DOI: 10.2352/ISSN.2470-1173.2016.16HVEI-144

Swapping swatches: Adapting to and from an artist's palette

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Abstract

We describe a method for representing and manipulating the color gamuts used by different artists to explore how the color schemes employed by artists might appear to the artist or to others. The method involves modeling the visual response to color and then adapting that response to simulate how color percepts change across different states of adaptation. Analyses of paintings and nature photographs suggest that there are both important differences and regularities in the color palettes of artists and that these regularities reproduce prominent characteristics of the natural color environment. In particular, the works of many artists include a bluish-yellowish bias that is also a distinguishing feature of both the color statistics of natural images and of the neural coding of color. The algorithm adjusts the colors in an image so that they are equivalent to the colors that would be experienced by an observer adapted to a different environment, or for two observers with different spectral sensitivities but who are adapted to the same environment. This provides a novel method for visualizing how the colors in artwork are experienced by an artist or an audience, and could be generalized to explore similar questions for visual attributes beyond color.

Introduction

The relationship between visual art and visual perception has attracted the enduring fascination of many vision scientists [1-4]. On the one hand, how art is portrayed and interpreted must obviously be shaped by the processes underlying the perception of all images, and thus knowledge about these processes are likely to inform our understanding of artistic principles. Thus basic mechanisms of contrast coding may explain how and why artists exploit and portray contrasts in their work [5]. On the other hand, analyses of art can provide important insights about sensory mechanisms. For example, the use of color has been taken to reveal fundamentals of color coding such as complementary colors, color contrasts, and opponency [6]; pictorial cues highlight the information we use to recover depth and interpret retinal images [7]; and the properties of portraits hint at the possible attributes and processes underlying face recognition [8, 9]. Moreover, important clues to perceptual processing can also be gleaned from analysis of the failures of artists to capture the physical properties of scenes. For example, errors in how they depict certain aspects of lighting and shade suggest that the visual system itself is insensitive to many properties of the lighting geometry [10, 11].

One recent interest in the visual science of art is whether and to what extent art incorporates and reproduces regularities in the visual environment [12]. The visual diet of both natural and carpentered scenes is often highly constrained, in ways that are thought to have fundamentally shaped the neural mechanisms of visual coding. For example, the images of most scenes we encounter have a roughly 1/f amplitude spectrum, such that contrast varies inversely with scale. Natural images also have a fractal geometry in which similar structure occurs at different scales. Artists may consciously or unconsciously exploit these statistics. For example, the abstract drip paintings of Pollock mimic the fractal dimensions typical of natural scenes [13], while the works of many artists conform to the amplitude spectra and luminance distributions expected from the visual environment [14, 15]. Moreover, audiences are sensitive to these statistics, and how natural an image's properties are can strongly influence artistic preferences. Thus while Pollock's paintings may appear random they are preferred to paintings with unnatural fractal dimensions [16]. Similarly, deviations from natural amplitude spectra, such as increasing the relative energy at the middle spatial frequencies that we are most sensitive to, can predict why some artists' works are perceived as more uncomfortable or stressful to view [17-20].

A further recurring interest in art is the possibility that an artist's style or techniques might reflect unique characteristics of the artist's own visual system, and potentially point to specific deficits in their vision [21]. For example, analyses of self-portraits and photographs of many artists suggest that as a group, artists have a higher tendency for strabismus and thus stereoblindness, and this has been confirmed in comparisons of stereoacuity in professional artists versus lay persons [22]. The loss of binocular vision could conceivably make them more sensitive to the monocular depth cues available in paintings. Similarly, many conjectures have been made about the color vision of artists from the colors in their palette. The strong saturation of van Gogh's paintings have suggested that he might have a color deficiency, while the yellow bias in many of his works has been attributed to xanthopsia (an insensitivity to blue) owing to the yellowing of his lens (possibly as a toxic side effect of digitalis prescribed for his heart condition) [23]. A number of studies have also explored changes in artists' work over their lives to examine the consequences of visual aging or disease. Thus Monet's final works may reflect the progression of his cataracts and vision loss [24].

The notion of whether art can reveals the artist's eye has been famously debated in the context of the "El Greco fallacy," in which the elongated figures in El Greco's paintings have been attributed to astigmatism and thus a distortion in his retinal image [25]. The fallacy is that in order to replicate the world as he saw it, the painted figures should have the same physical proportions as the subjects so that they are distorted in the same way (though this in fact requires compensation for the effects of blur at different distances [26]). Similarly, the argument that van Gogh's work overemphasized yellow or saturations, to make up for anomalies of his color vision, faces the problem that the colors in his paintings would not match his perception of the colors in the world. Thus to the extent that artists are trying to recreate their visual impressions, the stimulation provided by the world and canvas should match.

However, there is another important sense in which artists might not depict their visual characteristics, because these characteristics may be discounted from their perceptual experience. Specifically, visual perception is often compensated for the sensitivity limits of the observer, such that the individual is potentially unaware of their own visual properties or capacities. For example, as the lens ages it becomes increasingly yellower, yet older individuals continue to see or describe stimulus spectra in

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DOI: 10.2352/ISSN.2470-1173.2016.16HVEI-144

ways that match the percepts of younger observers, suggesting that their color vision has adjusted for the lens brunescence [27]. In the same way, observers may be compensated for the blur introduced by the eye's optics, such that the world appears in focus even when the retinal image is strongly degraded [28-30].

An important mechanism contributing to this compensation is visual adaptation. The visual system is continuously recalibrating to match visual coding to the current visual stimulus, and these adjustments affect most if not all perceptual judgments, from the hue of a patch to the attractiveness of a face [31]. Moreover, these adjustments provide a fundamental link between the observer and the environment, because they adjust percepts according to the environment. Consequently, two observers exposed to the same world should tend to perceive the world in similar ways, even if their visual systems (e.g. spectral or spatial sensitivities) are inherently different. Similarly, adaptation should tend to maintain perceptual stability as some aspects of their visual system change over time, such as a gradual change with aging or an abrupt change with a spectacle correction or cataract surgery [32]. In other words, the reason young and old see colors the same is plausibly because they are adapted to the same world. Conversely, the same observer should perceive the world differently when it is the world that changes, for the visual system is now tuned to a different diet. For example, colors vary with the environment or the seasons [33, 34], and color percepts may track these changes [35].

How the visual system adapts to color is reasonably known in principle [36], and thus it is possible to theoretically model how colors should look to an observer under different adaptation states. In previous work we have used this approach to predict the properties of color appearance in different color environments or in different observers, by rendering images to incorporate visual adaptation [37-39]. This technique has the advantage that it allows modeling very long-term states of adaptation that are difficult or impossible to test by instead adapting observers. It also has the advantage that the adaptation effects can be pushed to their theoretical limit, allowing tests of the functions and consequences of adaptation for perception and performance [40]. Finally, we have argued that incorporating adaptation in this way is an important but often overlooked facet of simulating how the world appears to others [39]. Specifically, many attempts have been made to illustrate how an image might look to someone with a visual deficit or varying visual sensitivity. However, these simulations are typically performed by filtering the image according to the sensitivity losses of the observer, and thus do not take into account the probable compensations for these losses. The simulations therefore portray what information is lost to the observer, but not how the world actually "looks." In this study we apply this approach to examine art through the eyes of the artist.

Our work had three aims. The first was to sample the color gamut of different works and artists to explore how they vary and the extent to which they might provide a defining signature of different artists. The second was to examine how these gamuts are related to the color distributions typical of the natural world. Despite the extensive analyses of the visual properties of art, the color statistics remain relatively unexplored, and thus it is not clear whether artists apply their palette to match the world in ways that parallel their spatial compositions to match the spatial structure of the environment [12]. Our third aim was to use adaptation to simulate how paintings might appear to the artists themselves, by simulating adaptation to their own palette. Artists often spend days or months composing a work and thus are exposed to their creations in ways that most other viewers can never be. It is reasonable to expect that this exposure alters their perception through adaptation. For example, portrait artists may adapt to faces as they depict them, losing sensitivity to asymmetries in the face (leading to the practice of viewing a mirror image of the painting in order to detect the asymmetries) [41]. Here we explore how the colors in different paintings might vary in artists or observers adapted to the same or different worlds or art collections.

Methods

Image Sets

Paintings were sampled from a variety of artists. For this exploratory study the sampling was largely arbitrary, and most were collected by undergraduate students who were asked to find examples from their favorite artists. Table 1 lists the primary artists examined. In a second set we also collected images from professional nature photographers. All of the images were taken from the internet and thus were uncalibrated. To assess and partially control for variations in the renderings, for most images we obtained three versions of the same work. However, we emphasize that the present study represents analyses of images of artwork as they are reproduced for public consumption, rather than directly of the original or calibrated versions of the works.

Table 1: The list of artists sampled and the number of their works. Typically three versions of each image were included to partially offset variations in the color rendering.

Artist	**Number of Works**
Mary Cassatt	9
Edgar Degas	9
Frida Kahlo	17
Henri Matisse	12
Claude Monet	21
Rembrandt	9
Diego Riviera	17
Vincent Van Gogh	9
Photographers	**Number of Photos**
Alain Briot	15
Burrard-Lucas	12
Robert Glenn Ketchum	12
Thomas Mangelsen	14
David Muench	13
Eliot Porter	12
Galan Rowell	11
Camille Seaman	12

Color Statistics

For each image we sampled the RGB values over a regular array of up to 256 by 256 pixels, averaging blocks of pixels so that the images were all effectively of the same resolution (Figure 1). The RGB values were converted to luminance and chromaticity with the reference triplet of 128 set to a fixed luminance and the

DOI: 10.2352/ISSN.2470-1173.2016.16HVEI-144

chromaticity of Illuminant E. Individual values were then represented as contrasts in a cone-opponent space defined by three dimensions corresponding to LvsM, SvsLM, and achromatic axes [42]. Contrasts along the axes were scaled based on previous studies to roughly equate sensitivity to the different dimensions and to allow comparison with our previous measurements of natural color distributions. The scaling corresponded to:

$$LM = 1955 * (l_{mb} - 0.66563)$$
$$S = 6537 * (s_{mb} – 0.015446)$$
$$LUM = 70 * (luminance - Lumavg) / 128$$

Where l_{mb} and s_{mb} are the coordinates of the MacLeod-Boynton chromaticity diagram [43].

In the analyses we first examined the mean image color and the distribution of color contrasts. Images were then adjusted for the mean (equivalent to von Kries adaptation) with the contrast distributions again evaluated. These distributions were summarized by calculating the three orthogonal principal components of the color gamut, with each representing a vector whose angle corresponds to the direction of variation in the color-luminance space and whose length corresponds to the variance of the color signals along the axis. We also analyzed the color distributions by calculating the average responses along different directions in the color-luminance space. These were sampled at intervals of 22.5 deg within the chromatic or color-luminance planes. The mean responses in each corresponded to the dot product of the pixel's color vector and the sampled direction. These sampled values correspond to the mean responses in the contrast mechanisms described in the adaptation simulations.

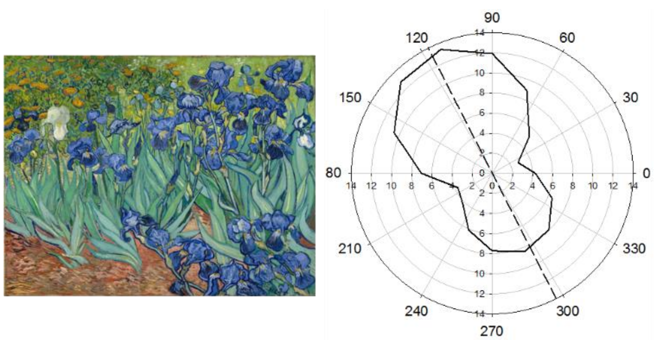

Figure 1. An example of an image (Van Gogh's "Irises") and the computed color distribution in the cone-opponent space. The bounding contour shows the mean contrast responses along different directions in the chromatic plane, while the dashed line shows the principal axis of chromatic variation in the image. (Digital image courtesy of the Getty's Open Content Program)

Adapting Images

In the second phase we rendered individual images by applying a model of color adaptation in the human visual system [39, 40]. The model, which we developed previously, is based on simple but plausible assumptions about how color is encoded and calibrated, and has two stages, corresponding to the cones and to postreceptoral channels (Figure 2). The cones are adapted for the average color and luminance in the image by scaling their sensitivity so that the responses to the mean of the adapting distribution is equivalent to the response to a reference white. This implements von Kries adaptation according to the mean of the color ensemble. At the postreceptoral stage, the channels combine the scaled cone signals linearly to respond to the contrasts along different directions in the color-luminance space. As noted above, the mechanism sensitivities correspond to the vectors calculated above. For the purpose of the modeling, we used a set of 26 mechanisms tuned to angles at 45 deg intervals in the space. The large number of these "higher-order" mechanisms is necessary and sufficient to represent the observed selectivity of chromatic contrast adaptation for arbitrary directions in color space [44, 45]. The number also reflects the fact that each axis is represented by a pair of unipolar mechanisms (e.g. the LvsM axis is encoded by two channels sensitive to +L/-M and –L/+M). As in the first stage of the cones, adaptation at the second stage is achieved by scaling the sensitivity of each mechanism independently so that the mean response to the current image or color distribution equals the mean response to a reference distribution. Thus after adaptation the model observer gives the same mean color response to the current distribution as they did to a given reference distribution. Finally, the colors in the image are rendered by summing the contrasts along the three cardinal axes of the space and converting these adapted signals back to RGB values for display.

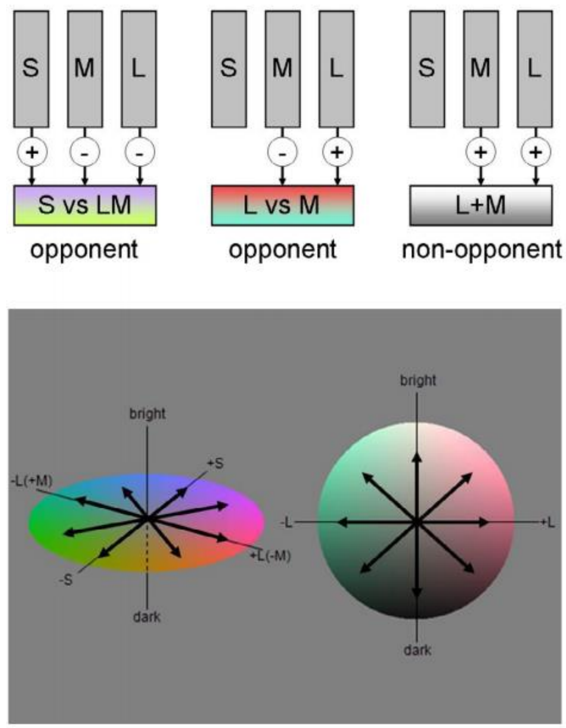

Figure 2. A schematic of the model of color coding and adaptation. (Figure reproduced with permission from [46]).

Results

Color Distributions

Figure 3 shows plots of the color statistics of the sampled art images. The left panel plots the mean chromaticities in LvsM and SvsLM space. The right panel instead plots the dominant angle of the color distributions. A conspicuous feature of the variations in both the average color and the color contrasts is that they are strongly clustered along the negative diagonal (i.e. second and fourth quadrant) of the chromatic plane. This is a direction that corresponds to bluish and yellowish hues, suggesting that the

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DOI: 10.2352/ISSN.2470-1173.2016.16HVEI-144

images of the paintings as a whole tend to vary more in bluish and yellowish contrasts. Note that the peak axes tend to lie along angles of about -40 deg, which are more reddish (orange) and greenish (cyan) than a typical unique blue and yellow [47]).

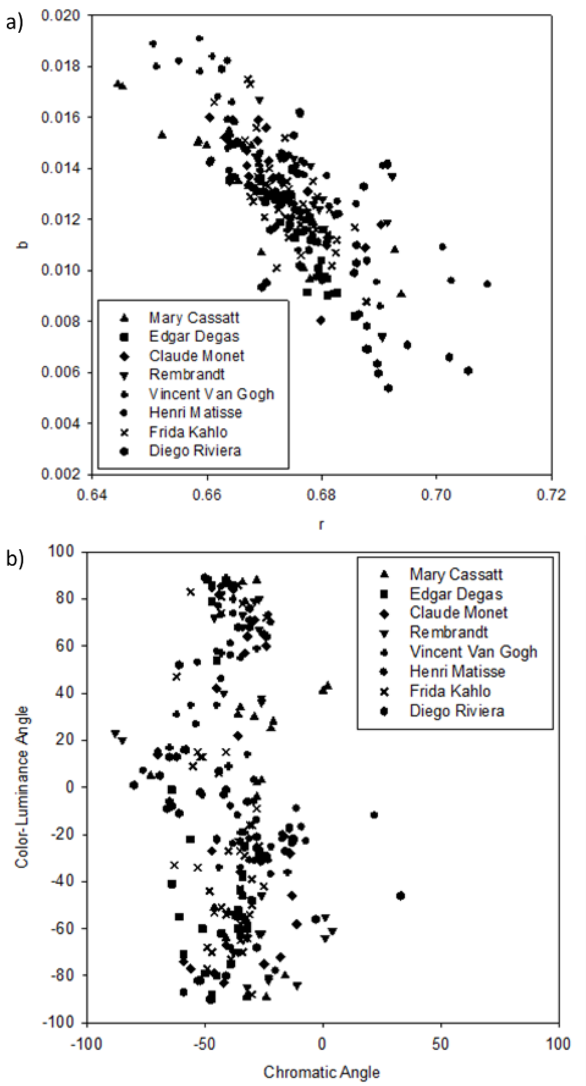

Figure 3. a) Average chromaticities of the art images, plotted in the MacLeod-Boynton space. b) Dominant angles of the color distributions within the scaled LvsM and SvsLM space.

This “bluish-yellowish” bias is further illustrated in Figure 4, which plots the mean contrasts along the different directions in the chromatic plane. Here each contour represents the responses averaged across all of the sampled paintings from a given artist. The different artists vary widely in mean contrast, from the fairly muted colors used by Degas to the high saturations in the paintings of Matisse. However, painters are again similar in terms of the biases in the color gamuts, with the contours consistently rotated toward the negative diagonal.

A similar bias in the color gamut is observed in the color distributions found for many natural outdoor environments [33, 34]. Natural scenes include blue sky and brownish and yellowish terrains, and thus again have distributions that are rotated toward a blue yellow axis, though these can vary with the type of vegetation. For example, lush scenes dominated by foliage tend to vary more along the S axis of the color space, while arid panoramic scenes are more dominated by blue and yellow [33, 48]. This suggests at least a general correspondence between the color palettes applied by artists and the palettes the world exposes them to.

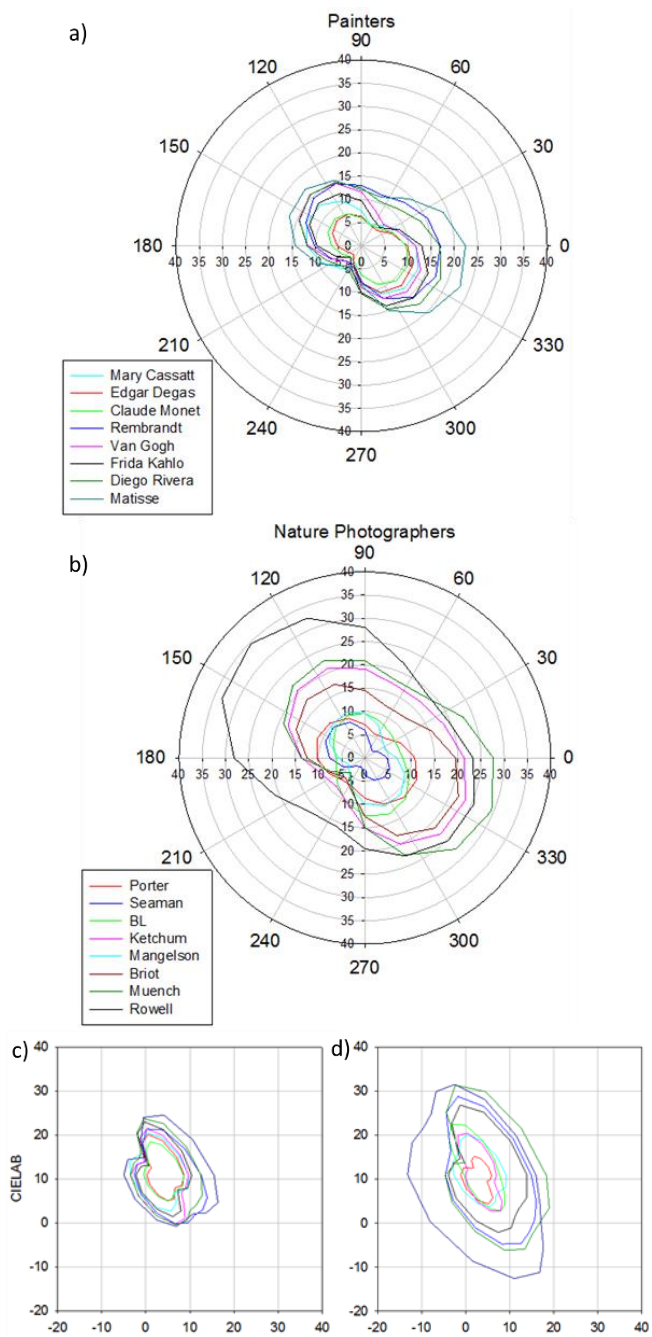

Figure 4. a) Mean contrast responses along different directions of the chromatic plane. Each contour plots the average from all paintings sampled for a single artist. b) Mean contrast responses for images from different professional outdoor photographers. c) and d) The contours of panels a) and b) replotted within a perceptually uniform color space (CIE Lab).

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DOI: 10.2352/ISSN.2470-1173.2016.16HVEI-144

To further test this idea we also compared the gamuts from the paintings to the color distributions taken from a set of nature photographers. Again these images were uncalibrated samples from the internet, but in this sense provide an appropriate baseline for assessing how images of the actual world compare to images of painted renderings. As illustrated in Figure 4b, there is once again a clear bias in the color distributions, consistent with the general biases observed in measurements of actual environments. (A notable exception in our limited sample is the images of wildlife photographer Burrard-Lucas, whose images have color gamuts stretched along the vertical SvsLM axis. However as noted, such distributions are characteristic of scenes with lush foliage and thus are within the range of variations found in natural environments.)

One possible account for these blue-yellow biases is that observers – both lay and artists – are adapted over the long-term to the color characteristics of the environment. Specifically, they may be less sensitive to bluish and yellowish directions because these directions have higher stimulus contrasts, so that their color percepts are roughly uniform. Consistent with this idea, the relative salience of different color and luminance variations are roughly predictable from the relative contrasts of the axes in natural scenes [49]. Moreover, this bias is a prominent feature of perceptually uniform color spaces, in which equal distances within the space are scaled to represent equal perceptual steps [50]. When a uniform distribution of cone-opponent signals is represented in these spaces, the distribution again becomes elongated along bluish-yellowish axes [50, 51]. This also predicts that the gamut biases we found for both paintings and photographs should be removed or reduced if the gamuts are instead plotted in a uniform color space. This is shown in Figures 4c and 4d, which shows that the contours are now more circular when represented by their coordinates in CIELAB. To conclude, these analyses suggest two points: first, the color gamuts employed by painters and photographers – at least as depicted in digital media – show characteristic biases consistent with the biases found in natural outdoor environments; and second, these biases are consistent with roughly more perceptually uniform representations of color, which could reflect an adaptation to the natural color environment.

Adaptation

Despite these strong regularities, the color composition of the images also vary markedly both within and between artists. As noted, a further goal of our work was to explore how an image from one artist might appear when "adapted" to the colors from the palette of a different artist. In this case, we used the values in Figures 4a and b to define the reference and test responses for a given pair of artists. The mean responses to the test palette were then scaled to match the mean responses for the reference palette. Figures 5-7 show examples of the images rendered in this way. In Figure 5, the paintings from Edgar Degas and Rembrandt are each adapted to the average color scheme of the other painter. The upper panels show the original images, while the lower panels illustrate how the colors might appear to an observer looking at Degas but adapted to Rembrandt, or vice versa. In Figure 6, we instead compare two images from the same artist, Claude Monet. In this case, the panel on the left depicts a work from late in life, while the panel on the right depicts the same image adjusted to show the average color gamut from body of his sampled work. Finally, Figure 7 shows an example where the painting is adapted to the range of colors in a typical outdoor environment. That is, in this case the mean response to the painting is equivalent to the average outdoor response. The changes depict how Cassatt and Van Gogh

Figure 5. Comparison of two images, cross-adapted to the palettes of each artist. a) and b) paintings by Edgar Degas and Rembrandt. c) and d) The same paintings adapted to the estimated palette of the other artist. (Digital images courtesy of the Getty's Open Content Program)

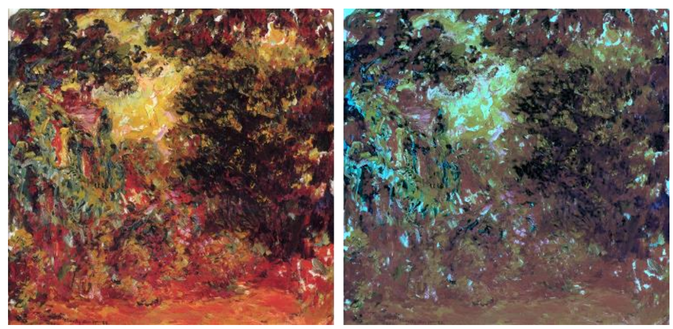

Figure 6. 2 A paint from late in Monet's career, adapted to his average sampled palette. (Digital image courtesy of the Metropolitan Museum's Open Content Program)

Figure 7. A Cassatt or van Gogh adjusted to match natural color distributions. (Images courtesy of the Metropolitan Museum's Open Content Program)

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DOI: 10.2352/ISSN.2470-1173.2016.16HVEI-144

might have experienced their own work if they were fully adapted to the colors in the painting (and if that adaptation was equivalent to the adaptation state induced by the sampled natural world).

Discussion

Our results suggest that the color gamuts employed by artists tend to parallel the gamuts typical of the natural visual environment, and in particular exhibit the "bluish-yellowish" biases characteristic of many natural environments. At some level this is perhaps unsurprising, for artists are often trying to portray properties of the world in their paintings. However, these properties themselves are not fully established, and it is for example still uncertain what the dominant color variations in our environments are, and how these are related to the dimensions underlying visual coding of color. For example, early mechanisms appear tuned to the LvsM and SvsLM cardinal axes [42] and thus do not appear optimal for representing bluish-yellowish distributions, because these distributions produce correlated variations along the cardinal axes. However, a number of lines of evidence point to blue-yellow biases in color coding, such that visual sensitivity is weaker for bluish-yellowish directions compared to reddish-greenish directions with the same cardinal axis contrasts. For example, achromatic settings show larger variability along the blue-yellow axis [27, 52-54], suprathreshold blues and yellows appear less salient [55, 56], and neural responses in primary visual cortex as measured by fMRI are weaker for blue and yellow [57]. Moreover as described above, this bias is in fact built into the structure of most uniform color metrics [51, 58]. The present results add to this list by showing that blue-yellow biases are prevalent not only in the world and the brain, but in artists' portrayals of the world.

Of course art is often driven by ideals of aesthetics rather than reproduction, and our findings also suggest that the color schemes employed by artists may in part be seen as more harmonious or pleasing precisely because they mimic properties of natural color distributions. Juricevic et al. in fact found that when observers judged color distributions presented as filtered noise or random Mondrians, blues and yellows were rated as more comfortable and more aesthetic than other hue axes with equivalent cone-opponent contrasts [19]. Recently Nascimento et al. have also observed that observers prefer art images when rendered in close to their original (intended) colors [59]. The present results suggest that this may occur because both artists and their audience prefer natural color palettes. In both the Juircevic and Nascimento studies the colors were manipulated by rotating the distributions within a color space. However, the present approach provides an alternative way to test these hypotheses by explicitly rendering an image with natural or unnatural color distributions. This could test whether observers might actually prefer a painting with a natural color gamut even when the artist chose an unnatural color scheme.

The method we developed for "adapting images" has a number of potential applications for the representation and analysis of art. First as we have emphasized, adaptation is arguably critical to incorporate in simulations that attempt to portray how the world might look to others. Our approach allows simulations of how artists might experience their own works or each other's. Further, including this adaptation may better simulate the consequences of visual deficiencies, and in general help illustrate that an artist's impression of the world is less susceptible to a visual deficit or change than their sensitivity alone might predict [39]. The method we describe also provides a novel technique for rendering images for specific effects or even specific audiences. For example, observers living in and adapted to different worlds – or to the same world as its colors cycle over the day or the year – may perceive color differently [35, 60], and images could be tailored to the changes in their adapted states.

Adapting images in this way is not specific to color, and could be generalized to a number of other stimulus attributes. For example, face perception may involve similar norm-based coding schemes to color, and the norms may also be calibrated by adaptation in similar ways [61, 62]. That is, an individual face may be represented by how it differs from a prototype, in the same way that a hue is encoded by how it differs from gray; and both the face and spectral stimulus that appears neutral or gray are likely set by adaptation to the ambient social or spectral environment. Average faces appear more attractive [63], and it has been suggested that when an artist portrays an idealized attractive face they may be painting a self-portrait. Such ideas follow naturally from the assumption that we are more strongly adapted to our own familial or social group's characteristics and that this can affect judgments of attractiveness [64, 65]. As we have shown here for color, portraits could similarly in principle be adapted to simulate how the faces might appear through the artist's eyes.

Acknowledgements

Supported by EY-10834. Dedicated to the memory of John Krauskopf.

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