

shows the results for a white room (albedo 98%) illuminated by an orange light and an orange room (average reflectance 1%) illuminated by a white light. The corresponding delta E image (Figure 3B) is very similar to the one for the black and the white rooms. A scission of the illumination (Figure 3A) shows that the direct illumination images are identical (mean luminance 178 cd/m^2), but the indirect illumination images are not (mean luminance orange room: 1.6 cd/m^2; white room: 271 cd/m^2).

For a blue room (average reflectance 61%) illuminated by a green light and a green room (average reflectance 32%) illuminated by a blue light, we also find that the corresponding delta E image is very similar to the one for the black and the white rooms (Figure 4B). A scission of the illumination (Figure 4A) shows that the direct illumination images are identical (mean luminance 4,670 cd/m^2), but not the indirect illumination images (mean luminance blue room: 2,862 cd/m^2; green room: 2,083 cd/m^2). The indirect illumination image of the blue object room has a more bluish tint than that of the green object room.

To summarize, as for the achromatic case, the indirect illumination component of these images is what allows the potential discrimination between a “room pair.”

Will we always be able to tell the two rooms apart?

In Figure 5, we show results for a dark grey room (albedo 8%) under orange light and an orange room under dark grey light (same orange as in Figure 3). Neither the indirect illumination images (direct illumination image mean luminance value identical for both rooms: 15 cd/m^2; indirect illumination image mean luminance, dark grey room: 0.8 cd/m^2, orange room: 0.13 cd/m^2; Figure 5A) nor the resulting delta E images suggest that observers would be able to tell the two rooms apart (Figure 5B).

The mean luminance values of the rooms suggest that this is due to the fact that the luminance values in the indirect illumination areas are at mesopic or even scotopic levels, where color discrimination is difficult (Brown, 1951). For

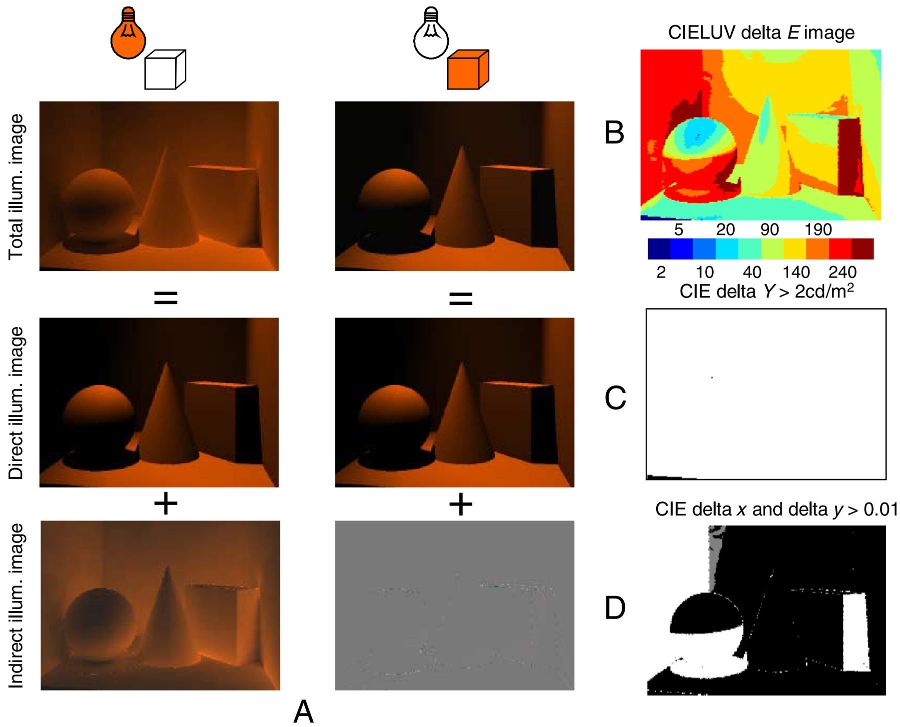

Figure 3. The white and orange room pair. (A) Total, direct, and indirect tone mapped illumination images. Due to tone mapping for visualization purposes, the indirect illumination image of the orange room (bottom right) appears grey rather than dark. (B) Delta *E* image. (C) Delta *Y* image; white areas indicate a luminance difference of at least 2 cd/m^2. (D) Delta *x* and delta *y* image; white areas indicate a chromaticity difference in *x* and *y* of at least 0.01, grey areas only in *x* or *y*.

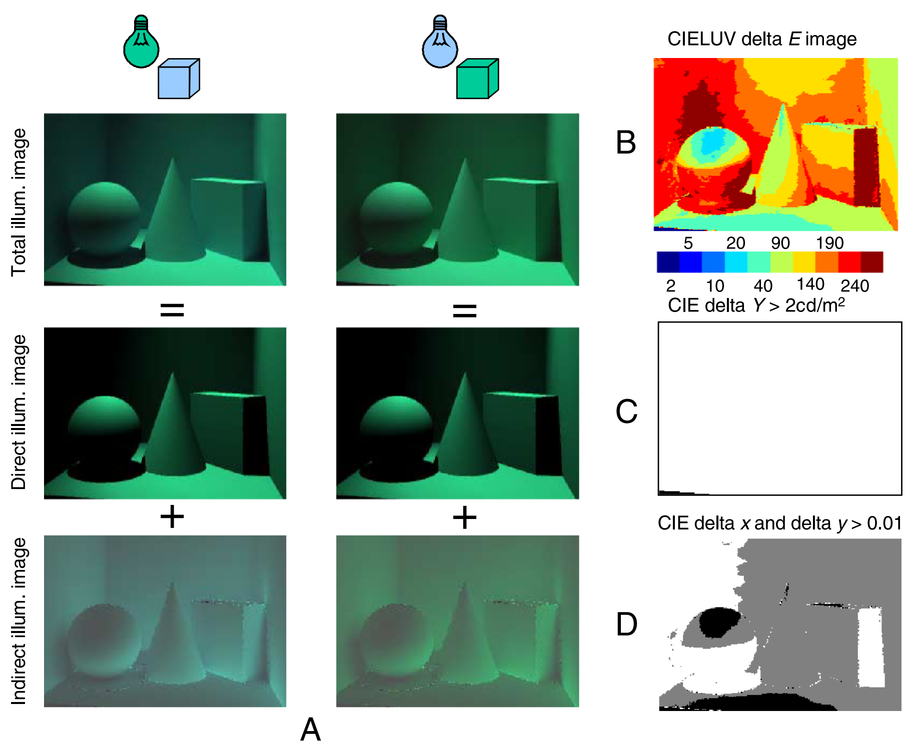

Figure 4. The green and the blue room pair. (A) Total, direct, and indirect tone mapped illumination images. (B) Delta *E* image. (C) Delta *Y* image; white areas indicate a luminance difference of at least 2 cd/m^2. (D) Delta *x* and delta *y* image; white areas indicate a chromaticity difference in *x* and *y* of at least 0.01, grey areas only in *x* or *y*.

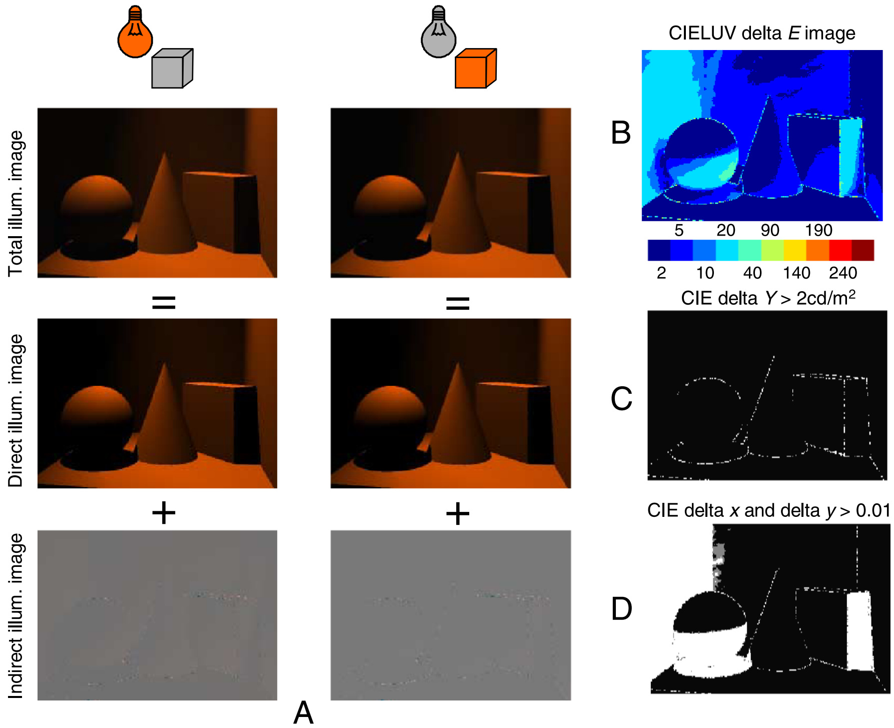

Figure 5. The dark grey and orange room pair. (A) Total, direct, and indirect tone mapped illumination images. Due to tone mapping for visualization purposes, the indirect illumination images of both rooms (bottom row) appears grey rather than dark. (B) Delta E image. (C) Delta Y image; white areas indicate a luminance difference of at least 2 cd/m^2. (D) Delta x and delta y image; white areas indicate a chromaticity difference in x and y of at least 0.01, grey areas only in x or y.

the white/orange (Figures 3C and 3D) and the dark grey/orange (Figures 5C and 5D) room pairs, we computed two other types of difference images, a delta Y image (difference in luminance) and a combined delta x and delta y image (difference in chromaticity). White areas in the delta Y image indicate a difference between the room pair of at least 2 cd/m^2 and in the delta x and delta y image of at least 0.01 chromaticity units in x and y (grey areas indicate a 0.01 difference in only one of the two dimensions). Comparison of the delta x and the delta y images shows that the rooms differ in chromaticity in the very same areas, but the delta Y image shows that the dark grey/orange room pair hardly differs in luminance. So, although there are chromatic differences in the dark grey/orange room pair, they are not associated with luminance differences and occur in areas of absolute low luminance levels making them no longer distinguishable.

Discussion

We set out to answer whether a room pair in which the spectral power distribution of the illuminant in one room matched the surface reflectance function in the other room, and vice versa, was distinguishable. According to the most common description of a color signal reaching our eyes as the product of the spectral power distribution and the surface reflectance function (Equation 1), this would not be the case. But by taking one further step toward real-world complexity and considering a rendered 3D scenario in which light is allowed to reflect several times, we show that distinction might be possible under certain conditions.

A previous study that had used real 3D rooms each homogenously painted a single different grey shade and illuminated by different light sources (Gilchrist & Jacobsen, 1984) provided an interesting suggestion why distinction should be possible, namely because of indirect illumination. However, in Gilchrist and Jacobsen's (1984) study, the rooms were not setup such that the spectral power distribution of the illuminant in one room matched the surface reflectance function in the other room, and vice versa, and it therefore does not provide an answer to our opening question.

Using a computer rendering program that precisely models the physical interaction of light and surfaces, we were able to keep most properties of our scenes constant except for the swapped spectral distributions. Our simulations—with all the shortcomings of a simulation—allowed testing our proposed question.

For the achromatic room pair, we found shallower luminance contrasts in the white room than that in the black room, matching Gilchrist and Jacobsen's (1984) finding from real rooms. We then computed direct and indirect illumination images for our rooms and found that the direct illumination images were identical (as they should be according to Equation 1) and that only the indirect illumination image was the reason why the two total illumination images differed. Computing the color difference between two direct illumination images yielded no difference; hence, the difference in the delta E images in Figures 1, 3, 4, and 5 stems from the differences in the indirect illumination image.

Color difference formula for complex images

Applying a color difference formula like delta E to entire images might stretch its intended use as it was developed for single color patches under direct illumination. But this approach has been applied to photographs and was found to correlate well with visual perceptibility and tolerances (Stokes, Fairchild, & Berns, 1992). Zhang and Wandell's (1996) development of S-CIELAB addressed the need to compare entire images. Before computing the pixel-wise CIELAB delta E difference, a spatial filtering stage is implemented, which takes the viewing distance and the different spatial resolutions of the achromatic and the chromatic systems into account. Although Zhang and Wandell's method was intended for images displayed on a monitor, they chose CIELAB, which is for surface colors rather than CIELUV, a space more appropriate for self-luminous colors. We chose CIELUV because we are still hopeful that, as further technical progress is made, these images will be displayable on a high dynamic range monitor (Ruppertsberg et al., 2007). CIELAB has almost exclusively been used for color specification, and most of the work on prediction of color difference and appearance is based on CIELAB. We found for our scenes that in comparison with delta E values based on CIELAB, delta E values in CIELUV are slightly smaller. CIELAB delta E is still the current CIE recommendation for large color differences (delta $E > 5$), and newer color difference formulae such as CIEDE94 and CIEDE2000 are still based on CIELAB coordinates (Westland & Ripamonti, 2004, chap. 5). Recently, Johnson and Fairchild (2003) implemented the CIEDE2000 color difference formula in S-CIELAB but failed to mention that CIEDE2000 is recommended only for small color changes (delta $E < 5$; Westland & Ripamonti, 2004, chap. 5). CIELUV and CIELAB require the choice of a white point, which is usually the spectral radiant power distribution of D65 (or of another CIE standard illuminant) reflected into the observer's eye by the perfect reflecting diffuser. Under these circumstances, X_n, Y_n, and Z_n are the tristimulus values of the standard illuminant with Y_n equal to 100 (Wyszecki & Stiles, 2000). Zhang and Wandell (1996) chose as their white point the monitor white point, which they admit is a poor choice, as the white point becomes dependent on the display device and not on the illumination of the scene. In our scenario, the two rooms had different illuminants; hence, the choice of a white point is not immediately clear, as there are effectively two white points, one for each room. Because each room contains only one reflectance, it is difficult to estimate the individual white point. To assess the effect of choosing individual white points, we generated new rooms that did contain a white patch. The results for individual white points showed a reversal of the delta E value pattern, that is, indirect illumination areas now showed little differences and direct illumination areas showed larger differences. However, this difference pattern does not tie in with our observation about the direct and the indirect illumination images of room pairs (Figures 2, 3, and 4). Direct illumination images of a room pair were identical, whereas indirect illumination images were not. Hence, any measurable difference between the rooms must come from the indirect illumination areas. However, the delta E value pattern when using individual white points does not support this observation. Therefore, we do not think that choosing individual white points is a correct approach and we have decided to use a single standard white point for all comparisons (XYZ = [100, 100, 100]). Another approach is to use the mean of the median luminance values for each room as the luminance value for the white point. This simply scales the color space and therefore the color difference. For the room pairs in Figures 2, 3, and 4, the differences become smaller but they are still substantial, whereas for the room pair in Figure 5 the differences become even larger. So, although the choice of the white point discussed here changes the resulting delta E values, the overall conclusions are not affected.

Displaying rendered images

When we tried to display images of our room pairs on a standard 8-bit/channel CRT monitor, we found that images that were within the gamut, as the dark grey/orange room pair (Figure 5), for example, could not be distinguished at all, which supports the significance of the delta E image (we—unsuccessfully—tried a large number of different chromatic pairings using natural spectra (Parkkinen, Jaaskelainen, & Kuittinen, 1988) to find a setup that would fit within the gamut of the monitor without manipulation and be distinguishable). Scenes, for which the delta E image indicated big differences, as the white/orange room pair (Figure 3), for example, had such a large dynamic range that they could not be displayed on currently available computer monitors. Langer and Gilchrist (2000) reported presenting RADIANCE-rendered scenes of room pairs on a CRT and found that observers could distinguish between them. Because this study is available as an abstract only, experimental, rendering, and display details are unavailable and it is not possible to assess any potential differences between our methods.

Wider implications

Our results for the room pairs are related to the phenomenon of color constancy. We have established that the indirect illumination allows the observer to distinguish between the rooms, which can be seen as equivalent to the ability of an observer to recover the different surface colors of each room. Based on the direct illumination image, the observer would assign the same surface color for both rooms because the images are the same. In a color constancy task, where the same object is illuminated by different illuminants, the observer has to derive the surface color of the object despite the illumination change. Here, areas that receive direct illumination will not be the same, but areas that receive indirect illumination will be less affected by the illumination change and therefore would provide a good estimate of surface color (Funt et al., 1991). Funt et al. (1991) showed that color samples from regions with indirect illumination lead computationally to accurate surface reflectance estimates, and therefore color constancy could be achieved. Figure 6A shows our room in a color constancy scenario. In this case, the room contained an orange sphere, a green cone, and a blue box. The back wall was orange, the sidewall was yellow, and the floor was green. We illuminated this scene once with white light and once with green light (all other rendering parameters were as described in the Methods section). In Figure 6B (left), the delta E image shows the difference between the room being illuminated by white or by green light. Areas receiving indirect illumination, like the bottom half of the sphere, the shadow area below the sphere, the left wall, and the right side of the box, show smaller delta E values than areas receiving direct illumination.

If indirect illumination is excluded from the rendering process (direct illumination only), then this leaves only the top half of the sphere as potential cues for the visual system (Figure 6B, right). All black areas in this delta E image do not receive any illumination; they are effectively holes in the image. There are countless surface reflectance functions and illuminants that could lead to the

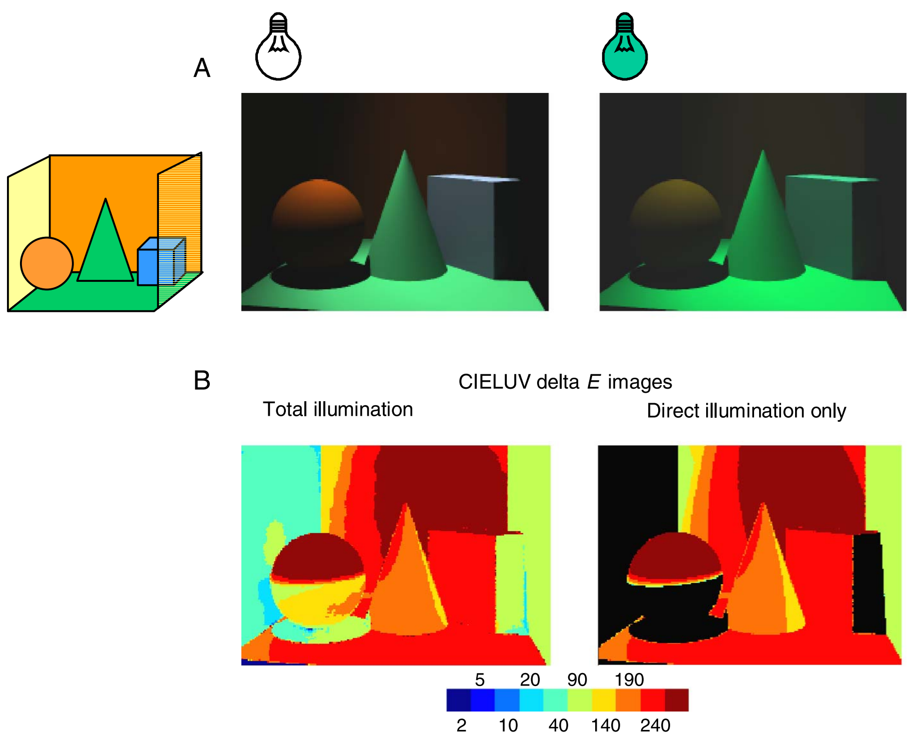

Figure 6. Color constancy scenario. (A) A colored room containing differently colored objects is illuminated by white or by green light. (B) Delta E image based on total illumination (left) and delta E image based on direct illumination only (right). Areas in black do not receive any illumination.

color pattern and hence to the resulting difference. Thus, based on direct illumination information alone, recovering the surface color would be difficult. But indirect illumination fills these holes and those areas undergo smaller appearance changes, which supports the recovery of accurate surface color descriptors. If we want to succeed in understanding human surface color perception, we need to include indirect illumination; otherwise, the results may only reflect how the human visual system copes with an artificial situation.

Conclusions

In this study, we carried out a numerical analysis of the properties of a room pair where the relative spectral power distribution of the illuminant in one room matched the surface reflectance function in the other, and vice versa. We confirmed an earlier suggestion by Gilchrist and Jacobsen (1984): indirect illumination differences between room pairs can be used to distinguish between them. As indicated by Langer (1999) and our study, the areas where indirect illumination produces the largest color differences are also areas of shadows. In a color constancy scenario, we show that indirect illumination plays also a pivotal role as areas of indirect illumination undergo a smaller appearance change than areas of direct illumination. In human surface color perception, indirect illumination plays a critical role and computer rendering programs, which model the light–object interaction according to the laws of physics, are valuable tools that allow us to analyze and to explore what image information is available to the visual system in 3D scenes.

Appendix A

Here we give the geometrical description of the objects, the illuminant, and the scene composition. For spectral rendering with RADIANCE, refer to Ruppertsberg and Bloj (in press). The material and light files are available as Supplementary data.

For our simulations, we used RADIANCE version 3.5 on Red Hat Linux version 8 (compiled binaries for Linux from the RADIANCE Web server http://www.radiance-online.org/).

A room was built from the following four objects (in RADIANCE code; Ward, 1994). The units are in principle dimensionless, but we assumed them to be meters.

```
floor_w84.rad
w84            polygon        wall
0
0
12      0       0       0
        0.4     0       0
        0.4     0       0
        0       0.4     0
sidewall_w84.rad
w84            polygon        wall
0
0
12      0       0       0
        0       0.4     0
        0       0.4     0.35
        0       0       0.3
cone_w84.rad
w84     cone    mycone
0
0
8       0       0       0
        0       0       0.202
        .07     0
ball_w84.rad
w84     sphere  ball
0
0
4       0       0       0       0.075
box_w84.rad
!genbox w84     mybox   0.15    0.15    0.07
```

The light source is described by the IES-file.

```
mylight.ies
TILT = NONE
1       1000    14.198  12      1       1       1       −0.04   0       0
1       1       75
0       5       10      15      20      25      30      35      40  45  50  90
0.0
295.53  291.59  248.23  116.82  4.73    2.10    1.71
1.31    1.05    0.79    0.53    0
```

The whole room composition is described in file w84.all. The origin (0,0,0) is to the left of the observer, with the x-direction going from left to right, the y-direction from front to back, and the z-direction from bottom to top. The last line in the file specifies the position of the light source.

```
w84.all
!xform  −n  wall_left     −t   0.875  1.5   0.735  sidewall_w84.rad
!xform  −n  wall_right    −t   1.275  1.50  0.735  sidewall_w84.rad
!xform  −n  wall_back     −rz  −90    −t    0.875  1.9       0.735  sidewall_w84.rad
!xform  −n  floor         −t   0.875  1.5   0.735  floor_w84.rad
!xform  −n  box_right     −rx  90     −rz   135    −t        1.225  1.66   0.735  box_w84.rad
!xform  −n  ball_left     −t   0.95   1.65  0.81   ball_w84.rad
!xform  −n  cone_center   −t   1.085  1.7   0.735  cone_w84.rad
!xform  −n  spotlight_15  −ry  −15    −t    0.875  1.6425    1.93   mylight.rad
```

The rendering parameters for the total illumination images were as follows.

rpict −vp 1.158 1.0 0.94 −vd −0.173 0.984 0

−ab 5 −*x* 512 −*y* 512 < $1_$2.oct | pfilt −*x* /2

−*y* /2 > $1_$.pic

pvalue −o −h −H −dF < $1_$2.pic > $1_$2.bin

In the case of the direct illumination only images, the parameter −ab was set to zero. Note, that this above description alone will not render the image spectrally as this requires a script (Ruppertsberg & Bloj, in press). The spectral information is contained in the material and the light color files.

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Footnotes

[1]"…reported the rooms to be homogeneous in reflectance…" (Gilchrist & Jacobsen, 1984, bottom page 11).

[2]See Gilchrist & Jacobsen, (1984, Figure 3, p. 12).

[3]Even if a given value falls within the monitor gamut, there is no guarantee that it will be displayed accurately due to the resolution of the graphics card.

[4]See the Colour difference formula for complex images section for a discussion on the suitability of this approach and choice of color space and white point.

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