The Effect of Image Size on the Color Appearance of Image Reproductions

Mahdi Nezamabadi and Roy S. Berns, Munsell Color Science Laboratory, Chester F. Carlson Center for Imaging Science, Rochester Institute of Technology, Rochester, New York, USA

Abstract

Archiving images of cultural heritage based on spectral imaging techniques is an active research area in imaging science. Original and reproduced art are usually viewed under quite different viewing conditions. One of the interesting differences in viewing condition is size difference. This leads to different surrounds and adaptation states. In order to investigate the effect of size in color perception of rendered images, a visual experiment was conducted using a colorimetrically characterized digital projector and LCD display. An image was rendered and projected on the screen. The same image was processed using various algorithms followed by rendering for the LCD display. These LCD rendered images, by definition, were considerably smaller than the projected image. Using a paired-comparison method, the effect of image size was investigated using a colorimetric image of Georges Seurat's, "Sunday Afternoon on the Island of La Grande Jatte - 1884". The Image rendered for LCD display with a linear increase in lightness resulted in a closer match to the image projected on screen than the original colorimetric rendered image and was perceived as a more accurate reproduction than the majority of algorithms tested.

Introduction

The physical size or viewing angle of a stimulus is one of several factors affecting color perception. Differences in size or viewing distance leads to different surrounds and as shown by Bartleson and Breneman,[1] the perceived contrasts will be different. Furthermore, images with the same content but different sizes have the effect of a different adapting field, which in turn will produce different color perceptions. Hannah made a series of paintings to demonstrate the color change due to change in observation distance.[2,3]

In architecture, a small sample, which is offered as an aid in selecting a paint color does not exactly match the color appearance of the finished exterior and interior surfaces. Anter[4] has conducted outdoor observations to investigate the effect of size and viewing conditions on the color perception of facades. In an experiment by Xiao and coworkers,[5] performed to specify the color appearance of a room, eleven colors were selected and used to paint all four walls of the room. Two light sources were used to illuminate the room, a D65 simulator and typical office lighting. For each light source, the color appearance of the target wall was matched with a calibrated CRT display and then measured by a spectroradiometer. In a similar setup, small chips from an NCS Color Atlas were observed in a viewing cabinet. An increase of lightness and chroma were reported when the physical size changes from a small chip or a patch on the monitor to room size. Little or no effect on hue attribute was found. In another experiment by Xiao and coworkers,[6] ten paint colors were selected to make samples of different sizes. Samples with sizes varying from 2° to 50° viewing fields were used in two viewing conditions to investigate the change of color appearance due to the size effect. Regardless of scaling techniques and viewing conditions used in the experiment, an increase of lightness and chroma, but no effect on hue, were reported for an increase in sample size.

The majority of this research has been done on uniform patches, but what are the size effects on the appearance of complex stimuli? How does size of a rendered image affect its appearance?

An ideal system of image reproduction includes two main subsystems, devices and software for data acquisition at the input side and devices and software for image display at the output side. The fidelity of the overall systems depends on the performance of each subsystem. Different techniques for spectral data acquisition have been developed and image reproduction of cultural heritage based on spectral imaging techniques has been an active research area in the last ten years.[7-9] Many art objects have a size much larger than their reproductions, whether displayed on a monitor or in print. In order to investigate the effect of size in color perception of rendered images, a target image was selected and rendered for displaying on a liquid crystal display (LCD) and also projected on a screen by a digital projector. The projector and LCD display are light emitting devices and in this sense are similar soft copy media. The physical sizes of the reproduced images on the LCD display and projector screen were very different. It was hypothesized that two images with the same colorimetric values for each pixel but having different physical sizes would have different color appearance. Several algorithms were tested that might account for size difference.

Experimental

A colorimetric image[10] of an oil painting on canvas by Georges Seurat, "Sunday Afternoon on the Island of La Grande Jatte - 1884", was selected. The painting is 206 cm × 305 cm. The image was cropped so when projected, had the same size as the actual painting. Both LCD display and digital projector were colorimetrically characterized and a visual experiment was conducted under darkened conditions. A Plus Data Projector U4-232 from Plus Vision Corp., driven by an Apple G5, was used to project a rendered version of the original colorimetric image on the screen. This projector uses Digital Light Processing (DLP) technology and had a resolution of 1024 × 768. We will call this projector the DLP projector through the rest of the paper. The DLP projector has four primaries, red, green, blue, and white. The fourth primary has been added to increase the luminous output of this display device. In order to characterize this type of device, special models capable of handling four primaries are needed. A good description of the problem and a proposed solution was presented by Wyble *et al*,[11,12] and was used in this research. Primary ramps of red, green, blue, and white were sampled with interval of five digital counts in the range of 10 to 245 and sampling intervals of one digital count were used at the two ends (less than 10 and higher than 245 digital counts). For each sample, a uniform patch of the corresponding digital count was displayed on the screen in the dark room and measured by a Photo Research PR650 spectroradiometer. In addition to primary ramps, a set of 1000 samples were also projected and measured. The color differences, ΔE_{00}, for the 1000 samples from the projector forward model for the 1931 standard observer were calculated and Table 1 presents corresponding mean, maximum, and 90 percentile values. The DLP projector was working in the factory standard mode during the experiment.

An IBM T221LCD display, having a resolution of 3840 × 2400, was characterized in the dark room using the same Photo Research PR650 spectroradiometer and was used to display pairs of processed images.[13] Table 1 also lists the colorimetric results for the identical dataset. Both colorimetric characterizations had good performance.

Table 1: Summary of Characterization Results for LCD Display and DLP Projector for the 1931 Standard Observer

Display	Mean ΔE_{00}	Max ΔE_{00}	90 percentile ΔE_{00}
LCD Display	0.9	2.35	1.6
DLP Projector	1.0	8.4	1.6

The colorimetric image of the painting was rendered for the DLP display and projected on the screen in a dark environment. The background and surround of the image on the screen were set to a black color. All renderings were performed using the white point of the LCD display. The physical size and resolution of the projected image on the screen were 150 cm × 100 cm and 1024 × 768 pixels, respectively. The LCD display and DLP screen were positioned at a 180° angle. The observer was standing 50cm from the LCD display and about 200 cm from the screen. A pair of images, each 125 mm × 87 mm, was displayed on the LCD on the black background. Each image consisted of 1000 × 700 pixels and there was a 75 mm gap between the two images. As will be described in the image processing section, a total number of 10 images were prepared and all different pairs consisting of these 10 images, a total number of 45 pairs, (10 × 9)/2 = 45, were generated. All pairs were presented to the observers in a random order and the observer task was to select one of the images in each pair that best matched the image on the screen. Due to the specific experimental arrangement, an observer could not see both the LCD and screen at the same time and the selection of the image was based on short-term memory matching. Twenty observers participated in the experiment.

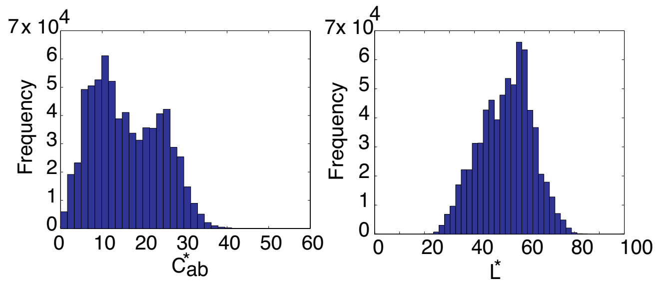

Figure 1. Histogram of lightness L, and chroma C^*_{ab} of colorimetric image rendered for IBM LCD display.*

Image Processing

The original image was a colorimetric image in the format of CIE L*, a*, b* for each pixel. Two image attributes, lightness and chroma, were selected for further processing. The new images generated from the modification of lightness or chroma were pushed through the inverse LCD model and final rendered images for the LCD were calculated. The original CIE L*, a*, b* image was also passed through the projector inverse model and a rendered image for projection on the screen by the DLP projector was prepared. Figure 1 shows histograms of lightness and chroma of the original colorimetric image prepared for the LCD display.

Lightness is one of the most important attributes of an image. Linear rescaling of lightness is a simple and fast algorithm that maps input lightness values to new output values through the following linear equation:

$$L_{out} = \frac{L_{in} - L_{mi}}{100 - L_{mi}}(100 - L_{mo}) + L_{mo} \qquad (1)$$

where L_{in} is lightness of the input for each pixel and L_{out} is mapped lightness for the output image (the "*" superscript is omitted for clarity). The L_{mi} and L_{mo} are minimum lightness in the input and output images, respectively. In other words, the input range of $\{L_{mi}, 100\}$ in the source image was rescaled to the range of $\{L_{mo}, 100\}$ for the output image. For this experiment, L_{mo} was assigned to values of, 10, 15, and 25, and then based on Eq. (1) three images with the same chroma and hue but different lightness values were generated. Figure 2 presents transformation functions for linear rescaling of lightness and the corresponding histograms of the output images. As can be seen from Fig. 2, the linear rescaling functions with L_{mo} equal to 10 and 15 results in images darker than the original image while the transformation with L_{mo} equal to 25 produced an image lighter than the original image.

Linear rescaling was also employed to transform chroma of the original image. In this way Eq. (1) was modified for chroma, shown in Eq. (2):

$$C_{out} = \frac{C_{in} - C_{mi}}{C_{mxi} - C_{mi}}(C_{mxi} - C_{mo}) + C_{mo} \qquad (2)$$

where C_{in} is CIELAB chroma values for each pixel of the original image and C_{out} is the linearly rescaled chroma (the "ab" subscript and “*” superscript are omitted for clarity). The C_{mi} and C_{mxi} are minimum and maximum values of chroma in the original image, respectively. The desired minimum value of chroma in the output image was assigned to the C_{mo}. The linear rescaling presented by Eq. (2) remaps the input chroma $\{C_{mi}, C_{mxi}\}$ to output range of $\{C_{mo}, C_{mxi}\}$. Figure 3 presents two linear rescaling transformation functions and the resulting histograms for minimum chroma values of C_{mo} =1 and C_{mo} =5. As it can be seen from Fig. 3, both linear rescaling functions increased chroma values compared to the original image.

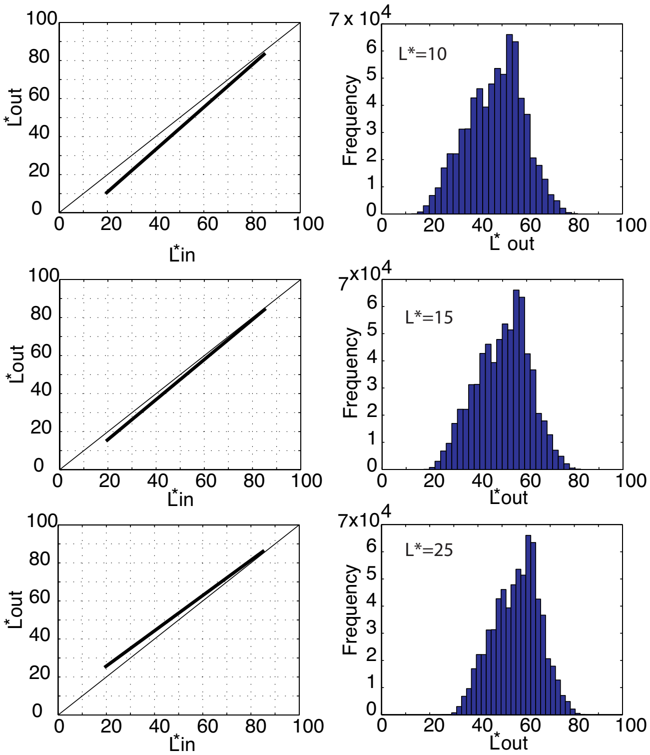

Figure 2. Transformation functions and corresponding histograms of linear rescaling of lightness with minimum lightness of L=10, 15, and 25.*

The sigmoidal lightness rescaling is another lightness remapping strategy.[14] This transformation function is derived from a discrete cumulative normal function as shown in Eq. (3):

$$S_i = \sum_{n=0}^{n=i} \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{(L_n - L_0)^2}{2\sigma^2}} \tag{3}$$

where L_0 and σ are mean and standard deviations of the normal distribution. The shape of the function is controlled by mean L_0 and standard deviation σ. The L_0 controls centering of the sigmoid and making it greater than L* = 50, shifts the straight-line portion of the sigmoid toward higher lightness. The σ controls the slope of the sigmoid curve and decreasing the σ values has the effect of increasing contrast for the output image. Figure 4 shows two sigmoidal transformation functions and corresponding histograms with L_0 equal to 40 and σ assigned to 30 and 50. As seen from Fig. 4, the sigmoidal rescaling with σ value of 50 remaps lightness of the original image to higher values in the output image. The sigmoidal function with σ of 30, increases L* values between 30 and 85, while it decreases lightness for values less than 30.

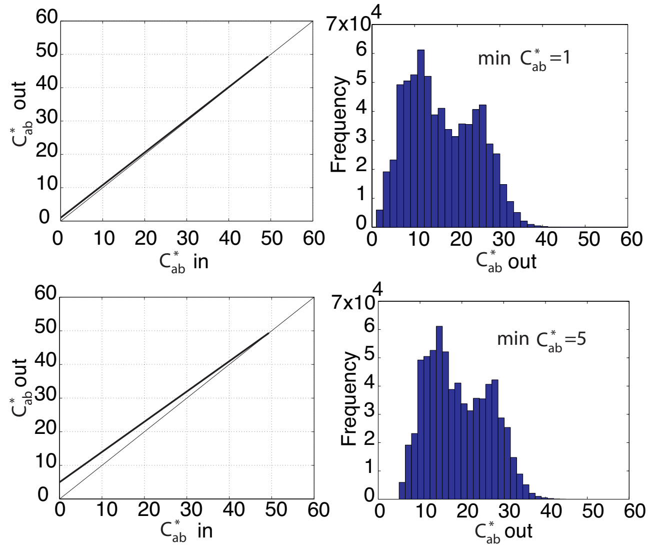

Figure 3. Transformation function and corresponding histogram of linear rescaling of chroma, C^*_{ab}, with minimum value of C^*_{ab} =1 and 5.

The CIELAB data of the original image were converted to tristimulus values (X, Y, Z) using the projector’s white point. The Y values were scaled in a way that the maximum values of Y could be equal to one and then followed by processing through a power law as shown in Eq. (4):

$$Y_{out} = (Y_{in})^{\gamma} \tag{4}$$

where Y_{in} and Y_{out} are luminance factors of input and processed images, respectively. The γ is a power factor which in this experiment was set to a value of 1.3. The modified tristimulus values were converted back to CIE L*, a*, b* space. Figure 5 shows the corresponding transformation in terms of CIE L* and the resulting histogram. This transformation had a darkening effect on the processed image. This effect was more profound in the lower values of lightness.

A spatial filtering was applied to the original image using Adobe Photoshop CS version 8.0. The crystallize filter with cell size of 3 was applied to the image to get an output image with less resolution and larger pixels. It is important to note that no color processing such as lightness or chroma rescaling were applied to this image. Therefore this image had the basic colorimetric nature as the original.

Table 2 summarizes the image processing algorithms used in this research. Images 1 through 10 will be referred in the rest of this paper as described in Table 2. In order to present the effect of each processing algorithm, a portion of the original image was processed by the different algorithms and shown in Table 2.

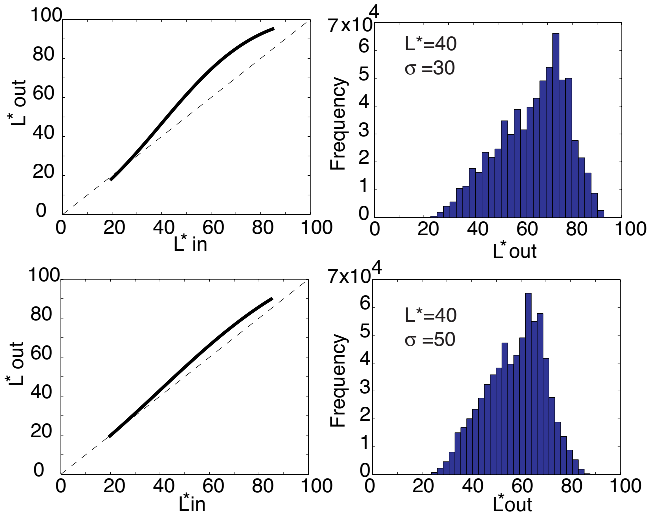

Figure 4. Transformation functions and corresponding histograms of sigmoidal rescaling of lightness, L, with mean value of L*=40 and standard deviation values of 30 and 50.*

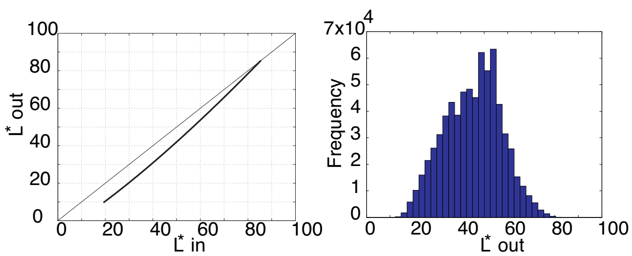

Figure 5. Transformation function and corresponding histogram for the power law processing (γ = 1.3).

Results and Discussion

Thurston's Law of Comparative Judgments, Case V, was used in the analysis of the results.[15] The collected data from the observers were converted to proportional observer data and an interval scale was computed from the z-scores. A 95% confidence limit was also calculated for each image.[16] Figure 6 presents the interval scales and corresponding 95% confidence limits for the 10 images used in the experiment. As it can be seen from Fig. 6, the lightness linear rescaling with minimum L* value of 25 has a higher scale value than the others. This image is also statistically different from the original colorimetric rendered image since the 95% confidence limits are not overlapping. In other words this image was selected as a closer match to the original image on the screen than the colorimetric version. A trend of increasing interval scales with increase of minimum L* value is seen for linear lightness rescaling (images 4, 5,and 6). The image generated based on minimum L* value of 10 (image 4) has the smallest and that with minimum L* value of 25 (image 6) has the highest interval scale values within the linear rescaling set. The image rendered based on power processing on luminance factor has been selected less than all other images and has the smallest interval values among all the other values. Linear rescaling of chroma with minimum C_{mo} =1 (image 8) was not statistically different from the colorimetric rendered image of the target. The extra increase in the minimum chroma produced a poorer matching image to the projected image on the screen and hence the interval scale for the image rendered with C_{mo} =5 (image 9) was reduced. The image made by Photoshop crystallize command was not statistically different from colorimetric version of the target image.

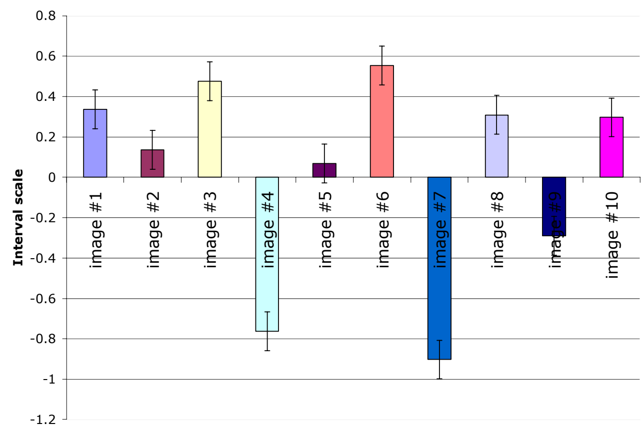

Figure 6. Interval scales and corresponding 95% confidence limits calculated based on visual experiment.

Conclusions

The experimental approach proved successful in evaluating the effect of image size on color appearance. Both displays had good colorimetric characterization accuracy. The short-term memory matching did not result in excessively large confidence limits. In fact, the limits were typical of paired-comparison experiments using a single display and adjacent images. Observers found that colorimetrically matching images of different size could be made to more closely match in appearance by image manipulation. In particular, changes in lightness in which lightness was linearly increased and rescaled were preferred over other tested algorithms. This result was consistent with previous experiments comparing small paint chips with painted walls. In both cases, size enlargement caused an increase in perceived lightness.

Future research will explore the use of image-dependent algorithms based on image appearance models. Ultimately, the goal is to develop a fundamental understanding of the effect of image size on color appearance.

Table 2: Summary of Image Processing Algorithms

	*Image 1. No image processing, just colorimetric rendering*		*Image 2. Lightness Sigmoidal rescaling,* $L^*=40$, $\sigma=30$, *followed by colorimetric rendering*
	*Image 3. Lightness Sigmoidal rescaling,* $L^*=40$, $\sigma=50$, *followed by colorimetric rendering*		*Image 4. Lightness Linear scaling with minimum* $L^*=10$ *then followed by colorimetric rendering*
	*Image 5. Lightness Linear scaling with minimum* $L^*=15$ *then followed by colorimetric rendering*		*Image 6. Lightness Linear scaling with minimum* $L^*=25$ *then followed by colorimetric rendering*
	*Image 7. Power law processing on Y then followed by colorimetric rendering*		*Image 8. Chroma Linear scaling with minimum* $C^*_{ab}=1$ *then followed by colorimetric rendering*
	*Image 9. Chroma Linear scaling with minimum* $C^*_{ab}=5$ *then followed by colorimetric rendering*		*Image 10. Photoshop crystallize command then followed by colorimetric rendering*

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Author Biography

Mahdi Nezamabadi received his B.S. and M.S. degrees in Textile Engineering from Amirkabir University of Technology in 1992 and 2001 respectively. He had worked as industrial engineering manager at Harir Dyeing & Printing Company from 1994 to 1997. From 1997 to 2002 he has been working as a lab instructor and researcher in the Color Science Department of Amirkabir University of Technology. Since 2002, he is a Ph. D. student in Imaging Science at the Munsell Color Science Laboratory of Rochester Institute of Technology.