Gradient Domain Salience-preserving Color-to-gray Conversion

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Figure 1: *Salience-preserving color-to-gray conversion. Left: original. Middle: our result ($\beta = 1, \gamma = \infty, \alpha = 0$). Right: L in CIELAB.*

Abstract

In this paper an algorithm for gradient domain color-to-gray conversion is described. By enhancing the luminance gradient with the chromatic difference in CIELAB space, a gradient field is created to construct the resulting gray-scale image using a Poisson equation solver. In our algorithm, we develop a modulated luminance gradient enhancement to produce artifact-free and salience-preserving grayscale images. A gradient sign control function is defined for isoluminance color images to keep the correct color ordering.

CR Categories: I.3.3 [Computer Graphics]: Picture/Image Generation — Display algorithms; I.4.10 [Image Processing and Computer Vision]: Image Representation—Multidimensional

Keywords: color removal, gradient domain, image processing, color difference

1 Introduction

Color-to-grayscale conversion for digital color images is an important issue in computer graphics. It is widely used in black-and-white printing, video and animation, etc. Although some algorithms have been successfully used in industry, there are still many problems to solve, such as color discriminability for isoluminant colors.

Algorithms for color-to-gray conversion can be classified into three categories: 1) Linear combination of original color channels, typically, the Y component of CIEXYZ system [Ohta and Robertson 2005]. This kind of algorithms are widely used in industry, but lack the discriminability of isoluminance colors. 2) Global optimization algorithms for the conversion [Gooch et al. 2005; Kim et al. 2009] try to solve the problem of category 1, but some of them are very time-consuming. 3) Local feature enhancement algorithms [Neumann et al. 2007; Smith et al. 2008] also aim at improving their performance, but still suffer from the low execution efficiency and the gray-scale distortion.

For an ideal color-to-gray conversion algorithm, several requirements should be satisfied. First, the resulting grayscale image must be coincide with the luminance vision of human eyes, which is typically defined by the L component of CIELAB [1] color model [Wyszecki and Stiles 1982]. Second, for an isoluminance color image, all the colors in the image must be discriminable in the resulting grayscale image. Third, no artifacts should be introduced into the resulting grayscale image. For an image generated by a *Poisson Equation Solver* (PES) , these artifacts usually appears in the form of “halo effect”, which must be reduced to be invisible by human eyes [Fattal et al. 2002].

In this paper, we present a new category 3 algorithm which solves the color-to-gray conversion problem in the gradient domain. In gradient domain image processing, the gradient can be treated as a partial derivative of the original image. When this partial derivative is solved by a PDE solver such as PES, the original image can be reconstructed. By modifying data in the gradient domain, a different image can be obtained for certain purpose. In [Fattal et al. 2002], this strategy is used to convert a HDR image into a LDR one. Similar applications can also be found in [Pérez et al. 2003; McCann and Pollard 2008].

In our algorithm, we generate a gradient field that is used to reconstruct the grayscale image from the color image. The gradient at each pixel is a measurement of the color differences between its neighbors. The color difference is calculated base on the CIELAB model [Ohta and Robertson 2005] which is a reflection of the color vision of human eyes, hence the converted grayscale image will be a best approximation of the original color image.

By enhancing the luminance difference with a modulated chromatic difference component in CIELAB space, the salience of the

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[1] For simplicity, in this paper, CIELAB refers to CIE 1976 ($L^*a^*b^*$)-Space, and variables a and b are used to stand for a^* and b^* respectively.

original color image caused by color vision can be well preserved in the resulting grayscale image (Fig. 1). By modulating the amount of the chromatic difference component, the grayscale distortion can be minimized and become imperceptible to human eyes. Additionally, a sign function $sign(\cdot)$ for the color difference is also defined to keep correct color ordering for isoluminance color images.

2 CIELAB-based Gradient Field for Color-to-gray Conversion

2.1 Gradient domain image processing

In gradient domain, a grayscale image I is a discretization of a continuous 2D function $I(x, y)$ defined in R^2, and can be represented by the gradient ∇I of the original $I(x, y)$:

$$\nabla I = (I_x, I_y) = (\tfrac{\partial I}{\partial x}, \tfrac{\partial I}{\partial y}). \qquad (1)$$

Given the discrete form of this partial differential equation in I^2 domain [2], a PDE solver such as Poisson equation solver (PES) [Fattal et al. 2002; Press et al. 1992] can be used to reconstruct the original image I as illustrated in Fig. 2. For the problem of color-to-gray conversion, if I is the luminance component L of CIELAB presentation of a color image C, then from the gradient field ∇I we can reconstruct the luminance of C (Fig. 3(d)).

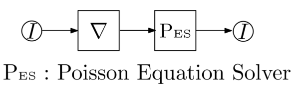


Figure 2: *Gradient domain image processing.*

2.2 The measurement of color difference

CIELAB is a uniform color space, where the Euclidean distance of two points measures the perceptive feeling of color difference in human eyes for the two colors they represent [Ohta and Robertson 2005; Steven K. Shevell 2003]. Given the differences ΔL, Δa, Δb of the two colors along each coordinate axis, the color difference ΔE is defined by:

$$\Delta E = \sqrt{(\Delta L)^2 + (\Delta a)^2 + (\Delta b)^2}. \qquad (2)$$

That means if we use only L component to reconstruct grayscale image, the resulting image will not coincide with the color difference that human eyes perceive [Gooch et al. 2005]. Hence, it is straightforward to use Eq.(2) in constructing the gradient field. Experiments show that more color difference can be successfully preserved in this way (Fig. 1). However, perceptible grayscale distortion may occur at the same time, especially where strong or noisy color differences exists (Fig. 3(b)). In order to remove these artifacts, we add a modulation function $A(\cdot)$ to Eq.(2), whose details will be given in Section 3. Then, the modulated color difference is formulated as:

$$\Delta E = \sqrt{(\Delta L)^2 + \left(A\left(\sqrt{(\Delta a)^2 + (\Delta b)^2}\right)\right)^2}, \qquad (3)$$

2.3 Color-difference-based color-to-gray conversion

Based on the idea of chromatic color difference, we propose a new color-to-gray conversion framework (Fig. 4). The input color image

(a) (b) (c) (d)

Figure 3: *Removing artifacts by adding chromatic color difference to the luminance difference. (a): Original color image. (b): Chromatic difference without modification ($\beta = 1$, $\gamma = \infty$, $\alpha = 0$). (c): Modulated chromatic difference ($\beta = 1$, $\gamma = \frac{1}{21}$, $\alpha = 0$). (d): No chromatic difference added($\beta = 0$, $\alpha = 0$).*

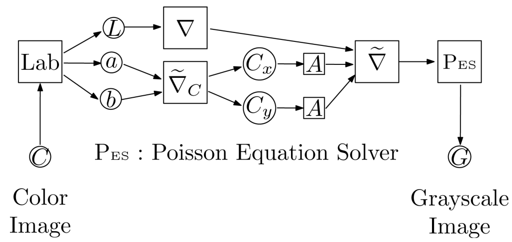


Figure 4: *Color-to-gray conversion based on color difference.*

C is represented in $L(x, y)$, $a(x, y)$, $b(x, y)$ channels of CIELAB model. Its gradient field $\widetilde{\nabla} C$ is composed of a luminance gradient ∇L and a chromatic gradient $\widetilde{\nabla}_C(a, b)$. The former is calculated as in Eq.(1), and the latter is obtained by:

$$\widetilde{\nabla}_C(a, b) = (C_x, C_y)\,, \qquad (4)$$

$$\begin{aligned} C_x &= \sqrt{(a(x+\Delta x, y) - a(x, y))^2 + (b(x+\Delta x, y) - b(x, y))^2}, \\ C_y &= \sqrt{(a(x, y+\Delta y) - a(x, y))^2 + (b(x, y+\Delta y) - b(x, y))^2}. \end{aligned} \qquad (5)$$

Then, $\widetilde{\nabla} C$ can be calculated from ∇L and $\widetilde{\nabla}_C(a, b)$ using Eq.(6), before it is fed into the PES to reconstruct the grayscale image G:

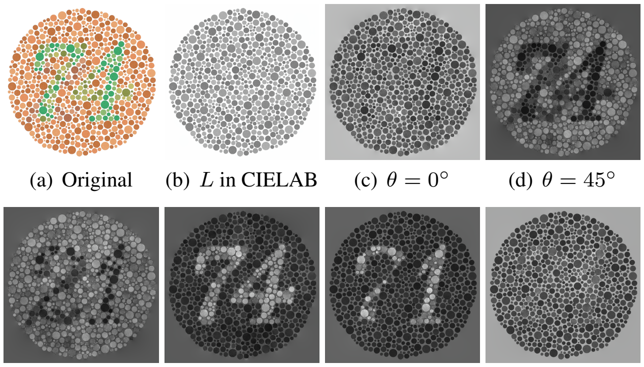
$$\begin{aligned} &\widetilde{\nabla} C = \\ &\Big(sign\left(L_x, a(x+\Delta x, y), a(x, y), b(x+\Delta x, y), b(x, y)\right) \cdot \\ &\sqrt{L_x^2 + A^2(C_x)}, \\ &sign(L_y, a(x, y+\Delta y), a(x, y), b(x, y+\Delta y), b(x, y)) \cdot \\ &\sqrt{L_y^2 + A^2(C_y)}\Big)\,. \end{aligned} \qquad (6)$$

Here, $A(\cdot)$ is the modulation function for color differences C_x and C_y, used to remove grayscale distortions caused by PES. Function $sign(\cdot)$ defines the sign of the gradient. It is used to determine the color ordering for isoluminance color images (Section 4).

3 Artifact removal

When creating new images with PES, a common problem is the existence of artifacts. In color-to-grayscale conversion, the artifacts lead to the grayscale distortion as shown in Fig. 3(b). There are many works aim to solve this problem, e.g. [Fattal et al. 2002] employs a multi-scale schema and [Neumann et al. 2007] removes the inconsistency of the gradient field. In our method, we employ a single-scale method and selectively attenuate the gradient enhancement to remove the artifacts. Experiments show that this scheme is fast and efficient (Fig. 3(c)).

[2]The discrete form of Eq.(1): $I_x = I(x+\Delta x, y) - I(x, y), I_y = I(x, y+\Delta y) - I(x, y))$, where $(x, y) \in I^2$, $\Delta x = \Delta y = 1$.



(a) Original (b) L in CIELAB (c) $\theta = 0°$ (d) $\theta = 45°$

(e) $\theta = 90°$ (f) $\theta = 135°$ (g) $\theta = 180°$ (h) $\theta = 225°$

Figure 5: *Different θ for a color blindness testing chart in (a) [Wikipedia 2010]. For all results, $\alpha = 1, \beta = 1, \gamma = \infty$ is used.*

The attenuation of gradient enhancement takes the form of a modulation function $A(\cdot)$ as mentioned in Section 2.2, which is defined as:

$$A(x) = x\left(\beta\left(1 - \left(\frac{x}{cx_{max}}\right)^{\gamma}\right)\right) = x \cdot A_0(x), \qquad (7)$$

where, $x \in [0, x_{max}], c \in [1, \infty), \beta \in [0, \infty)$ and $\gamma \in (0, \infty)$. The function works only on chromatic difference C_x and C_y, therefore the enhancement to the luminance difference is always valid for any $\beta \neq 0$. Function $A(\cdot)$ scales down the input signal x by a scaling function $A_0(x)$. Larger value of γ will preserve more high chromatic differences, while smaller γ will attenuate the high chromatic difference and preserve low chromatic differences. The constant c is used to ensure that the largest chromatic difference will not be completely scaled down. In our implementation, we choose $c = 2.0$.

4 Color Ordering for Isoluminance Image

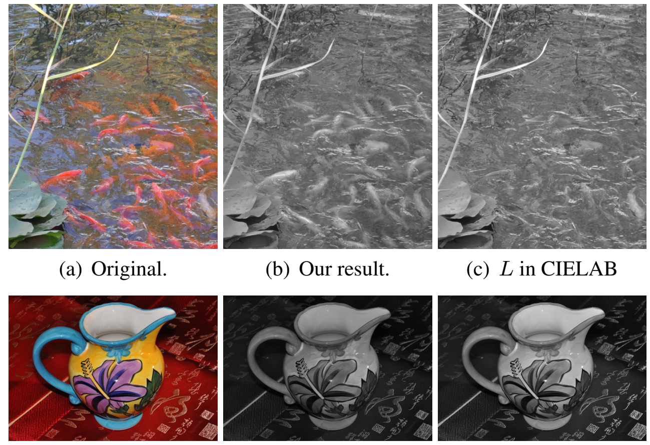
In a converted grayscale image, colors with different luminance are easier to discriminate, while for isoluminance colors, it is necessary to determine their ordering to preserve the difference. We achieve this goal by defining a sign function for the gradient field $\widetilde{\nabla}C$.

$\widetilde{\nabla}C$ is constructed from the modulated color difference (Eq.(4)), hence it is not a signed value by itself. If there is luminance difference between a pixel and its neighbor, the sign of the gradient at that pixel can be reasonably defined as the sign of the luminance difference. But that do not work for a pixel that has equal luminance with its neighbors. Instead, we employ a similar schema as in [Gooch et al. 2005]. By competing the luminance difference ΔL with the chromatic difference $\vec{\Delta_C}$, our sign function is defined as:

$$sign(\Delta L, a_2, a_1, b_2, b_1) = sign(\Delta L + \alpha \cdot (\vec{v_\theta} \cdot \vec{\Delta_C})), \qquad (8)$$

where, $(L_1, a_1, b_1), (L_2, a_2, b_2)$ are CIELAB coordinates of two colors, $\Delta L = L_2 - L_1$, $\vec{v_\theta} = (\cos\theta, \sin\theta)$, $\vec{\Delta_C} = (a_2 - a_1, b_2 - b_1)$. $\alpha \in [0, 1]$ defines the strength of the chromatic difference affecting the sign of the gradient , and $\theta \in [0, 2\pi)$ defines a direction in *a*-*b* plane of CIELAB space.

Fig. 5 shows the effect of our sign function. In the original image (Fig. 5(a)), the chromatic color differences between neighboring pixels are larger then their luminance difference, hence the sign function helps to reveal the color-blindness testing patterns in the converted grayscale images.



(a) Original. (b) Our result. (c) L in CIELAB

(d) Original. (e) Our result. (f) L in CIELAB

Figure 6: *Salience-preserving color-to-gray. Parameters: (b): $\beta = 1$, $\gamma = \frac{1}{41}$, $\alpha = 1$, $\theta = 0°$; (e): $\beta = 1$, $\gamma = \frac{1}{21}$, $\alpha = 0$.*

5 Experimental Results

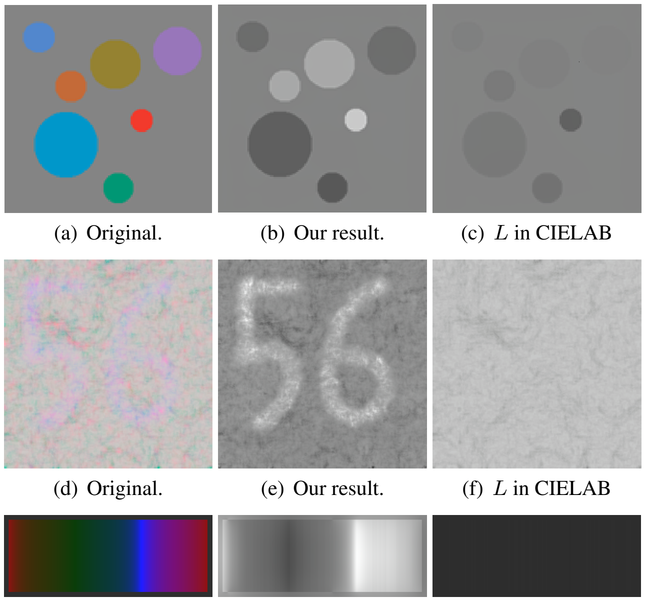
We implemented our gradient domain color-to-gray conversion method using a PES given in [Press et al. 1992]. As the PES has a linear time complexity [Fattal et al. 2002], our method has a steady execution speed of around 2 seconds per mega pixel (1024×1024 pixels in RGB) on a computer with Intel Core Dou CPU 2.2GHz and 2GB memory.

Experiments show that our method is insensitive to the size of the input image, because image down-sizing does not largely influence the dynamic range of the chrominance value. Taking advantage of this feature, we can quickly find optimal parameters for an input image by performing the algorithm on a low-resolution version. Then, applying the parameters on the original image, the same optimal result can be achieved. Currently, the optimal parameters are found interactively. We first turn on the chrominance enhancement by setting $\beta = 1, \alpha = 1$ and $\gamma = \infty$. Then different values of θ are tested to obtain a best color discrimination. If grayscale distortion appears after the optimal θ is chosen, the value of γ or α will be decreased until the distortion become invisible.

In our implementation, input RGB image is first converted to CIEXYZ and then to CIELAB. The RGB color is in PAL-RGB standard and reference white is D_{65} [Ohta and Robertson 2005; Pascale 2008]. After the L channel for the grayscale image is reconstructed by PES, it is converted back into RGB color and the dynamic range is scaled to $[0, 255]$. Before this conversion, the chrominance value of all the pixels are set as that of D_{65}.

Our method shows a satisfying salience-preserving ability. As demonstrated in Fig. 1 and Fig. 6, many details, e.g. the fishes in 6(a) and the painting details in 6(d), can be seen more clearly in our results while they are not identifiable if converted using only L channel of CIELAB model . Hence, our results preserve more details and thus appear visually closer to the original color images.

Fig. 7 shows the color discriminability of our algorithm. Images in the middle column are our results and the right are obtained by using L channel in CIELAB model. Fig. 7(g) is a computer-designed isolumminance image where $L = 50$. Our algorithm shows perfect color discriminability and ordering for both continuous color (7(d) and 7(g)) and discrete color (7(a)). The comparison with previous works in Fig. 8 and the supplemental materials also exhibit these advantages of our algorithm.

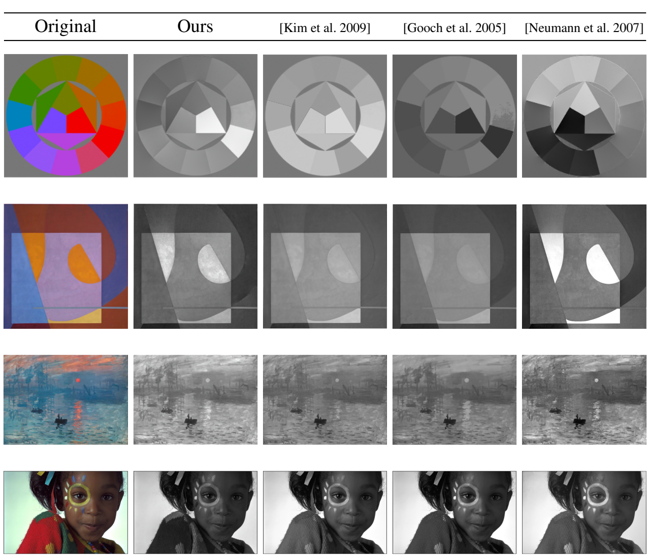


(a) Original. (b) Our result. (c) L in CIELAB

(d) Original. (e) Our result. (f) L in CIELAB

(g) Original. (h) Our result. (i) L in CIELAB

Figure 7: *Color discriminability of the algorithm. Parameters: (b):* $\beta = 1$, $\gamma = \frac{1}{21}$, $\alpha = 1$, $\theta = 80°$. *(e):* $\beta = 1$, $\gamma = \infty$, $\alpha = 1$, $\theta = 270°$. *(h):*$\beta = 1$, $\gamma = \frac{1}{66}$, $\alpha = 1$, $\theta = 315°$.



	(1)	(2)	(3)	(4)
β	1	0.9	1	1
γ	$\frac{1}{72}$	$\frac{1}{11}$	$\frac{1}{21}$	$\frac{1}{13}$
α	1	0.1	1	1
θ	15°	105°	0°	225°

Figure 8: *Comparison of our method with others. Source and reference images are from [Kim et al. 2009]. Parameters for our result are shown in the table above, where columns labeled (1) through (4) correspond to the images from top to bottom.*

6 Conclusion

In this paper we explored the gradient domain color-to-gray conversion. By controlling the strength of chromatic enhancement to the luminance, we are able to obtain a salience-preserving grayscale image with no visible grayscale distortion. It is based on an observation that grayscale distortion is mainly caused by strong chromatic differences, and Eq.(7) aims to attenuate these strong gradient. Experiments have proven the validity of the observation.

Although our method support interactively choosing of the optimal parameters during the conversion, automatically deciding of the parameters is still a problem to explore. We believe that our 4-parameter (β, γ, α and θ) model is suitable for an optimizing process if a suitable target function is defined.

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