IMAGE DISPLAY IN TEACHING IMAGE PROCESSING PART II: COLOR IMAGES

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ABSTRACT

With the proliferation of color display and input devices it has become less expensive to demonstrate and teach color image processing techniques. When teaching color image processing, it is important to emphasize that it is not a multichannel extension of monochrome image processing. This paper indicates the elements of color image processing and color image displays that every student and instructor should know. We give examples that can be used to illustrate these concepts.

Index Terms— Image processing, Color, Education

1. INTRODUCTION

In a previous article [1], the importance of teaching the proper display of monochrome images was discussed. Here the discussion is extended to processing and displaying of color images. We emphasize that the processing of color images is a nonlinear vector process and not a simple extension of monochrome image processing, where each of the three bands is treated as an individual monochrome image. This paper describes the elements of color image processing that students should know. The basic points that should be covered include:

1. Definition of a color space and its importance in image recording and reproduction: Device-dependent and device-independent color spaces.

2. Measurement of color images.

3. Color Gamut: definition and determination.

4. Color performance measures.

2. COLOR SPACES

To properly process a color image, it is necessary to know the meaning of the numbers that make up the digital image. Color images are often defined by a triple of RGB values, but it is rare that the student knows exactly what these values mean. This meaning is directly related to the concept of a color space. The relation is between the actual appearance of the image, as sensed by a standard observer and the device control values that produce the display. It is important to remind the student that the sensation of color is our reaction to the continuous spectrum of radiation that is sensed by the eye. The triple of values that defines color for most image manipulations is a discrete sampling of this spectrum. The values for an input image are related to the sampling of the color by the eye; the values for an output image are related to the production of a continuous spectrum that will be sensed by the eye. The basic idea of a color space is that of a discrete representation of the continuous radiation spectrum.

To demonstrate the importance of color spaces, the process of observing, recording and reproducing color is simple. Let the students observe a simple color image that has distinct, well-defined colors, such as the color grid shown in Fig. 1. Measure the colors using a device that gives the CIE values (XYZ or LAB). The CIE values are *device-independent*, since they are measured relative to common standards and define the color in terms such that it can be reproduced by anyone. Scan this image (record) using any desktop scanner to produce a three-band digital image (RGB). These values are *device-dependent*, since they are specific to the characteristics of the scanner. Print the recorded image on a convenient desktop color printer. Let the students observe the input and output images. Unless this is done with great care with calibrated devices, the input and output images will show significant color differences. This allows the instructor to discuss the process in terms of color spaces.

Additional examples of the effects of using various device-dependent color spaces are seen in

- a comparison of CRT and LCD displays that are driven by the same RGB image file.

- a comparison of prints obtained from two types of printers, e.g., color laser and color ink jet.

The CIE has defined color spaces that are independent of a physical device. These color spaces depend upon a standard human observer. Examples of such spaces include, CIEXYZ, CIELAB, and CIELuv. The relation of these spaces to the human visual system (HVS) should be emphasized. In particular, CIEXYZ is a direct linear transformation of the color

Fig. 1. Color grid type image useful for comparing color spaces.

matching functions associated with the sensitivity of the eye in a *standard observer*; the CIELAB and CIELuv spaces are attempts to define uniform color spaces, where Euclidean distances correspond to perceptual differences of the *standard observer*. The transformations to these uniform spaces is nonlinear and leads to significant computational difficulties. The CIELAB color space is an *opponent color space* where the element L^* encodes luminance information and the elements a^* and b^* respectively encode red/green and blue/yellow chrominance information. The HVS performs a similar encoding [7].

It is possible to transform colors defined in a device dependent color space to an image in a device-independent color space. This is often required to allow different devices to communicate. This approach requires the determination of the relationship between the RGB values and the CIE colorimetric values created on the display. The opposite is not true. It may be impossible to accurately transform an image from a CIE color space to a device-dependent space, due to limits on the colors that the device can reproduce. The set of device-independent values that a device can reproduce define the em gamut of the device.

In many research papers and text books, RGB images are processed without relating the image data to a device and hence back to the standard observer. This is not color image processing but rather multi-band image processing. When the human observer is to be the final judge of the algorithm quality (as opposed to machine vision applications) it is important to stress the need to relate the image data back to the observer, which will allow quantification of the color errors created by the algorithm.

3. COLOR MEASUREMENT

In order to use the CIE color spaces effectively, the student must be acquainted with devices that measure color in those spaces. While few electrical and computer engineering departments have such instruments now, it is recommended that at least one low end device be purchased for demonstrations in class. Colorimeters can be purchased for well under $1000. Examples include Color Vision's PrintProFix and Gretag MacBeths Eye-One Design. The use of these devices allows the student to relate the CIE values to actual colors produced in the real world. The devices are also necessary for color calibration of input and output devices. If possible, we recommend at least one high-end device that measures color spectra, i.e., a spectrophotometer or spectroradiometer.

In the example of the color grid, it would be informative for the student to measure the input and output images. The error measures, as discussed later, should be computed. The differences of the results obtained from printing the same image file on different printers could also be measured. This allows the student to test the rule of thumb for detectable color errors: ΔE_{ab} errors less than 3 are usually not noticeable.

4. COLOR GAMUT

While it is true that monochrome output devices produce only a limited range of densities, the effect of the limited range of color is much more important. The range of colors that a device can produce is called its *gamut*, and is represented by a three-dimensional solid. In [1], we discussed dealing with the display of images that had different ranges. In the case of color, it is much harder to bring two images into the same display range by simple manipulations, such as rescaling, which worked well with monochrome images.

We present an example that can be used to demonstrate artifacts from gamut mapping and the effect from gamut mismatch. An RGB image was created on a monitor, shown in Fig. 2, that consists of two figures. One figure is a disk that displays a continuum of RGB values such that one of the values is always 0, e.g., $RGB = [0\ 240\ 120]$). The other figure is a series of bars, each of which smoothly step from black to a primary color, e.g., red, green, blue, cyan, magenta, yellow, and then to white. For example, the red bar was created by stepping through the RGB vector sequence $\{[0\ 0\ 0],\ [1\ 0\ 0], \ldots,\ [255\ 0\ 0],\ [255\ 1\ 1], \ldots,\ [255\ 255\ 255]\}$. The smooth transitions between highly saturated colors make these figures ideal for demonstrating gamut mapping artifacts.

Using a colorimeter and the methods discussed in [2, 3], the display gamuts for a CRT monitor and a 3-color CMY dye sublimation printer were determined. The actual gamut intersections are shown in Figure 3.

The RGB values of the image in Figure 2 were then converted to CIELAB values. The CIELAB values that were within the gamut of the color printer were converted to the CMY values necessary to obtain the desired CIELAB values. The CIELAB values that were outside of the display gamut of the printer could not be created by the printer. To demonstrate the extent and the number of colors outside the gamuts,

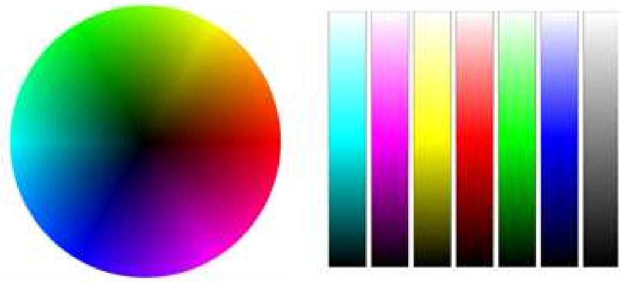

Fig. 2. Image used to evaluate gamut mapping artifacts.

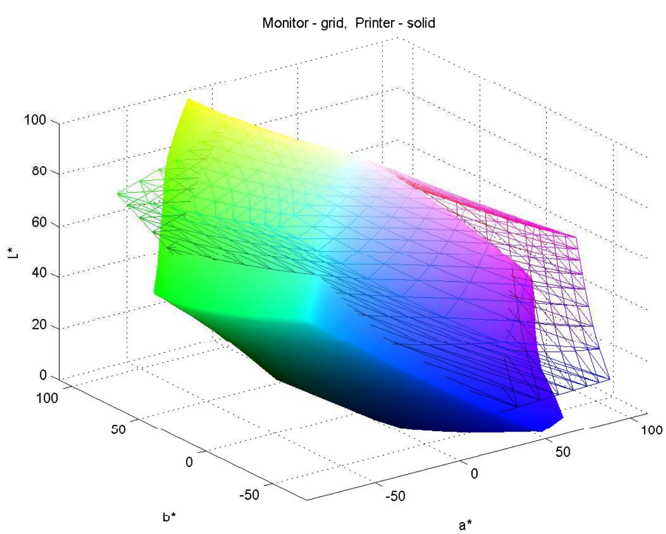

Fig. 3. Monitor gamut given by grid and printer gamut given by solid figure

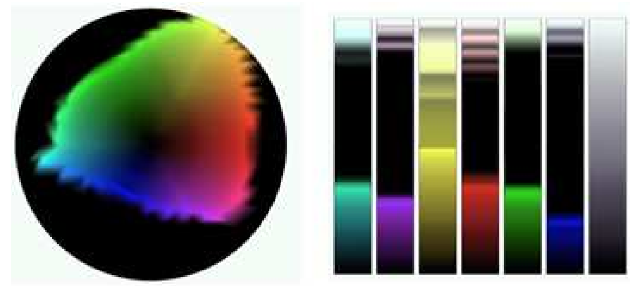

Fig. 4. Result of mapping the monitor defined image in Figure 2 through a mapping that maps colors outside the printer gamut to black.

these points in the image were mapped to a value of maximum black. The resulting image is shown in Figure 4.

As can be seen in Fig. 4, a significant number of colors are outside of the gamut of the printer. In the bar figure of Fig. 4, the banding, especially in the yellow bar, indicates that the values are going in and out of the printer gamut as the monitor device-dependent control values are stepped from black to a primary color and then to white. Note also that the monitor pure red does not map to a pure red on the printer.

5. PERFORMANCE MEASURES

Often in image processing, a comparison is made between the images created by different algorithms. In monochrome image processing, the standard measure of comparison is the root mean square difference between the ideal image and the processed image. It is usually recognized that this metric does not match human perception but it is highly correlated. Occasionally, other weighted metrics are introduced. In color image processing, the color space in which the image is defined greatly affects this number. It would be desirable if the computed difference related well to the perceived difference.

When comparing solid colors, the color metrics defined by the CIE are appropriate. There are a variety of measures including ΔE_{ab}, ΔE_{uv}, $\Delta E94$ and CIEDE2000 [4, 5, 6]. In the case of comparing color images, the spatial variations are a significant component of the perceived quality of the match. For this case, it is necessary to use a measure that accounts for the spatial color frequency response of the human visual system. The fact that the human observer is less sensitive to chromatic variations compared to luminance variations is well known and used in a variety of algorithms and devices.

Zhang and Wandell [7] introduced a color image metric that incorporated color spatial filtering characteristics of the HVS. The measure takes two color images and performs the following operations.

- Transforms each to an opponent color space.

- Spatially filters each channel with filters derived from visual experiments. The support (size) of the spatial filters depends upon the viewing distance and the display resolution.
- Recombines the filtered channels into a color image in CIELAB color space. This color space is approximately uniform, which implies that mean square error is a good indicator of color difference.
- Computes the standard ΔE or $\Delta E94$ color difference metric between the filtered images.

This measure, which is denoted as ΔE_s can provide some quantification of the effectiveness of an algorithm to distribute errors where they are less visible. Fairchild and Johnson developed an appearance model (iCAM) that accounts for the various adaptations of the HVS based upon the viewing conditions [8].

Often, to maintain mathematical tractability, algorithms are derived based on mean square error methods. Some of these methods are quite useful. Unfortunately, some introduce objectional color errors. Thus, it is important to emphasize to the student that when evaluating the performance of color image processing algorithms the error in one of the CIE uniform color spaces should be computed.

We present a simple example to help illustrate the problem, shown in Fig. 5. This figure demonstrates the perceptual nonuniformity of a color space like sRGB and hence the inappropriateness of using MSE as a measure for many algorithms. In the figure, starting at the top left and going clockwise are sRGB values {32,38,83}, {29,53,71}, {27,245,17} and {14,244,1}. The euclidean distance in sRGB color space of the colors on the left to those on the right is 20. The ΔE_{ab} difference in CIELAB color space is 21.5 for the top colors (easily noticeable) and 1.2 (not noticeable) for the bottom colors.

Another simple example is to take an image such as shown in Figure 1, add noise and compute the difference measures. Doing this for various noise distributions and an SNR of approximately 30dB in each RGB color band results in error measures shown in Table 1. Note in the table that the MSE computed in sRGB color space is smaller for the uniform noise but the ΔE errors are greatest for the uniform noise.

Table 1. Error metrics for different noise distributions added to image in Figure 1

METRIC	Gaussian	Uniform	Poisson
MSE	69.36	69.12	68.80
ΔE	3.72	3.85	3.72
ΔE_s	1.38	1.42	1.39

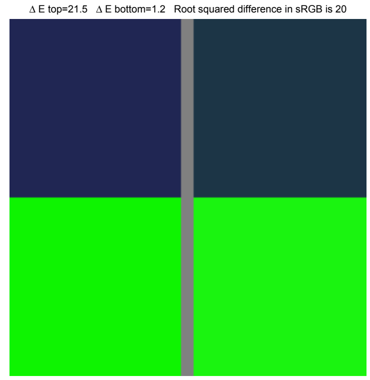

Fig. 5. Example of color space nonuniformity. Top and bottom pairs have the same difference in sRGB color space (20) but in CIELAB, top pair $\Delta E_{ab} = 21.5$, bottom pair $\Delta E_{ab} = 1.2$.

6. REFERENCES

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