Memory Color Based Preferred Color Reproduction with Psychophysical Evaluation

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Abstract

Reproduction of pleasing colors is one of the efficient methods to improve the perceived image quality of digital color imaging devices. Observer preference in the color reproduction of pictorial images has been a topic of research for many years. Preferred color reproduction, following certain rules upon the behavioral study of visual preference, is a deviation from colorimetric color reproduction, which aims at absolute color accuracy. Memory colors play an important role in the preferred color reproduction. This paper introduces methods to manipulate images in order to achieve preferred color reproduction. The methods are tested through psychophysical experiments. Conclusions are drawn and discussed in the paper.

Introduction

With the rapid advance of digital imaging technologies, people are expecting high image quality performance from the new generations of digital imaging devices. Reproduction of pleasing color of natural objects is one of the efficient methods to improve image quality. Much research has been done to understand the shift of memory color from the original color. The general results indicate that memory colors have more saturation than the corresponding natural objects, and certain memory colors such as skin, foliage and sky are remembered with slightly different hues and lightness and with higher color purity [1]. Topfer [2] presented measurements on the decrease of image quality as the rendition moves away from the memory colors. Yendrikhovskij, etc. [3, 4] described a technique for evaluating naturalness of color reproduction and a naturalness index predicting perceived naturalness of color reproduction of real-life scenes. In photographic applications, the desirable color reproduction of the natural object colors might be biased toward the idealized memory color of these objects. In addition, image color preference might also be different even for the same objects with a variety of image contents, capturing illuminants, background colors, relative lightness, and observers' culture. While the effect of cultural differences was studied in previous research [5, 6], influences of other factors are still in question. These potential influential factors need to be further investigated in complex pictorial images in the view of image appearance preference.

In photographic applications, there are three most important memory colors in natural images: human skin tones, green grass and blue sky. They are located in different hue regions, which is convenient for designing image segmentation algorithms for automatic color correction. Furthermore, it is well known that an observer maintains the ability to rate the quality of an image with or without the original image being present. Without the original image being present, the observers are rating the quality of an image in reference to some psychological concept of an idealized image. So the goal of our color reproduction should sometimes be to match the psychological concept of an image, i.e. the preferred image reproduction, rather than a colorimetric image reproduction.

Preferred image reproduction techniques should be viewed as an enhanced or customized version of a colorimetric reproduction. Thus, when evaluating preferred image reproduction, we need to move from a metric of color match to a metric of appearance match between a reproduced image and its mental reference, i.e. the entity labeled as "naturalness". It is commonly understood that pictorial image quality has a positive correlation with naturalness [3, 4, 8]. Therefore, an image of high quality should be the one that has a high degree of naturalness.

Description of the Proposed Algorithm

The algorithms to be studied are as follows. (1) White pedestal subtraction from the image. (2) Automatic sigmoid tonal curve. (3) Adaptive tone mapping as described by US Patent 7023580 [12]. (4) The memory color enhancement algorithm described as follows.

In short, the memory color enhancement algorithm modifies memory colors differently in a hue-saturation-intensity color space or similar color spaces. As people are most sensitive to skin color, we prefer not to change it unless product localization sets specific requirements. The main changes in this study will be on foliage green, sky blue, and some other natural colors such as flowers. The saturation change in the hue-saturation-intensity color space will be inhomogeneous. Different parameters are applied in different zones. These parameters can be determined from the psychophysical literature or the observer studies performed in house.

A. Memory Color Clustering in Imaging Device Friendly Color Space

Previous memory color clustering analyses were mainly performed in CIELUV color space, which is an approximately perceptually uniform color space. However, this color space is too complex to fit in a mobile imaging device. Luminance-chrominance spaces such as YCbCr or YUV space are usually available in these devices for image compression. YCbCr is used here as an example to cluster memory colors. The distribution of memory color clusters in YCbCr color space is illustrated in Figure 1. The clusters of skin tone, foliage green, and sky blue are located in relative small regions. Depending on the lighting levels, these clusters can be closer or farther away from the origin, moving along the radial direction. So the clusters can best be described by the equations of the two lines located on both sides of each cluster. The distribution of flowers is very large, but one may notice that flowers usually have a larger red component compared to green ($R \geq G$), and it covers the skin tone cluster.

By assuming hue constancy in the CbCr plane (this assumption is only an approximation), a cluster of specific memory color can be defined by a region contained within two lines:

$$L_1 : \ C_b > k_1 \cdot C_r \ \text{and} \ L_2 : \ C_b < k_2 \cdot C_r \tag{1}$$

The coefficients are determined to make sure the clustering ellipse cover more than 95% of the samples. Specifically, the memory colors are detected using the following line equations (notice that for skin color detection, an extra line equation is used in order to differentiate skin color from orange color):

$$\begin{aligned} Green&: \ C_b < C_r \ \ \& \ \ C_b > 10 * C_r \\ Skin&: \ C_b < -0.1 * C_r \ \ \& \ \ C_b > -1/0.8 * C_r \ \ \& \ \ R < 1.75 * G \\ Sky&: \ C_b < -1/0.4 * C_r \ \ \& \ \ C_b > -0.6 * C_r \\ Other&: \ P_{other} = 1 - Green \cup Skin \cup Sky \end{aligned} \tag{2}$$

B. Nonlinear Curve for Contrast/Saturation Adjustment

In this section, a nonlinear curve is introduced for image contrast and saturation adjustment [13]:

$$\begin{cases} y = a^{1-\gamma} x^{\gamma}, & 0 \le x \le a; \\ y = 1 - (1-a)^{1-\gamma} (1-x)^{\gamma}, & a < x \le 1. \end{cases} \tag{3}$$

where a is the transition point, and γ is the parameter controlling the degree of nonlinearity. Keep in mind that $\gamma = 1$ always results in a linear identity operation. To adjust the saturation of images, one would do little for pixels near neutral, and boost the saturation in the middle range, and compress the pixels with really high chroma values. So the transition point should be close to zero but not zero. The degree of nonlinearity is different for different memory color clusters. In our experiment, these parameters are selected for image saturation adjustments: Transition point 0.02 in the range of [0, 1]. $\gamma = 2.0$ for foliage green cluster, $\gamma = 1.5$ for sky blue cluster, $\gamma = 1.0$ for skin color cluster, and $\gamma = 1.25$ for all colors which do not belong to these three memory color clusters. The resultant nonlinear curves are plotted in Figure 2(a).

C. Contrast Enhancement

It is well known that histogram equalization produces contrast-enhanced image. In histogram equalization, the gray levels in an image are redistributed evenly to make better use of the range of the display devices. However, this operation may destroy the relationship between the contents of the image and makes the resulting image far from the perception of an observer. Furthermore, the extent of enhancement is not controllable. S-shape tone scale process curve is recently used for improving the contrast and saturation for an image output device, and it can retain a balance of the contents of the image. In this section, the contrast enhancement is realized through four steps, (1) Histogram calculation for the luma channel; (2) Calculation of confident black level and white level; (3) Generate tone mapping curve; (4) Apply the tone mapping curve to the red, green, and blue channels.

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(1) Histogram calculation

The expected percentage of pixels in each bin is 1/16, if the lightness of pixels in an image is uniformly distributed. However, in reality, this distribution is unlikely to be uniform, and due to device limitation, the histogram may have little distribution at the dark end and/or the bright end. In such conditions, the black level in the dark end can be removed and the white point in the bright end can be expanded to extend the dynamic range of the image and hence increase the contrast. To avoid clipping one or two channels, the maximum envelope of the three histograms is calculated.

(2) Calculation of confident black level and white level

If the percentage of pixels in the first one or two bins at the dark end is extremely low, for example, less than 10% of the uniform distribution, which means there are not many pixels, we can mark part of these bins as black level (x0). Similarly, if the percentage of pixels in the first one or two bins at the bright end is extremely low, for example, less than 10% of the uniform distribution, which means there are not many pixels, we can mark part of these bins as white level (x1). Assuming nY is the histogram of the maximum envelope, for N=16, the determination of black level and white level is realized by the following pseudo code:

```
if nY(1)<(1/16*0.10),
   x0=1/16/2+(1-160*nY(1))*1/16/2;
else
   x0=0;
else if (nY(1)<(1/16*0.10))&(nY(2)<(1/16*0.10)),
   x0=1/16/2*3+(1-160*nY(2))*1/16/2;
end;
if nY(16)<(1/16*0.10),
   x1=1-1/16/2-(1-160*nY(16))*1/16/2;
else
   x1=1;
else if (nY(16)<(1/16*0.10))&(nY(15)<(1/16*0.10)),
   x1=1-1/16/2*3-(1-160*nY(15))*1/16/2;
end;
```

(3) Generate tone mapping curve

Once the black level and white level are obtained, the real range [x0, x1] can be expanded to the full display range [0, 1] through the following transformation in order to use Equation (3):

$$a = \frac{x_0 + x_1}{2},\ x' = \min\left[\max[x - x_0,\ 0]*1/(x_1 - x_0),\ 1\right] \quad (4)$$

Currently a predefined power number ($\gamma = 1.20$) is applied to achieve a mild sigmoidal effect. For example, $x_0 = 0.2$, $x_1 = 0.7$ yield a sigmoid curve as Figure 2(b).

(4) Apply the tonal mapping curve to the red, green, and blue channels

After the tonal mapping curve is obtained, it is applied to each of the RGB channels respectively. An alternative way is to apply the tonal mapping curve only to the luma channel. Based on experimental results, the images were processed by the former option.

Psychophysical Evaluation

Images were processed using different algorithms and different sets of parameters to achieve preferred color reproduction. Figure 3 shows an example of one image processed using four different algorithms. Psychophysical experiments were performed to: (1) Validate the hypothesis that preferred color and tonal reproduction enhances image quality compared to the baseline color and tonal position; and (2) Identify the parameter combination for saturation and tonal curve manipulations that observers perceive as having the best image quality. Ten subjects participated in the study. They all had normal visual acuity (tested using an eye chart at 40 cm) and normal color vision (tested using Ishihara's Tests for Color-Deficiency). Images were viewed under Judge II D50 (5000K, 1100lux) and the viewing distance is not controlled.

The images were printed 4x6 using a HP Z3100 large format color printer via a color managed path. The rendering intent was set to perceptual. A semi-glossy paper (HP Satin paper) was used in the printing.. In total ten scenes were used to evaluate eleven different algorithms. The ten test scenes included a mixure of people, non-people scenes, indoor/outdoor scenes, and various illumination conditions.

A rank order method was used in this study. The instruction is as below:

Here is a set of 110 images for you to evaluate today. These prints vary in color and tone reproduction quality. There may also be changes in apparent graininess and sharpness. There are 10 scenes, and 11 variations for each scene. Each time you will receive 11 images of the same scene. Please place them in order of perceived overall image quality from the best to the worst. There is no tie, meaning you cannot place one image on top of another one. When you are done with the evaluation of these 11 images, please hand them to me from the best to the worst, and I will record the score. Please ignore any defects due to the printing process.

The rank order results were converted to JNDs (just noticeable differences) using Thurston's Law of Comparative Judgment. The results were plotted in Figure 4. The effects of various factors on JNDs, including scene content and illumination conditions, were also analyzed.

Some conclusions based on the statistical analysis are as follows:

A global position (for average scene and average observer) for preferred color and tonal mapping can boost image quality by 1 JND compared to the baseline position:

- The default black level subtraction is judged inferior to all other color and tonal positions.
- In general boosting contrast and saturation up to some point is good.
- Patent described algorithm with default parameters increases image quality by 0.7 JND.
- The proposed algorithm with a range of parameters increases image quality by 0.6-1 JND.
- The best parameter setting for the proposed algorithm is contrast level= 1.2, saturation level= 1.5.
- This quality enhancement over the baseline is statistically significant.

Scene intelligence can help to enhance color and tonal reproduction quality further:

- For people scenes high contrast decreases image quality. Effect of saturation is small.
- For non-people scenes high contrast enhances image quality significantly. Medium saturation is favored compared to low and high levels.
- Enhancing contrast is in general good for high light level scenes, where noise is not an issue.
- For low light level scenes, the treatment in color and tone has only moderate effect on perceived image quality. This is because the scenes lack memory colors (blue sky and green grass), and tradeoffs need to be made between color saturation, contrast, shadow details, and noise.

The pooled Just Noticeable Difference (JND) results are plotted in Figure 4.

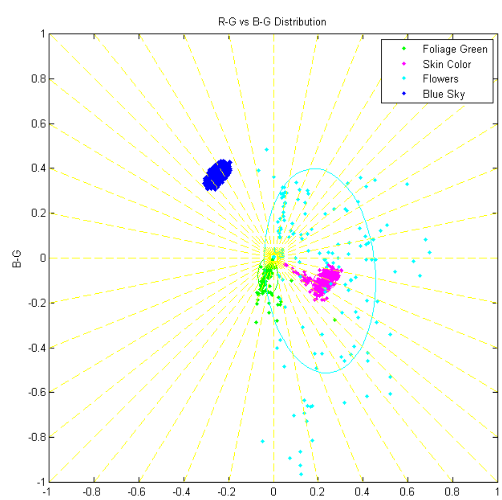
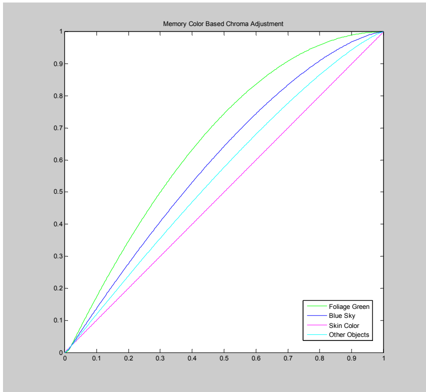
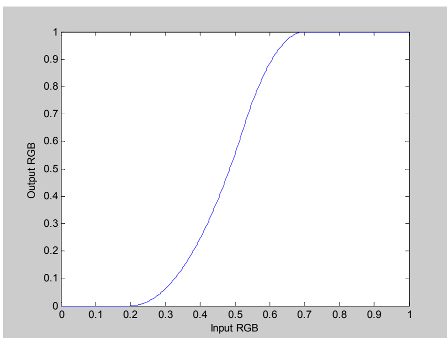


Figure 1. *The distributions of memory color clusters in Cb-Cr plane.*



(a)



(b)

Figure 2. *Nonlinear curves for (a) chroma adjustment and (b) contrast enhancement.*

(a)

(b)

(c)

(d)

Figure 3. *(a) Memory color saturation adjustment; (b) Typical black level subtraction and auto S-curve; (c) New contrast enhancement algorithm; (d) Sigmoid curve processed image by US Patent 7023580.*

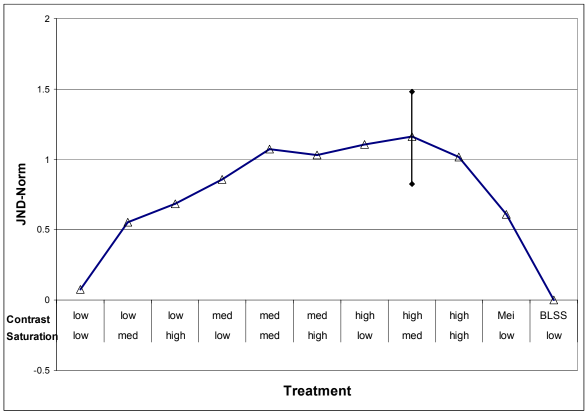


Figure 4. *Psychophysical evaluation on the combinations of the proposed algorithm versus available algorithms.*

References

[1] R.W.G. Hunt, I.T. Pitt, L.M. Winter, "The Preferred Reproduction of Blue Sky, Green Grass and Caucasian Skin in Colour Photography," J. of Photographic Sci. 22, 144-149, (1974).

[2] K. Topfer, R. Cookingham, "the Quantitative Aspects of Color Rendering for memory Colors," IS&T 2000 PICS Conference, (2000).

[3] S.N. Yendrikhovskij, F.J.J. Blommaert, and H. de Ridder, "Color Reproduction and the Naturalness Constraint," Col. Res. Appl. 26(4), 278-289, (2001).

[4] S.N. Yendrikhovskij, F. J. Blommaert, and H. de Ridder, "Optimizing color reproduction of natural images," the 6th Color Imaging Conference, 140-145, (1998).

[5] Scot R. Fernandez, Mark D. Fairchild, "Preferred Color Reproduction of Images with Unknown Colorimetry," 9th Color Imaging Conference, 274-279, (2001).

[6] Scot R. Fernandez, Mark D. Fairchild, "Observer Preferences and Cultural Differences in Color Reproduction of Scenic Images," 10th Color Imaging Conference, 66-72, (2002).

[7] J. Kuang, X. Jiang, S. Quan and A. Chiu, "A psychophysical study on the influence factors of color preference in photographic color reproduction," in Proc. SPIE Electronic Imaging, vol. 5668, San Jose, CA (2005).

[8] H. de Ridder, "Naturalness and Image Quality," Journal of Imaging Science and Technology, 40(6), 487 – 493 (1996).

[9] R. W. G. Hunt, "How to make pictures and please people," IS&T/SID Color Imaging Conference, Scottsdale, AZ (1999).

[10] D. Sanger, T. Asada, H. Haneishi, and Y. Miyake, "Facial pattern detection and its preferred color reproduction," IS&T/SID Color Imaging Conference, Scottsdale, AZ (1994).

[11] C. Boust, F. Cittadini, M. B. Chouikha, H. Brettel, F. Vienot, S. Berche, and G. Alquie, "Does an expert use memory colors to adjust images?" IS&T/SID Color Imaging Conference, Scottsdale, AZ (2004).

[12] X. Zhang, R. W. Jones, I. Baharav and D. M. Reid, US Patent 7023580 – "System and method for digital image tone mapping using an adaptive sigmoidal function based on perceptual preference guidelines".

[13] T. Watanabe and Y. Hoshino, "Gamma Transformation by Sigmoid Function in Digital Camera System", IS&T NIP16: International Conference on Digital Printing Technologies, 678-681, 2000.

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