Color Gamut Mapping by Optimizing Perceptual Image Quality

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Abstract

This paper describes color gamut mapping technique as an optimization problem for finding an image which is perceptually closest to the original one among the images which only contain reproducible colors for the destination device. Perceptual difference between images is defined as a color difference of band-pass-filtered images rather than simple summation of ΔE of each pixel within the image.

Introduction

Since the shape of a color gamut differs for each device, it is necessary to transform the colors in order to fit them into the reproducible colors, called *gamut mapping*. Conventional methods for gamut mapping, such as linear compression of chroma or clipping, basically focus only on the tristimulus values, such as CIEXYZ or LAB, for each pixel independently. It is well-known that we can not get satisfactory reproduction using such pixel-by-pixel method since human color appearance strongly depends on spatial arrangement of colors in an image.[1]

To overcome this problem, this paper describes a technique of color gamut mapping as an optimization problem. That is, our goal is to find an image which is perceptually closest to the original one among the images with a set of all reproducible colors for the destination device. Perceptual difference between images is newly defined as difference of band-pass-filtered images with consideration to human's contrast sensitivity function (CSF) rather than simple summation of ΔE of each pixel within the image.

Formulation of Gamut Mapping as an Optimization Problem

Color gamut mapping can be described as an optimization problem of the form:

Find an image such that
(a) perceptually closest to the original
(b) all pixels are within the color gamut of the destination device

In the following section, *(a)* and *(b)* are formulated as an perceptual difference between images to be minimized and a constrant for gamut, respectively.

Definition of Perceptual Difference

Perceptual difference is defined as a color difference between an original and a reproduction both were filtered by an observation process beforehand.

$$\mathcal{PD}(r,o) \underset{\text{def}}{=} \left\| h * \left[o(x,y) - r(x,y) \right] \right\|^2 \tag{1}$$

where $\boldsymbol{o}(x, y)$ and $\boldsymbol{r}(x, y)$ are $L^*a^*b^*$ values of the pixel at the position (x, y) in the original and the reproduction, $\boldsymbol{h}$ is an impulse response of a *observation filter* and * represents convolution. This can be rewritten as follows.

$$\begin{aligned}\mathcal{PD}(r,o) = \sum_{C=L^*a^*b^*} \{ & \sum_{i,j=-\omega}^{+\omega} h^C(i,j) \\ & \times \left(C_o(x-i, y-j) - C_r(x-i, y-j) \right) \}^2\end{aligned} \tag{2}$$

where $2w + 1$ is the size of the filter.

$\boldsymbol{h}$ was described using DOG (difference of Gaussian) to have band-pass characteristics. Peak frequency for L^* ($\boldsymbol{h}^{L^*}$) is set to be slightly higher than those for a^* and b^* according to psychophysical evidence of human's CSF.[2] It should be noted that if delta function was used instead of $\boldsymbol{h}$, $\mathcal{PD}(r, o)$ would give ΔE^2 between $\boldsymbol{r}(x, y)$ and $\boldsymbol{o}(x, y)$.

Constraint for Gamut

There are several techniques for color conversion between device-independent and dependent color spaces, such as LUT or neural networks (NNs). To characterize the printer gamut, we here focus on the mutual conversion between device-independent and dependent color spaces using NNs.

We trained two NNs to perform color conversion from $L^*a^*b^*$ to CMY (NN_1) and the inverse mapping of that: CMY to $L^*a^*b^*$ (NN_2) (we will describe the details in **Color Calibration**. If two NNs were trained successfully, then functional relationship of the mutual color conversion: $L^*a^*b^* \to \text{CMY} \to L^*a^*b^*$ which is performed by cascading two NNs, should represent almost identity mapping for the points within the device gamut, from which the training data were selected. On the other hand, for the points outside the device gamut, such an identity mapping can not be obtained, because even the data located in relatively far distance from gamut in LAB-space are forced to be mapped into the gamut in CMY-space $[0, 100]^3$ due to the sigmoidal characteristics of NN_1. This allows us to recognize whether a given point in CIELAB-space is inside the color gamut or not, that is, color gamut can be extracted in LAB-space.

To do this, the accuracy of mutual color conversion is defined as follows.

$$\mathcal{M}(r) \underset{\text{def}}{=} \left\| r - \mathcal{F}_{NN2}(\mathcal{F}_{NN1}(r)) \right\| \tag{3}$$

where $\boldsymbol{r}$ = ($L^*a^*b^*$) represents CIELAB tristimulus value, $\mathcal{F}_{NN1}, \mathcal{F}_{NN2}$: $R^3 \to R^3$ are mappings from $L^*a^*b^*$ to CMY and CMY to $L^*a^*b^*$ by the trained *NN*s, respectively. A set of points where $\mathcal{M}(\boldsymbol{r})$ is smaller than a certain threshold can be extracted as a device gamut.

Optimizing Process

Gamut mapping is clearly defined as a problem of finding the set of $L^*a^*b^*$ values for printing which minimize the following cost function.

$$Cost = \sum_{x,y} \mathcal{PD}(r,o) + \lambda \sum_{x,y} T[\mathcal{M}(r)] \tag{4}$$

where λ is a positive number and $T[\cdot]$ makes $\mathcal{M}(\boldsymbol{r})$ zero for $\boldsymbol{r}$ inside gamut.

$$T[x] = \begin{cases} 0 & \text{if } x < threshold \\ x & otherwise \end{cases} \tag{5}$$

threshold is set to the maximum value of $\mathcal{M}(\boldsymbol{r})$ for $\boldsymbol{r}$ inside the gamut.

Optimizing process consists of the following steps.

Step 1: Set the initial value to $\boldsymbol{r}$.

Step 2: $\boldsymbol{r} \leftarrow \mathcal{F}_{NN2}(\mathcal{F}_{NN1}(\boldsymbol{r}))$ to make $T[\mathcal{M}(\boldsymbol{r})]$ zero (clipping pixels outside the gamut).

Step 3: $\boldsymbol{r} \leftarrow \boldsymbol{r} - \alpha \cdot \partial \mathcal{PD}/\partial \boldsymbol{r}$ to reduce $\mathcal{PD}(\boldsymbol{r}, o)$ by a steepest descent method. Where α is the update rate. $T[\mathcal{M}(\boldsymbol{r})]$ may slightly increase at this step.

Step 4: $\boldsymbol{r} \leftarrow \mathcal{F}_{NN2}(\mathcal{F}_{NN1}(\boldsymbol{r}))$ for clipping outside the gamut arising at Step 3.

Step 5: if *Cost* is small enough, then exit; else go to Step 3.

Figure 1 demonstrates the gamut mapping for a simple 1D monochromatic case to show the difference between the methods. A line clipped at the boundary of the gamut was obtained by minimizing the average color difference (minimized-ΔE). In this case, pixels inside the gamut were not influenced by gamut mapping. Normalize method altered all pixel values and a completely linear line was obtained although contrast of reproduction was reduced. On the other hand, a sigmoidal-shaped curve (a thick line) was obtained by the proposed method. The proposed method compresses the pixels not only outside but also a part of pixels inside the gamut to preserve contrast. We should note that although a similar curve may be obtained by a nonlinear compression for this case, the proposed method differs from such a pixel-by-pixel method, because the result obtained by the proposed method depends on pixel configuration of an image.

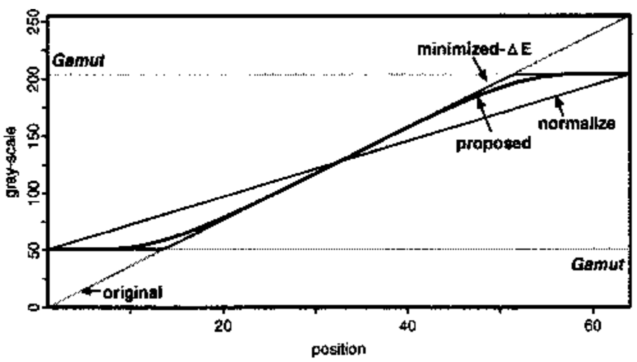

Figure 1. A demonstration of gamut mapping for a simple 1D monochromatic case. Original ranges from 0 to 255. Gamut is set to be between 51 and 204. A sigmoidal-shaped curve was obtained by the proposed method.

Application to Hardcopy Reproduction

Color Calibration

The color reproduction system used here consists of a CRT monitor (SONY, GDM-2000TC) and a full-color printer (Textronix, Phaser540J). These devices are calibrated using CIELAB tristimulus values.

For CRT calibration, color conversion between device coordinates (RGB) and $L^*a^*b^*$ is performed simply by a matrix calculation with gamma correction. Tristimulus values and gamma values for Red, Green and Blue phosphors were measured by spectroradiometer. Note that L^* for device-white (R = 255, G = 255, B = 255) and device-black (R = 0, G = 0, B = 0) were set to 0 and 100, respectively. White point was set to 5,500[K].

For the color printer, color conversion is performed by *NN*s as mentioned before. We printed color samples with 11 values for each of the 3 degrees of color freedom, 1331 color samples in total, and measured $L^*a^*b^*$. In order to train the *NN*s, 216 samples (6 levels for each variables) selected from measured samples were used. Remaining unlearned 1115 samples were used to evaluate the color conversion accuracy. For NN_1, the mean error in CMY space $[0, 100]^3$ was 8.0 %, and for NN_2, the mean color difference ΔE was 4.7. The mean color difference for the mutual conversion was 4.2. These results show that the accuracy of color conversion developed here was sufficiently high for practical use, though relatively small number of color samples were used for the network training compared with that required for constructing the conventional LUT.

Note that NN_1 consists of 3–13–3 units in the input, hidden and output layer and NN_2 consists of 3–12–3 units. Output units in NN_2 have linear input-output functions, while NN_1 have the sigmoidal units in the output layer which force the output values to be bounded between 0 and 100. This is an important point for a gamut extraction described in **Constrant for Gamut**.

Visualization of 3D Color Gamut

Figure 2 shows 3D view of the extracted gamut plotted in CIELAB-space. A curved surface is the boundary of the device gamut where $\mathcal{M}(\boldsymbol{r})$ is 12.0 (threshold for $T[\cdot]$: the maximum value of $\mathcal{M}(\mathbf{r})$ for color samples inside the gamut used for training). $\mathcal{M}(\mathbf{r})$ is also plotted on the constant L^* plane ($L^* = 55$) in gray scale. The gamut of the target printer was successfully extracted by the proposed method using the accuracy of the mutual color convertion.

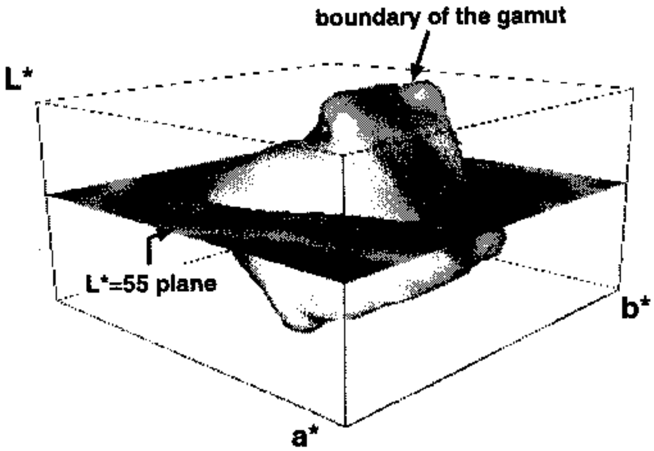

Figure 2. 3D view of the extracted gamut of Phaser 540J in CIELAB-space. $\mathcal{M}(\mathbf{r})$ on the constant L plane ($L^* = 55$) is displayed in gray scale (originally displayed in pseudo-color scale). A curved surface is the boundary of the device gamut where $\mathcal{M}(r)$ is 12.0 which is the maximum value for the color samples inside the gamut.*

Generation of Images

Proposed Method was applied to hardcopy reproduction. The original image (175 × 252 pixel-size) was displayed on the calibrated CRT monitor and $L^*a^*b^*$ values for all pixels were calculated. Our goal is to find the best quality reproduction which is perceptually closest to the original and also reproducible for a target printer.

Figure 3 shows the transition of Cost during the optimizing process. Horizontal axis indicates the iteration number of updating the reproduction $\boldsymbol{r}$ at **Step 5** in the process. This result demonstrates that the optimizing process successfully performs to decrease *Cost* smoothly.

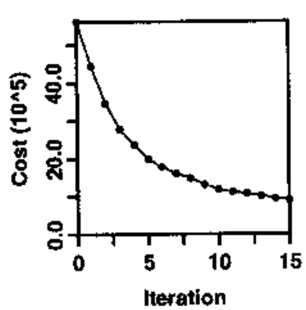

Figure 3. Transition of Cost *during the optimizing process. Horizontal axis indicates the iteration number of updating* $\boldsymbol{r}$ *at Step 5 in the process. This shows that the optimizing process successfully performed to decrease* Cost *smoothly.*

Figure 4 shows (a) original, (b) gamut alarm, (c) minimized-Δ E reproduction which was obtained by using delta function as $\boldsymbol{h}$ instead of band-pass filter, and (e) the reproduction obtained by the proposed method. In Figure 4(b), pixels of the outside gamut are alarmed by blacking out (almost of clothing and some of hair). Figure 4(d) and (f) show the color difference between original-(c) and original-(e), respectively. All these images are displayed in gray-scale for the printing reason.

In Figure 4(c), contrast was reduced especially for creases of the clothing. This is because minimized- Δ E method simply maps the pixels outside the gamut onto the surface of a gamut without any consideration to preserve contrast of the original. On the other hand, this problem was settled in the proposed method as Figure 4(e). That is, proposed method compresses not only the pixels outside the gamut but also other pixels inside the gamut to preserve the contrast of the image. In other words, this method reduced the color difference especially for middle-spatial frequency range, while almost equal or slightly higher value for low- and high-frequency ranges as compared with Figure 4(d).

Paired Comparison Experiment

A psychophysical experiment (paired comparison task) was also performed to evaluate the proposed method. Reproductions by the four methods were compared: (i) direct (original $L^*a^*b^*$ was directly converted to CMY by a NN_l without gamma mapping), (ii) 90%-normalize (reduced chroma to 90% and converted to CMY), (iii) minimized-Δ E [Figure 4(e)]. Observers examined an original displayed on a CRT and compared it to a pair of hardcopy reproductions in the light booth illuminated by D50 light source. Observers were asked to choose which of the two reproductions is most like the original, using a paired-comparison paradigm.[3] Ob servers were seated approximately 75 cm in front of the CRT and hardcopies. Peak frequencies of $\boldsymbol{h}$ for luminance and color were set to 11.0 and 6.0ºC/deg, respectively. All experiments were conducted in a dark room.

Table 1 shows the percentage of trials for which each method was chosen and the rank between methods. Results show that the proposed method performed best, while the minimized-Δ E method was chosen as the worst in this case although the reproduction by this method has the smallest color difference (Δ E = 2.46). Reproductions obtained by direct and the 90%-normalize methods had relatively large color differences since some pixels outside the gamut still remained and these pixels are converted to CMY forcibly, that is, there is no guarantee that such pixels outside the gamut were converted to appropriate CMY values. However, even these methods performed better than the minimized-Δ E method. Presumably, it was because the direct and the 90%-normalize methods preserved a certain amount of the contrast although color differed from the original. It is not necessarily that these methods always perform better than the minimized-Δ E method: a certain reproduction by these methods could not be acceptable, that is, high-saturated red of an apple was reproduced as pink, for instance.

Several observers reported that a criterion for judgement of the closeness between images was the balance of color difference and preservation of contrast. Proposed method is based on a consideration to that point and this is the reason why the proposed method taking this point into account successfully performed.

(a) original *(b) gamut alarm* *(c) minimized-Δ E* *(d) original minimized Δ E* *(e) proposed* *(f) original proposed method*

Figure 4. (a) original, (b) gamut alarm, (c) minimized-Δ E, (d) original-minimized-Δ E, (e) proposed method and (f) original-proposed method. All these images are displayed in gray-scale for the printing reason. Although (c) has the smallest color difference (Δ E = 2.46), contrast was reduced especially for creases of the clothing. In the reproduction obtained by the proposed method, on the other hand, this problem was settled: color difference is kept relatively small (Δ E = 3.30) and contrast is preserved well. This is because proposed method compresses not only the pixels outside the gamut but also other pixels inside the gamut to preserve the contrast of the image.

Table 1. Percentage of Trials for Which Each Model was Chosen and the Rank Between Methods.

(i) direct	(ii) 90%-norm	(iii) min-Δ *E*	(iv) proposed
37% (3)	47% (2)	33% (4)	83% (1)

Conclusions

A novel method for gamut mapping by optimizing perceptual image quality was proposed. Perceptual difference between images was defined as a color difference of band-pass-filtered images and the optimizing process was described based on a steepest descent method. A paired-comparison experiment showed that the closeness between images was not determined only by color difference but also preservation of contrast, and the proposed method taking this point into account successfully performed.

References

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