Real-time Contrast Preserving Decolorization

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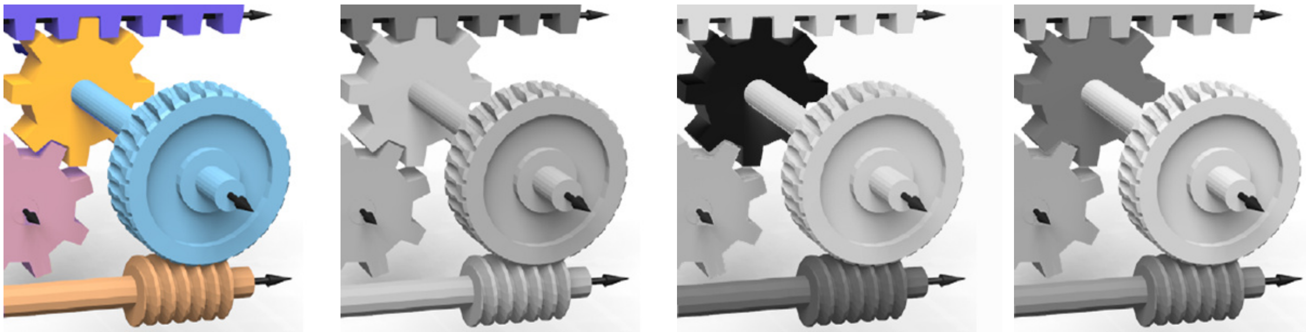

(a) Input (b) Matlab (8 ms) (c) [Lu et al. 2012] (1102 ms) (d) Ours (30 ms)

Figure 1: *Decolorization results of different methods with running time in the parentheses. All the methods are implemented in Matlab.*

Abstract

Decolorization – the process to transform a color image to a grayscale one – is a basic tool in digital printing, stylized black-and-white photography, and in many single channel image and video processing applications. While recent research focuses on retaining as much as possible meaningful visual features and color contrast, less attention has been paid to the speed issue of the conversion. Consequently, the resulting decolorization methods are typically orders of magnitude slower than standard procedures such as matlab built-in *rgb2gray* function, which largely hinders their practical use. In this paper, we propose a very fast yet effective decolorization approach aiming at maximally preserving the original color contrast. The effectiveness of the method has been borne out by a new quantitative metric as well as qualitative comparisons with state-of-the-art methods.

1 Introduction

Grayscale is one of the widely used pictorial expressions in digital printing and photograph rendering. Color-to-gray conversion is required in many single-channel image and video processing applications. Naturally, this type of conversion is a task of dimension reduction, which inevitably suffers from information loss. The general goal is thus to use the limited range in gray scales to preserve as much as possible the original color contrast. It is found that without explicitly capturing this important appearance feature, intuitive methods, such as extracting the lightness channel in the CIELab/CIEYUV color spaces [Hunter 1958], would easily diminish salient structures in the color input. One example is shown in Fig. 1(a) and (b).

In general, color-to-gray methods can be performed either locally or globally. Local methods make pixels in the color image not processed in the same way and usually rely on the local chrominance edges for enhancement. Bala and Eschbach [Bala and Eschbach 2004] added high frequency components of chromaticity to the lightness channel, in order to enhance color edges. Neumann *et al.* [Neumann et al. 2007] locally selected consistent color gradients and performed fast 2D integration to get the final grayscale image. Smith *et al.* [Smith et al. 2008] also employed a local sharpening step after obtaining the grayscale image by global mapping. Chrominance edges are enhanced by the adaptively weighted multi-scale unsharp masking. These mechanisms might occasionally distort the appearance of constant color regions and produce haloing artifacts, as discussed in [Kim et al. 2009].

In global mapping, Gooch *et al.* [Gooch et al. 2005] enforced color contrast between pixel pairs. Rasche *et al.* [Rasche et al. 2005] defined constraints directly on the different color pairs. A linear color mapping is adopted for acceleration. Kuk *et al.* [Kuk et al. 2010] extended the idea of [Gooch et al. 2005] by considering both the global and local contrasts. Grundland and Dodgson [Grundland and Dodgson 2007] proposed a fast linear mapping algorithm that adds a fixed amount of chrominance to the lightness, where the original lightness and color order can be better preserved by restraining the added chrominance. Parametric piecewise linear mapping is used to convert color to gray. Kim *et al.* [Kim et al. 2009] proposed a nonlinear parametric model for color-to-gray mapping. The parameters are estimated by minimizing the cost function that aims to preserve the color differences computed in the CIELab color space. In recent works [Lu et al. 2012], bimodal energy function is employed to rise a more flexible contrast preserving constraint.

Those works focus on retaining as much as possible meaningful visual features and color contrast, they typically involve complex optimization steps, which make the resulting decolorization methods orders of magnitude slower than standard procedures such as matlab *rgb2gray* function. It thus largely hinders the practical use of decolorization algorithm in different vision and graphics applications, especially when video process is involved.

In this paper, we address both contrast preserving and speed issues in color-to-gray conversion. The main contributions include a simplified bimodal objective function with linear parametric grayscale model, a fast non-iterative discrete optimization, and a sampling based $\mathcal{P}$-shrinking optimization strategy. We show that these strategies make the optimization have fixed number of operations, leading to a constant $O(1)$ running time, independent of image resolutions. Our matlab implementation takes only 30ms to process an one megapixel color input, comparable with the built-in matlab *rgb2gray* function. We also propose a perceptual-based CCPR measure in order to quantitatively evaluate and compare different decolorization methods.

2 Our Approach

The success of the contrast preserving decolorization [Lu et al. 2012] mainly stems from a bimodal energy function that relaxes the strict color order constraint. We describe in this section our color contrast preserving objective function based on a weak color order constraint, followed by an efficient numerical optimization solver.

2.1 Bimodal Contrast-Preserving

To begin with, We revisit the energy used in previous approaches for contrast preserving decolorization. The gray scales for pixels x and y, denoted by g_x and g_y respectively, are estimated by minimizing energy function

$$\min_g \sum_{(x,y)\in\mathcal{P}} (g_x - g_y - \delta_{x,y})^2, \quad (1)$$

where the output image g could be with [Kim et al. 2009] or without [Gooch et al. 2005] a parametric form. x and y index an ordered pixel pair, belonging to a pixel pari pool $\mathcal{P}$. $\delta_{x,y}$ is the color contrast, having a signed value indicating the difference of a color pair. Based on the Euclidian distance in the CIELab color space, the color contrast is generally expressed

$$|\delta_{x,y}| = \sqrt{(L_x - L_y)^2 + (a_x - a_y)^2 + (b_x - b_y)^2},$$

which represents the color dissimilarity in the human vision system [Wyszecki and Stiles 2000]. Eq. (1) can be interpreted in view of probabilistic inference. It implies that the differences of the grayscale values for two pixels x and y follow a Gaussian distribution with mean $\delta_{x,y}$. Each pixel pair is treated equally. Formally, minimizing Eq. (1) can be interpreted as maximizing the following likelihood

$$\prod_{(x,y)\in\mathcal{P}} \mathcal{N}_\sigma(\Delta g_{x,y} - \delta_{x,y}) \propto \prod_{x,y} \exp\{-\frac{|\Delta g_{x,y} - \delta_{x,y}|^2}{2\sigma^2}\}. \quad (2)$$

The grayscale difference for pixel pair x and y in a pixel-pair pool $\mathcal{P}$ are denoted as $\Delta g_{x,y} = g_x - g_y$. The Gaussian distribution $\mathcal{N}_\sigma$ has a single model peaked at $\delta_{x,y}$, which means that we not only constrain the contrast, but also determine the sign of difference for the gray pixel pair. However, when color order is not well defined, the sign does not has obvious physical meaning. So it is feasible generally to allow the difference of gray pixels to be either $+\delta_{x,y}$ or $-\delta_{x,y}$, which gives rise to a more flexible contrast preserving constraint.

We relax the original color order constraint by encouraging a bimodal distribution for automatic color order selection, expressed as

$$E(g) = -\sum_{(x,y)\in\mathcal{P}} \ln\left\{\mathcal{N}_\sigma(\Delta g_{x,y} + \delta_{x,y}) + \mathcal{N}_\sigma(\Delta g_{x,y} - \delta_{x,y})\right\}. \quad (3)$$

The proposed energy function is non-convex due to the involvement of Gaussian mixtures. While the optimization may seem to be computationally expensive, we show that a simplified parametric model together with proper energy conservation constraints could lead to a very efficient solver, and at the meantime not sacrificing contrast preservation.

2.2 Linear Parametric Model

We use the degree one multivariate polynomial model [Lu et al. 2012] to represent grayscale output g, which is indeed a linear combination of color channels, expressed by

$$g = w_r I_r + w_g I_g + w_b I_b, \quad (4)$$

where I_r, I_g, I_b are RGB channels of the input. w_r, w_g, w_b are the parameters to optimize. We further enforce a positive constraint and an energy conservation constraint on the weights so that the grayscale image is within the range $[0, 1]$. The two constraints can be written as

$$w_r \geq 0, w_g \geq 0, w_b \geq 0,$$
$$w_r + w_g + w_b = 1.$$

The constraints also serve a second purpose: the neutral color would have the same intensity after color-to-gray conversion. Simple though the defined constraints are, they work effectively in reducing the solution space in a discrete fashion.

2.3 Discrete Searching

Directly minimizing Eq. 3 using iterative optimization is still time-consuming. Empirically, we found that slightly varying the weights w_r, w_g, w_b would not change grayscale appearance too much. We propose to discretize the solution space of w_r, w_g, w_b in the range of $[0, 1]$ with interval 0.1. This is still a large searching space and hence we incorporate the constraint $w_r + w_g + w_b = 1$, which remarkably reduces the candidate value sets from L^3 to $\frac{L(L+1)}{2}$, where L is number of discrete label (11 in our case). The problem boils down to finding one best solution among 66 candidates, which can be easily computed through exhaustive search.

2.4 $\mathcal{P}$ Shrinking

The evaluation of Eq. (3) concerning all pixel pairs is still time-consuming, especially for large-sized images. To further speedup the decolorization process, we down-sample the high-resolution input to a small scale 64×64. This is valid due to the inherent color redundancy of natural images. Furthermore, we randomly sample 64^2 pixel pairs in the resized image to form pixel set $\mathcal{P}$. Extensive experiments show that the proposed $\mathcal{P}$-shrinking scheme can achieve real-time performance for high-resolution images, without obvious quality degradation.

3 Experimental Results

We in this section compare our approach with state-of-the-art methods both quantitatively and qualitatively. Figure 1 shows the comparison with matlab *rgb2gray* function and our baseline algorithm [Lu et al. 2012]. Our method preserves well the perceptually important color differences, using only 0.03 second with an Intel i3 3.10GHz CPU and 4GB memory.

3.1 Qualitative Evaluation

We compare our method with state-of-the-art methods [Gooch et al. 2005; Kim et al. 2009]. We evaluate our algorithm on the publicly available color-to-gray benchmark dataset [Cadík 2008], where results of many leading methods are available. Fig. 2 shows a few representative images in the dataset. Our results, shown in the last column, preserve very well color contrast presented in the input images, complying with our visual perception. For the images shown in the second, third and fifth rows, our method produces results with different color orders compared with others. It bears out the fact that during the decolorization process, for neighboring pixels with similar brightness, color difference magnitude preservation is much more important than keeping the sign. It is also note that the running time of our algorithm is less than 30ms and is almost constant for images with different resolutions.

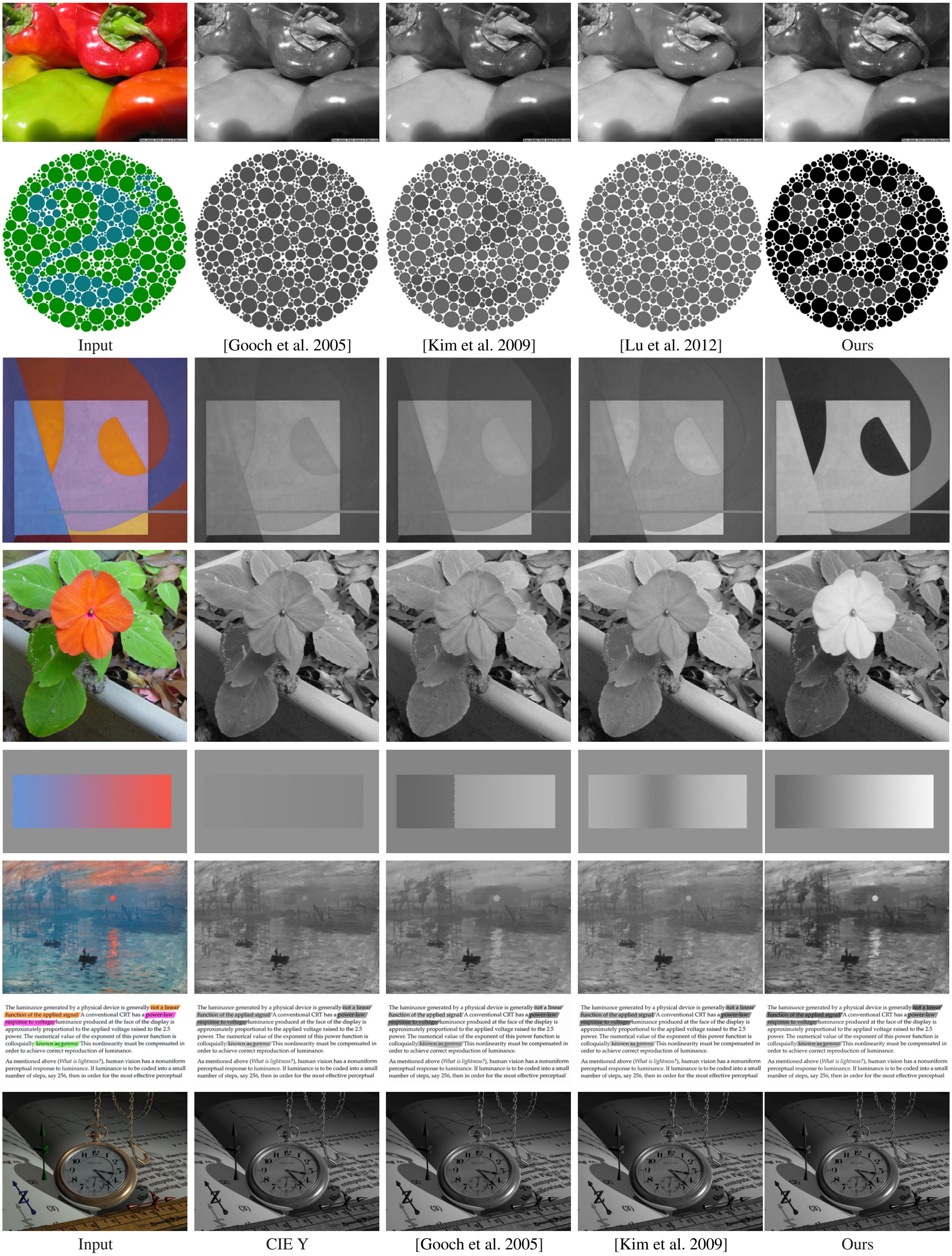

Figure 2: *Comparison with state-of-the-art methods.*

3.2 Quantitative Evaluation

To quantitatively evaluate the decolorization algorithms in terms of contrast preserving, we propose a new metric. It is based on the finding that if the color difference δ is smaller than a threshold τ, it becomes nearly invisible in human vision. The task of contrast-preserving decolorization is therefore to maintain color change that is perceivable by humans. We define a *color contrast preserving ratio* (CCPR) as

$$\mathrm{CCPR} = \frac{\#\{(x,y)|(x,y) \in \Omega, |g_x - g_y| \geq \tau\}}{\|\Omega\|}, \tag{5}$$

where Ω is the set containing all neighboring pixel pairs with their original color difference $\delta_{x,y} \geq \tau$. $\|\Omega\|$ is the number of pixel pairs in Ω. $\#\{(x,y)|(x,y) \in \Omega, |g_x - g_y| \geq \tau\}$ is the number of pixel pairs in Ω that are still distinctive after decolorization.

Based on CCPR, we quantitatively evaluate different methods using the 24 images in the dataset [Cadík 2008]. We calculate the average CCPR for the whole dataset by varying τ from 1 to 15[1]. Average CCPRs for other methods [Gooch et al. 2005; Smith et al. 2008; Kim et al. 2009] are also collected. They are listed in Table 1. The quantities indicate that our method can preserve satisfactorily the color distinctiveness.

No.	CIE Y	Smith08	Gooch05	Kim09	Ours
1	0.44	0.50	0.49	0.46	**0.51**
2	0.90	0.84	0.85	0.92	**0.94**
3	0.70	0.77	0.71	0.70	**0.85**
4	0.50	0.57	0.54	0.54	**0.60**
5	0.76	0.78	0.72	0.78	**0.81**
6	0.32	0.35	0.33	0.38	**0.54**
7	0.37	0.38	0.44	0.43	**0.68**
8	0.2	0.17	0.29	0.49	**0.58**
9	0.42	**0.58**	0.38	0.47	0.50
10	0.59	0.65	0.62	0.61	**0.75**
11	0.60	**0.75**	0.58	0.66	0.72
12	0.0	0.10	0.50	0.43	**0.80**
13	0.30	0.36	0.31	0.32	**0.42**
14	0.74	**0.83**	0.67	0.78	0.77
15	0.55	0.62	0.55	0.57	**0.65**
16	0.68	0.74	0.72	0.71	**0.74**
17	0.0	0.32	1.0	0.74	**1.0**
18	0.58	**0.62**	0.59	0.59	0.60
19	0.64	0.72	0.64	0.68	**0.75**
20	0.40	0.52	0.31	0.44	**0.54**
21	0.92	0.91	0.92	0.93	**0.93**
22	0.38	0.48	0.42	0.43	**0.62**
23	0.55	0.60	0.56	0.58	**0.70**
24	0.80	**0.87**	0.84	0.85	0.82

Table 1: *Color contrast preserving ratio (CCPR) comparison.*

4 Concluding Remarks

We have presented a new image color-to-gray method that can well maintain the original color contrast. We leverage a bimodal color constraint to allow for very flexible and optimal grayscale representation, based on the fact that human perception has limited ability in determining ordering of color with respect to brightness. So rather than intuitively defining the sign of gray scale difference, we propose a mixture of Gaussian functions to increase the search space in optimization. In order to achieve real-time performance, we further devise a discrete searching optimization which takes advantage of a linear parametric grayscale model as well as a sampling based $\mathcal{P}$-shrinking process. This strategy enables finding suitable gray scales to best preserve significant color change. Both the quantitative and qualitative experiments validate the effectiveness of the proposed method.

[1] It is suggested in [Chen and Wang 2004] that color difference $\delta < 6$ is generally imperceptible.

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