https://doi.org/10.2352/CIC.2024.32.1.28

Compensating for Individual Differences in Color Perceptionin Color Reproduction

Camilla Simoncelli and Michael Webster University of Nevada Reno (US)

Abstract

Individual differences in normal trichromatic color vision arise at many levels, from variations in the wavelength sensitivity of the eye to factors that influence how we see, categorize, and communicate about colors [1]. There is growing recognition of the value of accounting for these differences in order to provide more consistent color percepts across observers. Most of these efforts have concentrated on correcting for differences in spectral sensitivity and associated effects on color matching. However spectral sensitivity differences have limited influence on color appearance, which can be large, and which may potentially be a more important source of variation in how people respond to and interpret color information. We describe a simple method for measuring observers' hue percepts along with a technique for rendering images to compensate for inter-observer differences in appearance. The approach is easy to implement and does not require specialized equipment and offers potential advantages for many color applications including data visualization and communication.

Introduction

While perception intuitively seems universal, individual differences significantly influence how we experience the world [2,3]. These differences affect most if not all aspects of sensory processing, from differences in basic sensitivity to high-level interpretations and inferences and ultimately conscious awareness. Variations among observers with normal color vision are well documented and are pronounced at all levels of the visual system, from differences in the spectral transmittance of the eye's optics to phenomenological judgments of color appearance [4–8]. As a result, two different observers viewing the same spectral stimulus may often have very different color experiences.

There is growing interest in correcting visual displays to account for these different experiences, in order to increase consistency in the information perceived and communicated across observers. Thus far most of this effort has been focused on correcting for differences in spectral sensitivity, which result from differences in the density of lens and macular screening pigments as well as the absorption spectra and relative numbers of the of the cone photoreceptors [5,9,10]. These sensitivity variations affect color discrimination and color matching, and underlie the problem of observer metamerism, where two stimuli might appear different to one observer while identical to another [11,12]. These effects are exacerbated in modern wide-gamut displays, and there are active efforts to control for them by building observer differences into color profiles.

However, there is also a remarkable degree of observer variation in color appearance, for examplein which stimulus appears achromatic or a particular hue (e.g. pure red or green). These appearance differences are largely independent of differences in spectral sensitivity [13]. Thus, corrections for spectral sensitivity do not address (or could even amplify) individual differences in color percepts. These perceptual differences may be more salient and impactful for how observers judge or communicate the visual information carried by color, yet very few studies have considered how images could be processed to address appearance differences. Recently we developed a simple procedure for correcting images for differences in hue percepts [14]. A related approach has also been independently proposed by Shin and Fairchild [15]. In this report we illustrate a procedure for measuring hue percepts and then show how these measurements can be used to adjust image chromaticities to potentially align hue percepts, so that two observers – now viewing different spectral stimuli – may have more similar color experiences.

Color Appearance Measurements

Method

Participants

Hue percepts were measured for 21 observers with normal color vision and normal or correct-to- normal visual acuity. Color vision was assessed by the Cambridge Colour Test (Cambridge Research Systems). The participants were undergraduate or graduate students at the University of Nevada, Reno. Participation was with informed consent andsome of the students received course credit for enrolling in the study. Procedures followed protocols approved by UNR's Institutional ReviewBoard and adhered to the World Medical Association's Declaration of Helsinki (2013).

Experimental design

Stimuli were presented on a Cambridge Research Systems Display++ monitor using custom algorithms built with Matlab and Psychtoolbox. The monitor was calibrated with a spectroradiometer (Photo Research PR 655) and subtended a visual angle of 33.6°x 60°. Observers were seated at a distance of 60cm from the monitor and viewed the display binocularly in a dark room.

Hue measurements were preceded by a minimum motion experiment used to assess individual differences in luminance sensitivity [16,17]. The technique is based on apparent motion driven by luminance differences in chromatic gratings and is a standard technique for assessing when chromatic stimuli are equiluminant. From the settings, correction factors were calculated to adjust the luminance of all stimuli so that they were equated for each individual observer. However, we note that this step was included because the present experiment was part of a larger study probing individual differences in color perception. Similar results for hue differences would likely be obtained if luminance was instead defined photometrically for all observers.

In the hue experiment, stimuli were presented on a gray background with a luminance of 20 cd/m2 andthe chromaticity of

Illuminant D65 (CIE 1931 coordinates: x: 0.313, y: 0.329). Stimulus chromaticities were defined based on a modified version of the Derrington-Krauskopf-Lennie (DKL) cone-opponent colour space [18–20], which represents the constant-luminance chromatic plane in terms of two axes corresponding to differences in the long- vs, medium-wavelength sensitive cones (LvsM) or signals in the short-wavelength sensitive cones and the sum of the L and M cones (SvsLM). These two axes are called the "cardinal directions" of color space because they reflect the principal axes of color coding in the early visual system. The cone sensitivities were based on the fundamentals derived by Stockman and Sharpe andthe LvsM and SvsLM signals were scaled by factors of 2500 and 5000, respectively, so that a value (or "nominal contrast") of 1 along each axis corresponded very roughly to the just-noticeable difference from the white point for each axis.

For the display, 36 chromatic "chips" were shown arranged in a circle and sampling the color space at10° steps from 0 to 360° at a contrast of 80 (Figure1). Each chip had a diameter of 30 pixels (2° of visual angle) and had the same luminance (20 cd/m2) as the gray background, with narrow blackborders delimiting the field. The array was shown to provide a visual map of the color space that observers could navigate to select different hues byusing the mouse to control the cursor location on the screen. The chromaticities shown in the array were randomly rotated on each trial so that hues were not tied to a consistent spatial location, and observers were instructed that they were not restricted to the specific hues shown but could choose any angle along the circle for their selection. The color currently selected was shown in 4 uniform square fields in the center of the palette, each subtending 4.3°. Using 4 fields rather than a single field was again because the hue experiment was part of a larger study involving tasks that required showing different colors in the fields. However, it is again unlikely that this choice impacted the hue settings.

Procedure

Observers were asked to vary the mouse cursor around the palette to identify the best example of one of 8 hues identified by text at the bottom of thescreen (Figure 1). The hues corresponded to the 4 unique hues (pure red, green, blue or yellow), and 4 balanced binary hues (orange, purple, yellow- green, blue-green), for which the instruction was to choose the hue (e.g. orange) that appeared as an equal balance of the corresponding unique hues (e.g. red and yellow). The hue displayed in the center was alternated on for 0.25 sec and gray for 0.75 sec while observers made their setting, with no time restrictions for responding. Moving the cursor around the circle varied the displayed hue, and a mouse click was used to record their choice.Each hue was measured 6 times in random order for 2 separate sessions, for a total of 12 settings perhue. Results reported are based on the mean settings for each hue and observer

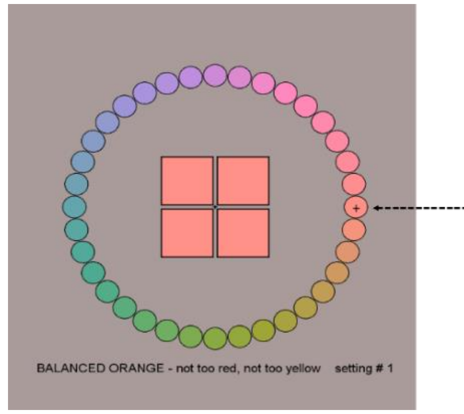
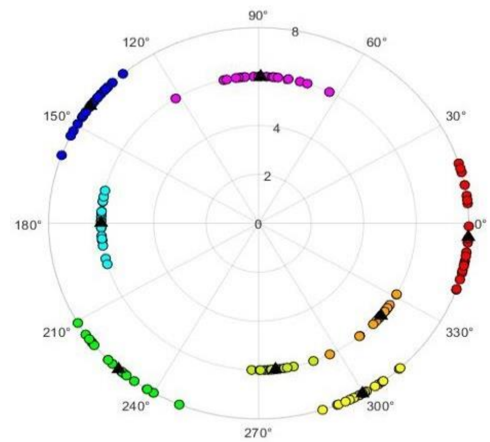


Figure 1. Example of the hue selection experiment. The hue to be selected and repetition number were indicatedat the bottom of the display. The example shows the display when the observer was selecting an "orange" hue, with the squares in the middle of the screen displaying the hue angle the participant is pointing at using the cursor.

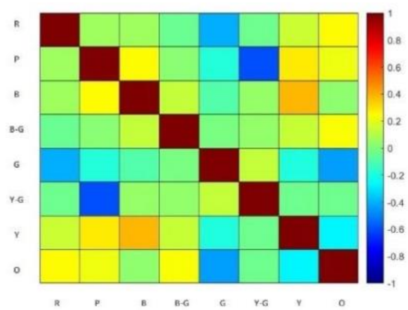
Results

Our results are consistent with previous measurements using a variety of tasks showing that hue percepts vary widely among color-normal observers [21]. Individual values for each observer and hue are depicted in Figure 2. Figure 2a plots the angles for the loci in LvsM and SvsLM chromatic plane. Consistent with earlier work [21], three of the binary hues (purple, blue-green, and yellow-green) cluster along one of the cardinal axes, while unique red straddles the remaining axis. However, differences between observers are so large that what some observers chose as the best example of yellow was selected as the best- balanced orange or yellow-green for others – i.e. in some cases different observers classified the same stimuli as best examples of different color categories. The standard deviation in hue angle across observers averaged 7.58° and was 1.39 times larger than the standard deviation in the repeated settings (5.45°), suggesting that thedifferences reflect actual observer differences and not measurement noise (Table 1). However, for some hues the within and between observer variance was similar. Figure 2b also shows that the settings for different hues were largely uncorrelated, which is also consistent with previous reports [21].

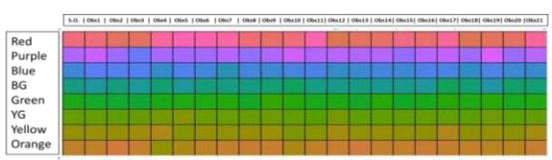
Figure 2c provides a visual depiction of the hue percepts. The palette shows the chromaticity selected by each observer for each of the 8 hues, with the mean or "standard observer" shown in the first column. Again, this range is typical for many studies of individual differences in color appearance and shows that these differences are pronounced and can sometimes cause the same stimulus to be perceived as a different color category by different observers



2a.



2b.



2c. Figure 2: Individual differences in the settings for the eight hues tested. a) Individual hue foci of the 21 observers and the standard observer (black triangles), represented in the DKL color space. Each point corresponds to an observer's focal color, based on the average of all the measurements in the two sessions. b) Correlations between the settings for different hue foci for the 21 observers. |c) Depiction of the stimuli corresponding to the focal colors (rows) for each observer. The first column is the Standard Observer, based on the average of all the participants.

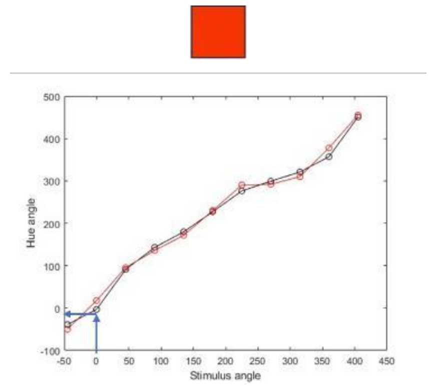
	R	G	B	Y	O	P	BG	YG
MEAN	-4.00	228.2	143.2	299.6	321.0	89.3	179.9	276.1
SD between-obs	12.1	9.73	7.30	6.09	7.50	12.1	7.82	5.02
RANGE	37.7	37.2	29.4	24.6	34.3	58.4	29.1	22.9
SD within-obs	4.36	6.59	3.60	3.91	3.26	7.74	7.36	6.81

Table 1: Mean and standard deviation of hue settings between observers and within observers for the 8 hues tested.

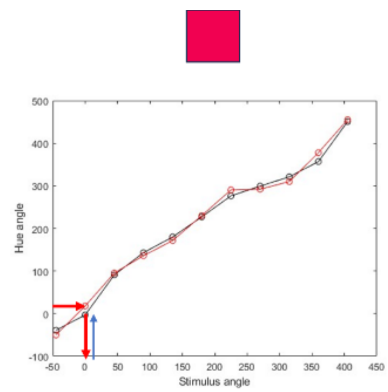
Color Appearance Corrections

Method

We used an algorithm detailed in Simoncelli and Webster [21] to adjust images to equate the hue percepts across observers. Briefly, a smoothed interpolation was fit to the hue foci as a function ofthe selected stimulus angle (Figure 3a and 3b). This allowed us to estimate for any stimulus angle the corresponding hue for the observer. For each pixelin an image, the hue was estimated for the standardobserver base on the mean of the 21 individual functions. The fitted function for an individual observer was then inverted to estimate the stimulus angle that was predicted to produce the same hue percept for that individual, with the resulting chromaticity replaced in the image.



3a.



3b.

Figure 3. a) The first step of the algorithm: estimation ofthe hue percept for each pixel RGB for the standard observer (black line). | b) The second step of the algorithm: for the same hue percept, we in turn calculated the RGB in the target observer (red line). Color patches show an example of the chromaticity transformation.

Results

Figures 4a-4d illustrate the application of the algorithm. The upper left image shows the original image while the three remining images are recolored based on the hue percepts for different individuals. Inspection of these images show that they appear conspicuously different for a single observer, and thus in principle illustrate the range of color percepts when different observers are looking at the same image. However, the hues experienced by these observers should instead be more similar when they are each viewing their own physically different image, since it has been corrected based on their individual hue percepts.

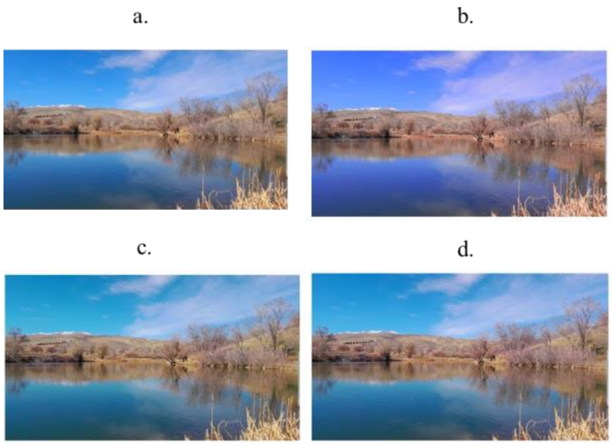


Figure 4. An example of the algorithm applied to an image. a) The original image. b-d) Examples of images adjusted for the individual hue percepts of three different observers.

Discussion

As noted, sensitivity differences are important to account for to ensure observers can discriminate similar information in color displays [22,23]. However, these sensitivity differences fail to capture individual differences in color appearance,because these are limited by fundamentally different factors [13]. These appearance differences are also pronounced and may be more salient for visual tasks where observers are judging or describing which colors they experience within the image, rather than simply trying to discriminate between colors. We, along with recent independent work by Shin and Fairchild [15], have shown that these differences can in principle be readily corrected by assessing color appearance and then applying these differences to the image chromaticities in order to match appearance. The assessments and corrections are simple and can be easily conducted on the displays of interest, unlike sensitivity assessments which may require specialized hardware.

The present analysis represents a proof of concept rather than a definitive technique, and there are many outstanding questions to address in future studies. One is to refine the color appearance task to optimize the sensitivity and efficiency of the judgments. A second is to explore the number of hue settings that are necessary to fully characterize the percepts. The lack of correlations between our unique and binary hues suggests that 8 may be desirable, though it remains to be evaluated whether fewer settings are sufficient. Yet another issue is whether other aspects of appearance, such as lightness and saturation, or individual differences in the achromatic point, are also important to include. Finally, further studies are needed to assess how well hue judgments based on uniform fields, and rendered at the level of individual pixels, translate to color percepts in complex images. In terms of applications, a further important set of questions involves exploring which tasks or conditions these appearance judgments can facilitate. For example, they may be valuable in cases where color categories are used to convey different information. Conversely, the adjustments we propose may be disadvantageous for images where observers have strong priors for object colors (e.g. skin tones). Regardless, these adjustments address an important and thus far largely overlooked aspect of building the observer into color pipelines, and we believe one that will be important for optimizing consistency in the visual experience and interpretation of color in visual displays.

Acknowledgments

Supported by the Danny Rich Memorial Scholarship from the International Color Consortium.

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Author Biography

Camilla Simoncelli received her BS in Linguistics from the University of Rome La Sapienza (2015) and her PhD in Language Science (department of Psychology) from University of Paris Nanterre (2022). Since then, she has worked in the Visual Perception Lab (University of Nevada Reno). Her main research interests link color science, language and neuroscience. Her current studies focus on color blindness and individual differences in color perception, through behavioral and computational techniques.

Michael Webster is Foundation Professor of Psychology and Neuroscience at the University of Nevada, Reno. He received his PhDfrom the University of California, Berkeley in 1988 and was a postdoctoral fellow at Cambridge University for 6 years before joining UNR. His research focuses on color and form perception andhow vision adapts to variations in the observer or their environment.