Edge-Aware Color Appearance

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Color perception is recognized to vary with surrounding spatial structure, but the impact of edge smoothness on color has not been studied in color appearance modeling. In this work, we study the appearance of color under different degrees of edge smoothness. A psychophysical experiment was conducted to quantify the change in perceived lightness, colorfulness and hue with respect to edge smoothness. We confirm that color appearance, in particular lightness, changes noticeably with increased smoothness. Based on our experimental data, we have developed a computational model that predicts this appearance change. The model can be integrated into existing color appearance models. We demonstrate the applicability of our model on a number of examples.

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1. INTRODUCTION

The appearance of color has been well-studied, especially in order to derive a general relationship between given physical stimuli and corresponding perceptual responses. Common appearance studies use neatly-cut color patches in conjunction with a variety of backgrounds or viewing environments and record the participants' psychophysical responses, usually regarding lightness, colorfulness, and hue [Luo et al. 1991]. The elements of the viewing environments typically include the main stimulus, the proximal field, the background, and the surround [Fairchild 2005]. Although this categorization suggests that the spatial aspect of the viewing environment is taken into account, previous appearance studies have only focused on patch-based color appearance w.r.t. background and surround. The spatial aspects of the main stimulus, such as its smoothness, have not been considered.

Figure 1 presents two discs with different edge smoothness. The right disc appears brighter than the left, even though the inner densities of these two discs are identical. The only difference between the two is the smoothness of their edges. This indicates that our color perception changes according to the spatial property of surrounding edges.

Perceptual color appearance in the spatial context has been intensively researched in psychological vision [Baüml and Wandell 1996; Brenner et al. 2003; Monnier and Shevell 2003]. Typically, frequency variations of the main stimuli or the proximal field are explored. The studies are usually set up as threshold experiments, where participants are asked to match two stimuli with different frequencies or to cancel out an induced color or lightness sensation. Although threshold experiments are easy to implement and more

Fig. 1: *The right patch appears brighter than the left, while the (inner) densities of the two are actually identical. The smooth edge of the right patch induces our lightness perception into the surrounding white, making it appear brighter. Note that the total amount of emitted radiance is the same for both, with and without blurred edges. We investigate the impact of edge gradation on color appearance in this paper.*

accurate, this type of data is not directly compatible with supra-threshold measurements of available appearance data [Luo et al. 1991], which allows one to build predictive computational models of color appearance.

In this paper, we study the impact of perceptual induction of edge smoothness on color appearance. This is motivated by Brenner et al.'s work [2003], which has shown that the edge surrounding a colored patch of about 1° is very important to its appearance. To this end, we conducted a psychophysical experiment and propose a simple spatial appearance model which can be plugged into other appearance models. Our main contributions are:

— appearance measurement data of color with edge variation,
— a spatial model taking into account edge variations.

2. RELATED WORK

This section summarizes relevant studies with respect to the perceptual impact of spatial structure.

Background CIE-based tristimulus values can represent the physical quantity of color, but the perception of a color depends on many parameters, such as the spatial structure of the surrounding background. For instance, identical gray patches will appear differently on white and black backgrounds, which is the so-called *simultaneous contrast* effect [Fairchild 2005]. In particular, perceived lightness and colorfulness are induced such that they are less like the surrounding background. We investigate this phenomenon and, in particular, how induction is influenced by the smoothness of the edge between a color and its surrounding background.

Spatial Color Appearance Many experiments have been conducted to investigate the influence of spatial structure on color perception; for instance, using a vertical sine-wave luminance grating that surrounds the test field [McCourt and Blakeslee 1993]. According to McCourt and Blakeslee [1993], the perceived contrast induction decreases when the spatial frequency of the surrounding structure is increased. Instead of vertical frequency stimuli, Brenner et al. [2003] experimented with non-uniform surrounding checkerboard patterns to test chromatic induction. Interestingly, they found that the directly neighboring surround (up to approx. 1°) is more influential than the remote surround. Monnier and Shevell [2003] tested chromatic induction from narrow, patterned, ring-shape surrounds, and found significant shifts.

Much research has been devoted to contrast, which is very related to edges. For instance, Baüml and Wandell [1996] use a square-wave grating as the main stimuli to determine contrast sensitivity thresholds. Border effects on brightness and contrast have been studied by Kingdom and Moulden [1988]. These perceptual effects have been exploited in *unsharp masking* (Cornsweet illusion) to increase perceived contrast [Calabria and Fairchild 2003]. In this paper, we do not focus on contrast (and contrast thresholds), but rather on modeling appearance induction due to edge smoothness. To the best of our knowledge, this is the first work to introduce and use a color appearance model for counteracting lightness and colorfulness shifts due to edge variations.

Appearance Modeling Luo et al. [1991] triggered intensive research into color appearance modeling by providing publicly available appearance data. More recently, CIECAM02 [Moroney et al. 2002] established a standard appearance model. Although it carefully accounts for viewing conditions such as background and surround, it does not model any spatial properties of the surround.

Nonetheless, there are appearance models that include some spatial aspects. Zhang and Wandell [1997] introduced a simple image appearance model which relies on straightforward spatial filtering of the different channels before using CIELAB. Fairchild and Johnson [2002] provide a more advanced image appearance model based on CIECAM02, which also employs spatial filtering. However, they only account for the local change in contrast sensitivity, as they are based on contrast sensitivity measurements [Baüml and Wandell 1996]. In contrast, we focus on the more specific question of how edge frequency (i.e., smoothness) changes color appearance w.r.t. the surrounding background. We answer and quantify this through a psychophysical magnitude-estimation experiment.

Edge-Aware Imaging There are a number of imaging techniques in computer graphics that rely on edges/gradients – usually in the context of high-dynamic-range compression [Tumblin and Turk 1999; Fattal et al. 2002]. However, these techniques are not concerned with modeling color appearance with respect to edges.

3. PSYCHOPHYSICAL EXPERIMENT

In order to quantify the influence of spatial context on color appearance, we conducted two experiments. First, we conducted a magnitude estimation experiment, where observers were presented with a number of colored patches, for which lightness, colorfulness, and hue values needed to be estimated. This magnitude experiment explored the luminance interaction between the main stimulus and the background; different phases were conducted, where the softness of the patch edges and background lightness level were varied independently. Second, we conducted a hue cancellation experiment for testing hue induction by colored background w.r.t. edge gradation. In this experiment, observers were presented with a number of random color patches on a different color background, for which hue needed to be adjusted to imaginary gray.

3.1 Stimuli

Edge-Varying Color Our basic setup for this experiment and the data analysis were adapted from Luo et al. [1991] and Kim et al. [2009]. However, our methodology focused on exploring the impact of the spatial context on color appearance. Each participant judged a color patch in terms of lightness (w.r.t. a reference white patch) and colorfulness (w.r.t. a reference colorfulness patch), see Fig. 3a. The pattern was observed at a 55 cm viewing distance, such that the patch covered a 2° field-of-view. We varied the softness of the patch edge (from hard to soft, see Fig. 2) but ensured that the center area Φ always covered at least 1°, with the width of the edge increasing up to $\Delta\Phi = 1.33°$. Prior to the main experiment, we ran a pilot experiment to examine the appearance impact of the size of the solid part. We found that the size of the patch did not affect color appearance significantly. This is important, since we varied the size of the solid inner part of our stimuli (see Fig. 2) to ensure that the overall emitted radiance remains constant.

The smooth edges were created with a smooth-step function (cubic Hermite spline), evaluated radially. Note that we represent the smoothness of the edge by its angular width (covering the complete edge, see Fig. 2) instead of gradient magnitude, as the angular width can be used directly to build a perceptual model. Three different background levels (0%, 50%, and 100% of the maximum luminance level) were used.

Colored Background The magnitude estimation experiment investigated induction by background luminance w.r.t. edge smoothness. We devised a second experiment to investigate chromatic induction from colored backgrounds w.r.t. edge smoothness. We hypothesized that if perceived lightness and colorfulness were in-

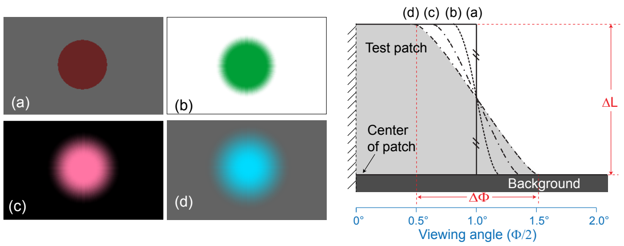


Fig. 2: *Edge smoothness variation of the test color patch. Participants performed a magnitude estimation experiment with different edges. The edge width values (ΔΦ) for (a), (b), (c), and (d) are* 0.08°, 0.50°, 0.92°, *and* 1.33° *respectively. Hence, the patch sizes* ($\Phi + \Delta\Phi$) *varied from* 2.08° *to* 3.33°.

fluenced by the gradating background, perceived hue would also be affected. However, due to concerns over chromatic adaptation (perceived hue is adapted to the brightest stimulus [Fairchild 2005]), we decided against a magnitude experiment as in the first experiment. Instead, we opted for a hue cancellation experiment [Brenner et al. 2003]. A single patch is shown on a colored background, see Fig. 3c. The background is one of eight different hues (average luminance CIE $L^* = 40.79$ and chrominance $C^* = 37.40$, see Fig. 3d), and the patch smoothness is varied in the same manner as the magnitude experiment (observer distance and patch size also remain the same).

3.2 Experimental Procedure

Magnitude Estimation We conducted a series of magnitude estimation experiments. To this end, the viewing patterns were presented on a calibrated computer monitor (23-inch Apple Cinema HD Display, characterized according to the sRGB color standard (gamma: 2.2); max luminance of 188.89 cd/m²). The spectral power distribution of all the color stimuli were measured in 10 nm intervals with a GretagMacbeth EyeOne spectrometer.

Six trained participants, who passed the Ishihara and City University vision tests, were shown twenty color patches in a dark viewing environment in random order in each experimental phase (different background luminance and edge smoothness). See Figure 3 for the distribution of the color patches and Table I for the different phases. Participants were asked to produce three integer scales for lightness (0–100), colorfulness (0 – open scale), and hue (0–400) of the solid center part of each color patch [Kim et al. 2009]. The participants completed the twelve phases in approximately three hours without counting break times. They also completed a one-hour training session in the same experimental setting.

We have tested the reproducibility of the experiment by repeating the same phase with three different participants on different days. The coefficient of variation (CV), which is the RMS-error w.r.t. mean, of these two phases of the same stimuli (repeatability) were 11.74% for lightness, 22.47% for colorfulness, and 4.43% for hue. The CVs of inter-observer variance were 13.18% for lightness, 25.91% for colorfulness, and 6.56% for hue. This is in good agreement with previous studies [Luo et al. 1991; Kim et al. 2009].

Hue Cancellation Magnitude estimation experiments were followed by hue cancellation experiments. Viewing patterns which contains only a random color on a colored background were adjusted by the same participants on the same display, similar to [Brenner et al. 2003]. For a given colored background, participants were asked to adjust a patch (varying edge smoothness, see Fig. 2) with an initial random main color such that it appeared as neutral gray. The participants were able to control hue and chroma but not luminance to yield neutral gray. Note that no white point was shown, just the

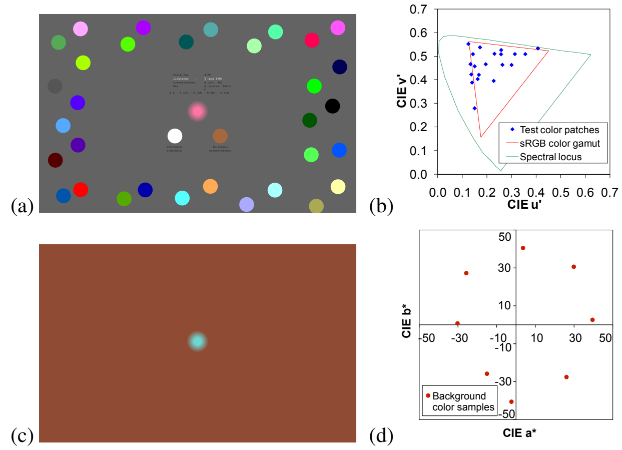


Fig. 3: *Viewing patterns and color distributions of the magnitude estimation experiments, (a) & (b), and the hue cancellation experiments, (c) & (d), as observed by participants. Each color patch was shown with four different levels of edge smoothness (random order, see Fig. 2), for each of the viewing conditions.*

background and the patch itself, to avoid potential hue adaptation to any reference color. We varied the initial patch color to have five different luminance levels and the background to have eight different hues, but consistent chrominance and lightness. The same six participants completed the experiment in approximately two hours (see Table II).

Phase	Edge Width (ΔΦ)	Background Lumin.	Peak Lumin.
1	0.08°	0.32 cd/m²	188.89 cd/m²
2	0.50°	0.32 cd/m²	188.89 cd/m²
3	0.92°	0.32 cd/m²	188.89 cd/m²
4	1.33°	0.32 cd/m²	188.89 cd/m²
5	0.08°	22.23 cd/m²	182.52 cd/m²
6	0.50°	22.23 cd/m²	182.52 cd/m²
7	0.92°	22.23 cd/m²	182.52 cd/m²
8	1.33°	22.23 cd/m²	182.52 cd/m²
9	0.08°	188.72 cd/m²	188.27 cd/m²
10	0.50°	188.72 cd/m²	188.27 cd/m²
11	0.92°	188.72 cd/m²	188.27 cd/m²
12	1.33°	188.72 cd/m²	188.27 cd/m²

Table I. : *Summary of the twelve phases of our first appearance experiment with twenty color samples each. Each participant made a total of 720 estimations. This experiment was conducted in dark illumination conditions, and took about three hours per participant.*

Phase	Edge Width (ΔΦ)	Back. Aver. L^*	Back. Aver. C^*
13	0.08°	40.79	37.40
14	0.50°	40.79	37.40
15	0.92°	40.79	37.40
16	1.33°	40.79	37.40

Table II. : *Summary of the four phases of our hue cancellation experiment with forty initial random color samples each (five different luminance levels (24/42/62/82/100) of the main patch with eight different background hues (3/45/84/133/178/239/266/313) with a fixed chroma ∼37.40). Each participant performed a total of 40 hue cancellations, such that the patch color appeared neutral on the colored backgrounds (dark viewing conditions). This experiment took about two hours per participant.*

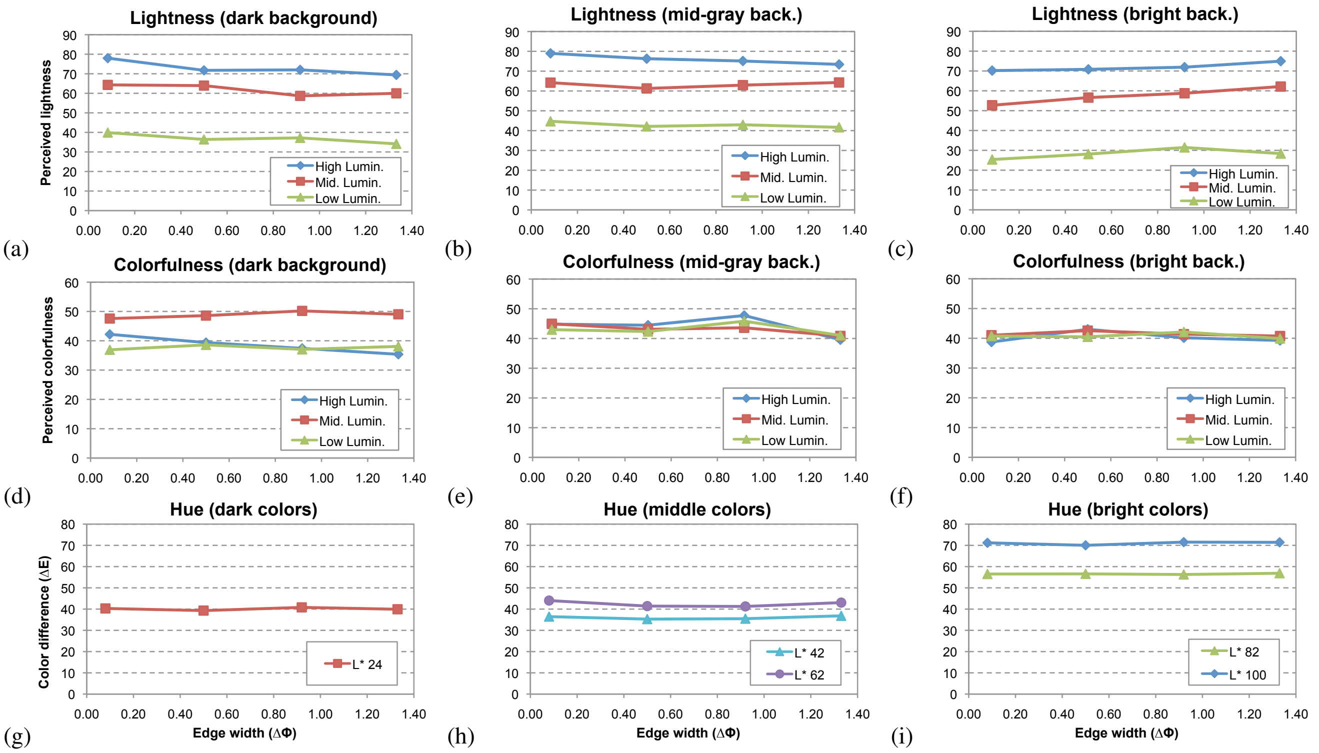


Fig. 4: *Comparison of the perceived lightness, colorfulness, and hue. The first two rows represent the differences of perceived lightness and colorfulness on different background luminances (each column). Horizontal axis indicates the smoothness of the edge in terms of angular edge width ($\Delta\Phi$). The stimuli are grouped by their respective level of luminance: high (6 patches), middle (9 patches), and low (5 patches). High luminance patches have higher values than CIE L^*=70. Low luminance patches have lower values than L^*=40. The dark background has a lightness of L^*=1.53; the mid-gray background has L^*=41.50; the bright background has L^*=100. The third row represents the color difference in CIE ΔE between the colored background and the neutralized patch for three different luminance levels (each column). The given patches are grouped by their luminance level: dark (L^* 24), middle (L^* 42 and 62), and bright colors (L^* 82 and 100). These color differences indicate the relative changes of perceived white against colored background.*

3.3 Findings

Our experiment quantifies the change in perceived color appearance with respect to edge smoothness as well as luminance difference between the patch and the background. Our initial findings can be summarized as follows.

Lightness Perceived lightness is affected by the change of edge smoothness. A softer edge induces perceived lightness more strongly, i.e., perceived lightness is induced more towards the level of background lightness. For instance, smoother edges on a dark background causes the perceived lightness of a patch to appear darker than on a mid-gray background; smoother edges on a bright background cause the lightness to appear brighter. See Figure 4(a)–(c).

Colorfulness In most phases, colorfulness – compared to lightness – shows a subtle change according to edge smoothness, see Fig. 4(d)–(f). In particular, high luminance colors on a dark background present a clear trend: colorfulness of bright patches decreases with smoothness, see Fig. 4(d). We believe that in this case colorfulness is indirectly influenced by the decrease in perceived lightness (Fig. 4(a), blue line), which is known as the Hunt effect [Hunt 1994].

Hue In contrast to our initial hypothesis on hue induction, participants were able to adjust the initially colored patch to neutral gray (CIE x=0.3176 & y=0.3263) with a very small variation (average std. dev.: 0.0058). This is despite the fact that the backgrounds were colored and that there was no reference white. Perception of the neutral grayscales shows a small trend of luminance-dependency (see Table III). In lower luminance levels, participants picked warmer grays as neutral, but in middle and high luminance levels, they chose colder grays as neutral. However, as shown in Fig. 4(g)–(i), no significant perceived hue changes against different color backgrounds or edge smoothness were observed in the hue cancellation experiment. Figure 5 presents a qualitative comparison for perceived color appearance (lightness/colorfulness/hue) with respect to the smoothness of the edge.

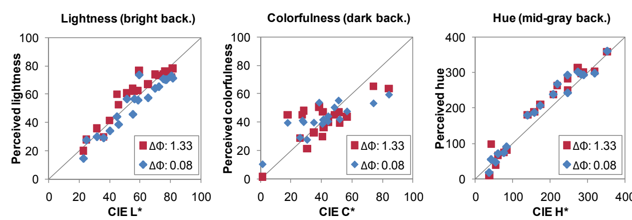


Fig. 5: *Qualitative comparison of two different edges ($\Delta\Phi = 0.08$ and $\Delta\Phi = 1.33$).*

L^*	X	Y	Z	x	y	CCT
24	8.44	8.23	8.31	0.3376	0.3302	5260K
42	23.18	23.70	26.91	0.3151	0.3224	6476 K
62	54.05	56.17	63.47	0.3119	0.3242	6628 K
82	106.69	111.51	124.46	0.3118	0.3261	6601 K
100	176.95	186.70	204.58	0.3116	0.3288	6571 K

Table III. : *Physical measurements of imaginary neutral gray scales in the hue cancellation experiment. The first column indicates the luminance levels of given random color patches, and the remaining columns—CIE XYZ, xy, and correlated color temperature (CCT)—are the averaged physical readings of the neutral patches chosen by the participants against the colored backgrounds. The display was calibrated to x=0.3112 and y=0.3280 (CCT: 6587* K*).*

In summary, edge smoothness consistently affects the induction of perceived lightness. With softer edges, the lightness of a patch is induced more towards the background lightness. Colorfulness shows subtle changes and hue seems unaffected.

4. MODELING

Classical perceptual models for color appearance, such as CIECAM02 [Moroney et al. 2002], assume that the edge of a color patch is sharp because their appearance measurements were based on sharp-edged color samples [Luo et al. 1991]. However, our perceptual study found that perceived appearance is affected by the smoothness of stimuli edges. We now present an appearance model that takes edge smoothness into account.

As shown in the previous section, color appearance strongly depends on the shape of the bordering edge, namely the lightness difference between the patch and the surrounding background $\Delta L = L_{\text{patch}} - L_{\text{background}}$, as well as the angular width of the edge $\Delta\Phi$. For instance, when a patch is shown with a background darker than the patch, ΔL has a positive value; when a patch is surrounded by a brighter background, ΔL has a negative value. The width of the edge $\Delta\Phi$ has a positive value only.

In order to model lightness and colorfulness induction, we choose to modify existing color appearance models, namely CIEMCAM02 [Moroney et al. 2002], Kim et al. [2009], and CIELCH [CIE 1986], instead of deriving a model from scratch. We will explain our model in the context of standard CIECAM02, but it is essentially identical when plugged into other appearance models – except for different constants.

As can be seen in Figure 4(a)-(c), lightness induction is fairly linear with respect to edge width. Hence, we model the change in lightness J^δ due to induction as:

$$J^\delta = f(\Delta J, \Delta\Phi) = -k \cdot \Delta\Phi \cdot \Delta J, \tag{1}$$

where $\Delta J = J_{\text{patch}} - J_{\text{background}}$ and $\Delta\Phi$ is the angular edge width, and k is parameter that we fit based on our experimental data[1].

We group the majority of the phases of our experiment as the training set (phases 1, 2, 4, 5, 7, 8, 9, 11, and 12) and the remaining ones as the test set (phases 3, 6, and 10). Given the changes in appearance $\delta_{\Delta J,\Delta\Phi}$ due to lightness differences ΔJ and edge widths $\Delta\Phi$ of the training data set Ψ, we optimize the parameter k by minimizing the following objective function O:

$$O = \sum_{\Psi} |f(\Delta J, \Delta\Phi) - \delta_{\Delta J,\Delta\Phi}|^2 \tag{2}$$

[1]CIECAM02 denotes perceptual lightness as J; we change notation accordingly.

The optimization yields $k = 0.0923$ (CIECAM02). We perform a similar optimization for the other appearance models, yielding $k = 0.1317$ (CIELCH) and $k = 0.0567$ (Kim et al. 2009).

The main difference between this model and the original CIECAM02 is that we need the perceptual background luminance level $J_{\text{background}}$. The original input parameter Y_b for the background is a percentage ratio of the background luminance. We first compute background XYZ values by scaling the reference white point $X_W Y_W Z_W$ by $Y_b/100$. From this XYZ, we compute the background lightness value $J_{\text{background}}$. The new perceptual lightness value J' is calculated by adding J^δ to the original lightness J_{patch}: $J' = J_{\text{patch}} + J^\delta$. Note that colorfulness and chroma must then be computed with this new lightness J'.

Colorfulness induction is more subtle, see Fig. 4(d)-(f). We note that modeling lightness induction already models colorfulness induction to a degree, since a change in predicted lightness will also change predicted colorfulness. For instance, prediction accuracy for colorfulness does indeed improve for CIECAM02 (cf. Section 5). We also experimented with modeling colorfulness induction using linear, quadratic, and cubic polynomials (similar to lightness); however, prediction of colorfulness did not improve. Since no hue changes were observed, hue prediction was left unchanged.

Our method is applicable to any color appearance model, e.g., CIELAB, RLAB, CIECAM02, or Kim et al. [2009]. As we will see in the following section, it significantly improves the accuracy of color appearance models that account for background luminance, such as CIECAM02 and Kim et al's.

5. RESULTS

Figure 7 presents the CV error between the predicted and perceptual appearance. The dashed red line indicates the result of the original CIECAM02 model. It fails to predict that perceived lightness increases with edge smoothness, see Fig. 7(a). The solid red line represents the CV error for CIECAM02 with our edge-aware model. The lightness prediction is significantly better. An even better improvement is achieved for Kim et al.'s model (blue lines). There is no improvement for either model for mid-gray backgrounds, which is to be expected, since lightness perception does not change in that case (see Fig. 4(b)). The improvement for CIELCH (orange lines) is not significant for any kind of background, which is unsurprising, as the original model does not take into account background luminance.

In Figure 7(b), the results for colorfulness prediction are shown. Colorfulness prediction for CIECAM02 with dark backgrounds improves with our model; this is also the only case where a clear colorfulness induction was observed (blue line in Fig. 4(d)). The colorfulness prediction of Kim et al.'s model does not improve, as the colorfulness computation in their model does not directly depend on relative lightness. Similarly, the chroma prediction of the CIELCH model does not improve.

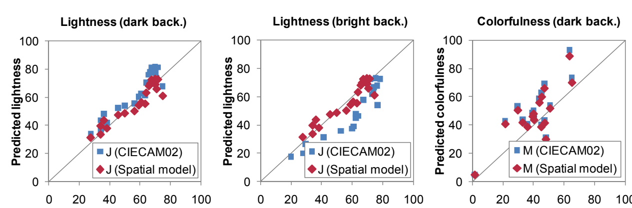
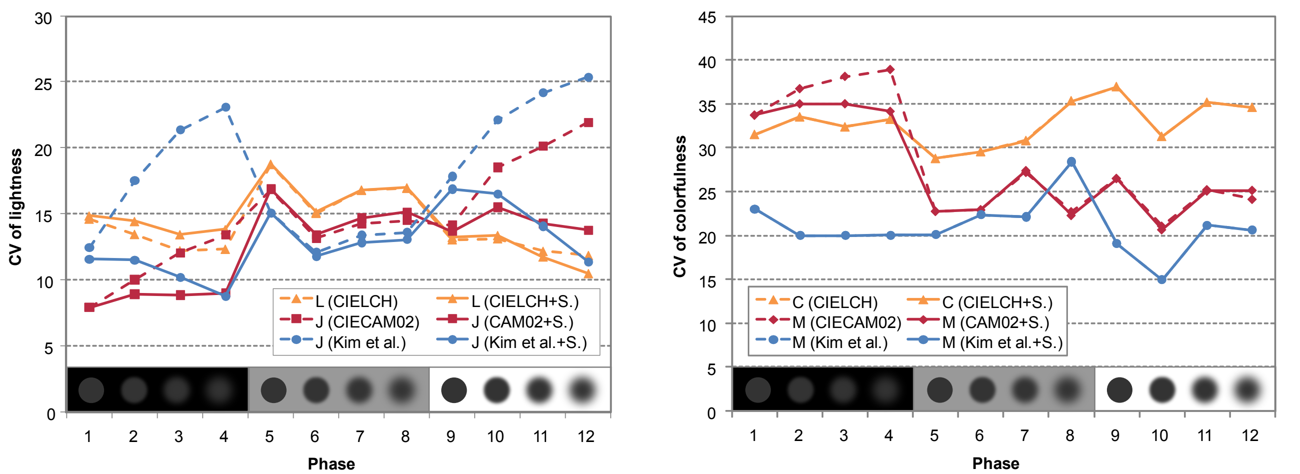


Fig. 6: *Qualitative comparison of the results of the* $\Delta\Phi = 1.33$ *on dark and bright backgrounds.*



(a) Lightness prediction (b) Colorfulness prediction

Fig. 7: *Comparison between CIELCH, CIECAM02, Kim et al. [2009] and their edge-aware counterparts. In both subfigures, (a) and (b), phases 1–4 are with a dark background; phases 5–8 are with a mid-gray background; phases 9–12 are with a bright background. Within these phase groups, higher phase numbers present smoother edge gradation. In particular, lightness and colorfulness predictions are significantly improved w.r.t. edge smoothness. Among them, the test data set include phases 3, 6, and 10. For quantitative results of each model, see Tables IV, V, and VI.*

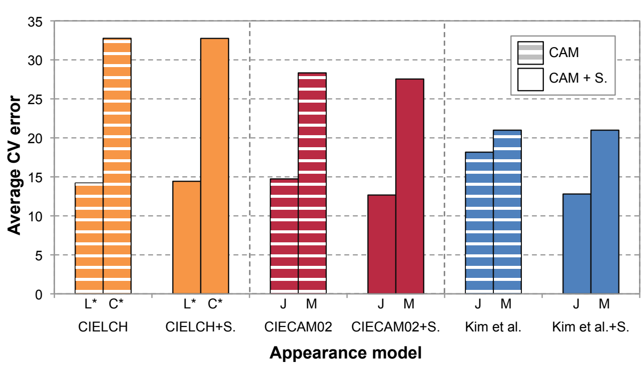


Fig. 8: *Overall CV errors for different color appearance models (CAMs), with and without our spatial enhancement. L^* and J denote lightness; C^* and M denote colorfulness. As can be seen, the CV errors of background-aware appearance models are considerably reduced, especially for lightness in CIECAM02 and Kim et al.'s model.*

Unfortunately, there is no other publicly available perceptual data for edge-based appearance, so we could not test our model with any external data. We used phases 3, 6, and 10 for cross-validation (not part of the training data), which also produced consistent results (see Fig. 7). The overall average results are presented in Fig. 8. Qualitative results for lightness and colorfulness are shown in Fig. 6.

5.1 Applications

In the following, we demonstrate how our edge-aware model (CIECAM02-based) can be used in practice. Note that all figures are optimized for a calibrated 23" display with 190 cd/m² at 55 cm viewing distance. A blurring filter is a commonly used manipulation tool in image editing software. As evident from our experiment (Fig. 4), blurring can lead to perceived lightness and colorfulness changes, which we have formalized in our model. We can now use our model to counteract these changes. The logo in Figure 9(a) contains uniform blue and red colors. After applying a Gaussian filter, the colors in image (b) appear not only brighter, but also more colorful, even though the actual color values in image (b) are the same as in (a). Before we can use our model, we have to relate the standard deviation σ of the (angular) Gaussian kernel to (angular) edge width. We numerically derive a direct linear relationship between σ and the resulting edge width, $\sigma = 2.656\Delta\Phi$, which also produces the same overall slope. We now apply our edge-aware CIECAM02 model (forward and inverse [CIE 2004]) so that the original color appearance is preserved even after blurring. The result can be seen in image (c), where color appearance now matches image (a).

Figure 10 presents the perceptual impact of anti-aliasing fonts. Fig. 10(a) shows the Arial Italic font without anti-aliasing. The font appears as high-contrast, albeit jagged edges are visible. Fig. 10(b) is the same font but rendered with smooth anti-aliasing. The font now appears smoother with reduced aliasing artifacts. However, the perceived lightness and contrast of the font is also altered. Note that

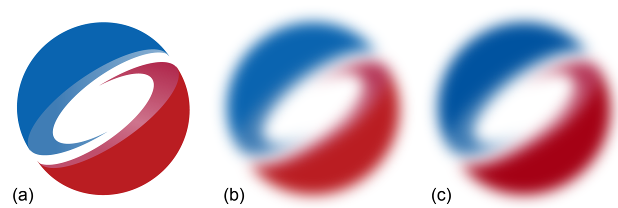


Fig. 9: *The logo in (a) is blurred by a Gaussian filter, yielding (b). Image (b) appears brighter and more colorful than the original (assuming 55 cm viewing distance and full-page view). Using our model, image (c) produces the same color appearance even after the blurring operation. Note that actual pixel values in image (c) are different from the original image (a).*

Fig. 10: *Image (a) shows the Arial Italic font without anti-aliasing (30* pt *font, zoomed in 200% using nearest neighbor upsampling for display purposes). Image (b) shows the same font but rendered with anti-aliasing. The font is rendered with the same pixel density, but appears lighter than the original due to edge smoothness. With our model, we can render anti-aliased fonts, see image (c), but with the* same appearance *as the original fonts.*

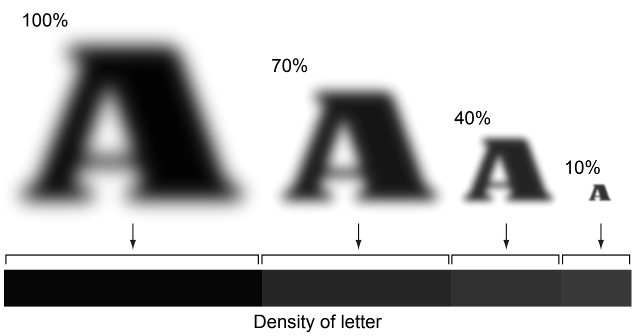


Fig. 11: *A blurred letter is successively downsampled which reduces the smoothness of its edges accordingly. The four letters have the same lightness appearance when applying our edge-aware appearance model. Comparing the actual densities of these letters (bottom) shows that smaller letters have lighter densities.*

the pixel intensity of characters are identical to Fig. 10(a). Fig. 10(c) shows the anti-aliased font with our edge-aware model applied, giving equally high contrast as in the original font. The contrast of Fig. 10(c) is physically different from Fig. 10(a), but *perceptually* identical to Fig. 10(a).

In Figure 11, we successively downsample a blurry letter. In order to maintain the same lightness impression even for the downsampled letters, we apply our model. At the bottom we show the actual gray-level that is used to maintain the same perceptual appearance.

Figures 13, 14, and 15 show more complex examples. Image (a) in Figs. 13–15 is a sharp source image. We simulate a depth-of-field effect by directly applying a progressively stronger Gaussian blur (bottom to top), yielding Image (b) in Figs. 13–15. Again, lightness and colorfulness increase in Fig. 13. In contrast, lightness and colorfulness decrease in Fig. 14 as the castle towers are surrounded by a dark background, compared to the original (assuming full-screen view of images at 55 cm distance). Image (c) in Figs. 13–15 shows that our model manages to preserve the original appearance. In Fig. 15(b), electronic displays on the building at the junction of the two avenues seem darker due to blurring. The displays on Fig. 15(c) preserves the original brightness, compared to Fig. 15(b).

5.2 Validation

We conducted a user study to verify the perceptual applicability of our method. To this end, ten participants were shown five sets of two different stimuli (a standard blurred image and our edge-aware blurred image) on the calibrated LCD display at 55 cm distance in dark viewing conditions. For each set, a source reference image without blur was inserted between these two stimuli to be compared with them. Participant were asked to choose which stimulus was closer to the reference in terms of color appearance (lightness, colorfulness, and hue). The five sets of images are all shown in this paper (see Figures 1, 9, 13, 14, and 15).

A one-way ANOVA test was employed to validate the statistical significance of our method. As shown in Figure 12, the result indicates that our model produces blurred images that are much closer to the original in terms of lightness and colorfulness, compared to the standard blurred image, and the difference in scores is statistically significant ($p < 1.1 \times 10^{-5}$; α=0.05). This shows that there is a clearly perceptible difference between the original and the standard blurred image in terms of color appearance, whereas our method preserves perceptual color appearance.

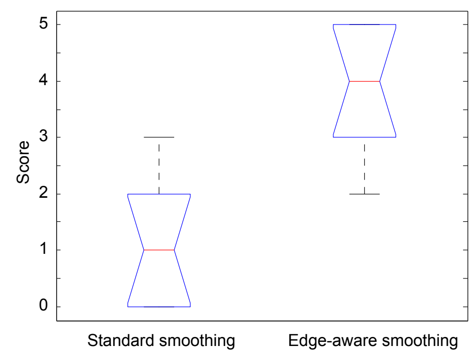


Fig. 12: *This graph from a one-way ANOVA test shows the mean (red line) and 95% confidence intervals (blue trapezoids) of appearance similarity of the standard blur and edge-aware blur to the reference. Score varies from 0 (different from the reference) to 5 (identical to the reference) in terms of color appearance. The mean similarity score of the standard blur is 1.0909; the mean of our edge-aware blur is 3.9091. The p value from this test shows statistically significant performance of our method w.r.t. perceptual similarity to the reference ($p < 1.1 \times 10^{-5}$).*

5.3 Discussion and Limitations

Prior to the presented magnitude experiments, we conducted several pilot experiments to determine if background patterns of different frequencies cause noticeable appearance changes. We found that for the same average background luminance but different frequencies, patches appear quite consistent. Previous work [Brenner et al. 2003] also found these appearance changes to be subtle (albeit measurable). We therefore do not take spatial frequencies into account. Monnier and Shevell [2003] found significant shifts for circular chromatic patterns around a patch. We speculate that these shifts may in fact be related to shifts due to edge smoothness.

Our stimuli provide a solid color at the center with varying edge smoothness. Participants were asked to make their judgements by exclusively considering the solid center part of the color patch. We have experimented with different edge profiles (Gaussian vs. spline) and conclude that induction depends on the overall edge width and slope, but not on the exact shape of the fall off.

With regards to the hue cancellation experiment, we found that participants consistently produced the same gray patches despite being shown different backgrounds, as discussed before. This is unexpected since chromatic adaptation depends on the brightest stimulus as the reference white [Fairchild 2005]. Unfortunately, we

Fig. 13: *The background of image (a) is softened by a Gaussian blur. Image (b) shows the naïve blurring result, where the dark red house appears brighter and bricks appear more colorful than the original. Image (c) shows our edge-aware smoothing result, with the appearance of the house being maintained as in the source image. We assume each image is displayed full-screen. Image courtesy and copyright of Ray Daly [2010].*

Fig. 14: *A depth-of-field effect is simulated by directly applying a progressively stronger Gaussian blur (bottom to top). Image (b) shows the naïve blurring result, where the further castle towers appear less bright and less colorful. Image (c) applies our model to preserve the original appearance. Image courtesy and copyright of Rebekah Travis [2010].*

Fig. 15: *Image (a) shows the source image without any blur. Image (b) and (c) show the comparison between naïve blurring and our model. Although our model compensates for the perceptual difference induced by the blur, the change of perceptual luminance is subtle in this case. Image courtesy and copyright of Juan Sanchez [2010].*

do not have a good hypothesis for why this is. However, based on our experiment we were unable to observe hue induction, and therefore excluded it from our model. Our model also excludes the *multiple surrounding* effect, as presented by Monnier and Shevell [2003], but focuses on lightness and colorfulness changes.

Lightness induction is often rather obvious, see Fig. 1, 9, and 13, but can also be subtle, see Fig. 15. This seems to be true for cluttered scenes on a dark background.

6. CONCLUSIONS

We have conducted a psychophysical experiment to determine and measure the influence of edge smoothness on appearance. We found that edge smoothness significantly affected perceived lightness. Colorfulness was also affected, albeit mostly for dark backgrounds. The perceived hue was not influenced. Based on the experiment, we have developed a spatial model that can be used to enhance existing color appearance models, such as CIECAM02. We demonstrated the applicability of our model in imaging applications.

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Appendices

Experimental Data The psychophysical experimental data that was used to develop our model is available as an electronic appendix to this article, which can be accessed through the ACM Digital Library.

Phase	L*	C*	h*	L*+S.	C*+S.	h*+S.
1	14.61	31.51	14.15	14.86	31.50	14.13
2	13.46	33.51	13.51	14.44	33.49	13.50
3	12.22	32.37	15.73	13.44	32.36	15.72
4	12.34	33.25	16.63	13.83	33.23	16.62
5	18.74	28.78	14.43	18.78	28.77	14.44
6	15.05	29.56	17.63	15.13	29.55	17.63
7	16.79	30.82	14.16	16.83	30.81	14.15
8	16.94	35.33	16.31	16.99	35.32	16.30
9	13.06	36.94	13.61	13.24	36.94	13.61
10	13.13	31.29	17.03	13.38	31.28	17.03
11	12.18	35.17	20.33	11.76	35.15	20.31
12	11.87	34.59	14.35	10.49	34.58	14.35

Table IV. : *Quantitative comparison results in CV errors between CIELCH and its edge-aware application.*

Phase	J	M	H	J+S.	M+S.	H+S.
1	7.91	33.69	10.79	7.91	33.69	10.79
2	10.01	36.70	8.32	8.92	34.96	8.32
3	12.05	38.09	7.89	8.86	34.97	7.89
4	13.40	38.88	9.65	9.00	34.11	9.65
5	16.82	22.77	8.49	16.89	22.77	8.49
6	13.14	22.90	9.87	13.43	22.95	9.87
7	14.27	27.20	6.49	14.68	27.39	6.49
8	14.51	22.74	10.80	15.13	22.30	10.80
9	14.14	26.51	7.11	13.68	26.49	7.11
10	18.52	21.10	9.62	15.49	20.67	9.62
11	20.13	25.23	12.85	14.26	25.06	12.85
12	21.92	24.14	6.71	13.77	25.15	6.71

Table V. : *Quantitative comparison results in CV errors between CIECAM02 and its edge-aware application.*

Phase	J	M	H	J+S.	M+S.	H+S.
1	12.43	23.02	11.03	11.56	23.02	11.03
2	17.52	19.99	9.30	11.50	19.99	9.30
3	21.35	20.00	9.57	10.20	20.00	9.57
4	23.07	20.02	11.12	8.77	20.02	11.12
5	15.07	20.11	8.40	15.08	20.11	8.40
6	12.09	22.37	10.34	11.77	22.37	10.34
7	13.38	22.12	7.36	12.82	22.12	7.36
8	13.60	28.39	10.95	13.06	28.39	10.95
9	17.82	19.06	7.28	16.88	19.06	7.28
10	22.11	14.96	9.68	16.52	14.96	9.68
11	24.17	21.16	12.82	14.06	21.16	12.82
12	25.34	20.60	6.82	11.37	20.60	6.82

Table VI. : *Quantitative comparison results in CV errors between Kim et al. [2009] and their edge-aware application.*

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