LOCAL AND GLOBAL CONTRAST PRESERVING DECOLORIZATION USING GRADIENT MATRIX CORRELATION

Soo-Chang Pei (貝蘇章) [1], Wan-Lin Su (蘇宛琳) [1], Chiou-Shann Fuh (傅楸善) [2]

[1]Graduate Institute of Communication Engineering,
National Taiwan University, Taipei, Taiwan
[2]Department of Computer Science and Information Engineering,
National Taiwan University, Taipei, Taiwan

peisc@ntu.edu.tw[1], pauline282937@gmail.com[1], fuh@csie.ntu.edu.tw[2]

ABSTRACT

This paper presents a gradient matrix correlation (GMC) measure-based decolorization model for faithfully preserving the appearance of the original color image. Contrary to the conventional GE measures, the GMC measure calculates the summation of the gradient correlation between each channel of the color image and the transformed grayscale image. The discrete searching strategy and sensitive weighted selection, two algorithms (i.e., GMC_1 and GMC_2), are developed to solve the proposed model. The extensive experiments under a variety of test images against existing state-of-the-art methods consistently demonstrate the potential of the proposed model and algorithms.

Keywords *Global, local, Color-to-gray conversion,* decolorization*, gradient matrix correlation, linear parametric model, discrete searching, weighted selection*

1. INTRODUCTION

Grayscale is widely used in digital printing and photograph rendering. Color-to-gray conversion is a basic tool for many applications in image processing and computer vision. This conversion aims to transform a color image into a grayscale image and enables the application of single-channel algorithms on color images. Other applications of color-to-gray conversion include black-and-white digital printing, stylized black-and-white photography, non-photorealistic rendering with black-and-white media, and so on. Unfortunately, color-to-gray conversion – the process to transform a color image with 3D vector to a 1D grayscale image - 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 the original color contrast as much as possible.

The widely used method in decolorizing an input image is to extract its luminance channel. However, using luminance channel alone cannot faithfully represent contrasts in some color images. In order to practically implement decolorization, color-to-gray conversion methods can be classified into two categories, i.e. local adjustment methods and global adjustment methods.

Depending on the local distributions of colors, local adjustment methods spatially vary the color-to-gray mapping of pixel values. Although they may have advantages in accurately preserving local features, constant color regions could be transformed out of sync with the changing mapping in the regions. Bala and Eschbach [1] added high-frequency components of chromaticity to the luminance channel, in order to enhance chromatic edges. Neumann et al. [2] reconstructed the grayscale image by the gradients measured from the color and luminance contrasts of a color image. Smith et al. [3] decomposed the image into several frequency components and adjusted combination weights by using chromatic channels.

Global adjustment methods purposefully minimize an objective function in order to remain the differences between mapped gray values close to the differences between original color values. Gooch et al. enforced color contrasts between pixel pairs [4]. Kuk et al. extended the idea of [4] by balancing the gradient among pixels, and considering both the global and local contrasts [5]. Kim et al. proposed a nonlinear parametric model for global color-to-gray mapping [6]. Lu et al. relaxed the strict order constraints and adopted a second order multivariate polynomial parametric model to maximally preserve the original color contrast [7].

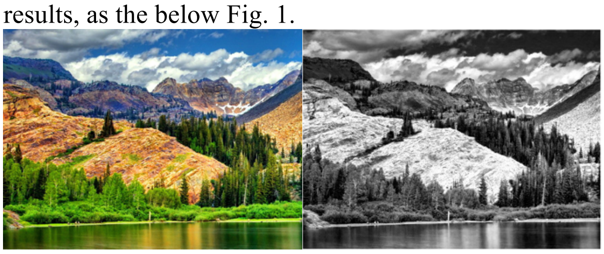
In summary, there are two key issues of local adjustment methods and global adjustment methods. One is the definition of data-fidelity and the other is the efficiency of proposed algorithms.

On one hand, many color-to-gray conversion methods adopted the gradient-based techniques to measure the fidelity between the input color image and transformed grayscale image [4]-[13]. Some approaches employed an error-norm based term in gradient fields as a data-fidelity measure. Other approaches enforced the correlation between variables in the gradient domain. In [8], Liu et al. proposed a gradient structure and texture decorrelating regularization method for image decomposition. Xue et al. [9] addressed a gradient magnitude similarity deviation for perceptual image quality assessment.

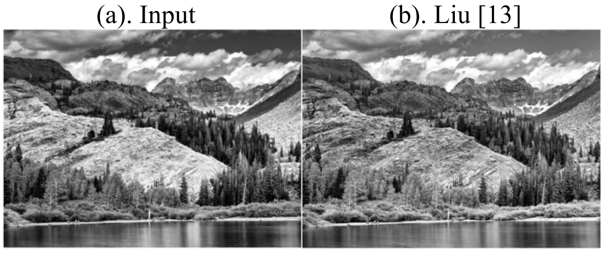
On the other hand, computational cost and robustness are two important issues. To alleviate the computation difficulty, Lu et al. [10] proposed a currently fastest algorithm by discretizing the solution space of a linear parametric model with 66 candidates and determining one candidate achieving the highest energy value as the optimal solution. Cˆadík [11], BSDS [12], and CSDD dataset introduced a psychological evaluation of several color-to-gray algorithms and showed that each of these conversion methods was ranked the worst for at least one test image, indicating neither of them outperformed each other.

In this paper, we address both contrast preserving and speed issues in color-to-gray conversion. First, motivated by the performances of correlation analysis in refs. [8], [9], [13], we propose a new gradient matrix correlation model as a criterion to design the linear local and global mapping in the RGB color space, which is different from the conventional gradient error (GE) model in refs. [4], [5], [6], [7], [10]. The presented gradient matrix correlation (GMC), conducted between each channel of the input color image and resulting grayscale image, well reflects the degree of preserving feature discriminability and color ordering in color-to-gray conversion. Therefore, the proposed GMC mapping model can successfully reproduce the visual appearance of color images.

Second, in order to improve the robustness and computational cost of GMC model, we address an approximated linear parametric model based on a non-iterative and real-time discrete searching strategy. It runs nearly two times faster than the currently fastest method. The performance of the proposed algorithm which is demonstrated on a variety of images gives more plausible results, as the below Fig. 1.



(a). Input (b). Liu [13]



(c). GMC_1 (d). GMC_2

Fig. 1. Color-to-grayscale conversion comparison of nature images [14].

This paper is organized as follows. Section 2 describes some conventional measures and introduces the proposed new GMC measure for decolorization. In Section 3, a discrete searching strategy is presented for real-time color-to-grayscale conversion with the addition of non-negative constraint. Section 4, the concept of sensitive weighted selection is applied to real-time color-to-grayscale conversion. In Section 5, the developed methods were compared with other standard results, showing that feature discriminability is better preserved on various color images. Finally, conclusions and future work are given in Section 6.

2. GRADIENT MATRIX CORRELATION (GMC)

To begin with, we study the previous approaches of employing gradient applications in contrast preserving decolorization. The classical data-fidelity term based on Gradient Error-norm (GE) measure and the latest Gradient Correlation Similarity (GCS) [13] measure in image decolorization are described. Then, we will introduce our main proposed Gradient Matrix Correlation (GMC) measure and its rationale in details.

To preserve feature discriminability in color-to-gray conversion, a common strategy is to minimize the distance of pixel differences between the input color and the resulting grayscale images. Assuming the input color image is in the RGB (Red, Green, Blue) format, where indexes r, g, b stand for the RGB channels. Let $\delta_{x,y}$ be the color contrast as follows:

$$|\delta_{x,y}| = \sqrt{\sum_{c=\{r,g,b\}} \left(I_{c,x} - I_{c,y}\right)^2} \tag{1}$$

where$\delta_{x,y}$ has a signed value indicating the difference of a color pair and $g_x - g_y$ denote the gray difference value between pixels g_x and g_y respectively, then the classical minimizing energy function [4], [6] is defined as follows:

$$\min_{g} \sum_{(x,y)\in P} \left(g_x - g_y - \delta_{x,y}\right)^2 \tag{2}$$

To avoid the difficulty caused by determining the sign of $\delta_{x,y}$, we propose a new gradient matrix correlation model. First, motivated by the model in [7] which uses degree one multivariate polynomial model to represent grayscale output g with a linear combination of color channels:

$$g = w_r I_r + w_g I_g + w_b I_b \tag{3}$$

Second, based on the idea [5] of considering both the global and local contrasts, We then propose a linear parametric grayscale matrix g_c:

$$g_c = I_c \times w_c \tag{4}$$

By using the similar mathematical notation ∇ to represent the nonlocal gradient operator and the difference mathematical increment Δ to represent the local nearest neighbors of pixel pair (x,y), where the matrix I_c can be written as

$$I_c = \begin{bmatrix} \nabla I_r & \nabla I_g & \nabla I_b \\ \Delta I_{rx} & \Delta I_{gx} & \Delta I_{bx} \\ \Delta I_{ry} & \Delta I_{gy} & \Delta I_{by} \end{bmatrix} \tag{5}$$

Based on [7], where I_r, I_g, I_b are the input of RGB channels. w_r, w_g, w_b are the parameters to optimize. The strategy to optimize the weight model is to 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

$$\begin{aligned} &w_r \geq 0,\ w_g \geq 0,\ w_b \geq 0, \\ &w_r + w_g + w_b = 1. \end{aligned} \tag{6}$$

The weight model is to find the best solution among *i* candidates, which can be written as:

$$w_c = \begin{bmatrix} w_{r1} & w_{r2} & \dots & w_{ri} \\ w_{g1} & w_{g2} & \dots & w_{gi} \\ w_{b1} & w_{b2} & \dots & w_{bi} \end{bmatrix} \tag{7}$$

To preserve the original color contrast as much as possible and avoid the difficulty caused by determining the sign of $\delta_{x,y}$, Liu et al. [13] proposed a Gradient Correlation Similarity (GCS) measure by calculating the gradient correlation for each channel rather than the whole channels at one time. It computes the overall pixel-wise similarity between the gradient magnitudes in each channel of the original color image and the resulting grayscale image, i.e.

$$\min_{w_c} - \sum_{(x,y)\in P} \sum_{c=\{r,g,b\}} \frac{2\left|I_{c,x} - I_{c,y}\right| \left|\nabla g_{x,y}\right|}{\left|I_{c,x} - I_{c,y}\right|^2 + \left|\nabla g_{x,y}\right|^2} \tag{8}$$

Motivated by the above model, we then address a new gradient matrix correlation model:

$$\min_{w_c} - \sum_{value\ of\ column} \frac{2\left(\left|g_c{}^T\right| \times I_c\right)^T}{g_{correlation} + I_{contrast}} \tag{9}$$

with the $I_{contrast}$ matrix:

$$I_{contrast} = \begin{bmatrix} \nabla I_r{}^2 + \Delta I_{rx}{}^2 + \Delta I_{ry}{}^2 & \dots & \nabla I_r{}^2 + \Delta I_{rx}{}^2 + \Delta I_{ry}{}^2 \\ \nabla I_g{}^2 + \Delta I_{gx}{}^2 + \Delta I_{gy}{}^2 & \dots & \nabla I_g{}^2 + \Delta I_{gx}{}^2 + \Delta I_{gy}{}^2 \\ \nabla I_b{}^2 + \Delta I_{bx}{}^2 + \Delta I_{by}{}^2 & \dots & \nabla I_b{}^2 + \Delta I_{bx}{}^2 + \Delta I_{by}{}^2 \end{bmatrix}_{3\times i} \tag{10}$$

and its $g_{correlation}$ matrix can be written as:

$$g_{correlation} = \begin{bmatrix} \nabla I_r \times w_{r1}{}^2 + \nabla I_g \times w_{g1}{}^2 + \nabla I_b \times w_{b1}{}^2 & \dots & \nabla I_r \times w_{ri}{}^2 + \nabla I_g \times w_{gi}{}^2 + \nabla I_b \times w_{bi}{}^2 \\ \Delta I_{rx} \times w_{r1}{}^2 + \Delta I_{gx} \times w_{g1}{}^2 + \Delta I_{bx} \times w_{b1}{}^2 & \dots & \Delta I_{rx} \times w_{ri}{}^2 + \Delta I_{gx} \times w_{gi}{}^2 + \Delta I_{bx} \times w_{bi}{}^2 \\ \Delta I_{ry} \times w_{r1}{}^2 + \Delta I_{gy} \times w_{g1}{}^2 + \Delta I_{by} \times w_{b1}{}^2 & \dots & \Delta I_{ry} \times w_{ri}{}^2 + \Delta I_{gy} \times w_{gi}{}^2 + \Delta I_{by} \times w_{bi}{}^2 \end{bmatrix}_{3\times i} \tag{11}$$

The novelty of GMC model lies in two aspects: first, the model is structured by the gradient matrix correlation;second, contrary to the previous works, the similarity is computed between the gray image and the color image in each channel of the RGB space instead of summing the sign $\delta_{x,y}$ of RGB whole channels at one time, well reflects the degree of preserving feature discriminability and color ordering in color-to-gray conversion.

3. GMC_1: DISCRETE SEARCHING STRATEGY

It is difficult to find the best solution of the weight model. Similar to [6], [7], [10], and [12], this problem can be solved by letting the estimate gray image be in a parametric form. Based on [10], the strategy to optimize the weight model is to 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

$$\begin{aligned} &w_r \geq 0,\ w_g \geq 0,\ w_b \geq 0, \\ &w_r + w_g + w_b = 1. \end{aligned} \tag{12}$$

We further discretize the solution space of w_r, w_g, w_b in the range of [0, 1] with interval 0.1 by utilizing discrete searching in [10], which remarkably reduces the candidate value sets from L^3 to $\frac{L(L+1)}{2}$. The problem boils down to finding the best solution among 66 candidates, which can be easily computed through exhaustive search matrix w_{GMC_1}:

$$w_{GMC_1} = \begin{bmatrix} w_{r1} & w_{r2} & \dots & w_{r66} \\ w_{g1} & w_{g2} & \dots & w_{g66} \\ w_{b1} & w_{b2} & \dots & w_{b66} \end{bmatrix} \tag{13}$$

Therefore, our proposed linear parametric grayscale matrix can be modified as:

$$g_c = I_c \times w_{GMC_1} \tag{14}$$

with the I_c matrix:

$$I_c = \begin{bmatrix} \nabla I_r & \nabla I_g & \nabla I_b \\ \Delta I_{rx} & \Delta I_{gx} & \Delta I_{bx} \\ \Delta I_{ry} & \Delta I_{gy} & \Delta I_{by} \end{bmatrix} \tag{15}$$

and our gradient matrix correlation model can be modified as:

$$g_{GMC_1} = \sum_{value\ of\ column} \frac{2\left(\left|g_c{}^T\right| \times I_c\right)^T}{g_{correlation} + I_{contrast}} \tag{16}$$

with the $I_{contrast}$ matrix:

$$I_{contrast} = \begin{bmatrix} \nabla I_r{}^2 + \Delta I_{rx}{}^2 + \Delta I_{ry}{}^2 & \dots & \nabla I_r{}^2 + \Delta I_{rx}{}^2 + \Delta I_{ry}{}^2 \\ \nabla I_g{}^2 + \Delta I_{gx}{}^2 + \Delta I_{gy}{}^2 & \dots & \nabla I_g{}^2 + \Delta I_{gx}{}^2 + \Delta I_{gy}{}^2 \\ \nabla I_b{}^2 + \Delta I_{bx}{}^2 + \Delta I_{by}{}^2 & \dots & \nabla I_b{}^2 + \Delta I_{bx}{}^2 + \Delta I_{by}{}^2 \end{bmatrix}_{3\times 66} \tag{17}$$

and its $g_{correlation}$ matrix can be written as:

$$g_{correlation} = \left[\begin{array}{ccc} \nabla I_r \times {w_{r1}}^2 + \nabla I_g \times {w_{g1}}^2 + \nabla I_b \times {w_{b1}}^2 & \dots & \nabla I_r \times {w_{r66}}^2 + \nabla I_g \times {w_{g66}}^2 + \nabla I_b \times {w_{b66}}^2 \\ \Delta I_{rx} \times {w_{r1}}^2 + \Delta I_{gx} \times {w_{g1}}^2 + \Delta I_{bx} \times {w_{b1}}^2 & \dots & \Delta I_{rx} \times {w_{r66}}^2 + \Delta I_{gx} \times {w_{g66}}^2 + \Delta I_{bx} \times w_{b66} \\ \Delta I_{ry} \times {w_{r1}}^2 + \Delta I_{gy} \times {w_{g1}}^2 + \Delta I_{by} \times {w_{b1}}^2 & \dots & \Delta I_{ry} \times {w_{r66}}^2 + \Delta I_{gy} \times {w_{g66}}^2 + \Delta I_{by} \times w_{b66} \end{array} \right]_{3\times 66} \tag{18}$$

GMC_1 deals with both local and non-local pixel pairs by randomly sampling strategy, and it uses an approximated linear parametric model based on a non-iterative and real-time discrete searching strategy on the weight parameter space to improve the robustness and computational cost.

4. GMC_2: SENSITIVE WEIGHTED SELECTION

Based on the luminance perception that human retina is more sensitive to medium wavelength signal (green luminance-sensitive elements). Motivated by the above concept, we then modify the weight model with green weight higher than red and blue weights. The constraints can be written as:

$$\begin{aligned} &1 > w_g \geq 0.5, \\ &0.5 \geq w_r \geq 0, \\ &0.5 \geq w_b \geq 0, \\ &w_r + w_g + w_b = 1. \end{aligned} \tag{19}$$

The problem boils down to finding the best solution among 21 candidates, which can be easily computed through exhaustive search matrix w_{GMC_2}:

$$w_{GMC_2} = \begin{bmatrix} w_{r1} & w_{r2} & \dots & w_{r21} \\ w_{g1} & w_{g2} & \dots & w_{g21} \\ w_{b1} & w_{b2} & \dots & w_{b21} \end{bmatrix} \tag{20}$$

Therefore, our proposed linear parametric grayscale matrix can be modified as:

$$g_c = I_c \times w_{GMC_2} \tag{21}$$

with the I_c matrix:

$$I_c = \begin{bmatrix} \nabla I_r & \nabla I_g & \nabla I_b \\ \Delta I_{rx} & \Delta I_{gx} & \Delta I_{bx} \\ \Delta I_{ry} & \Delta I_{gy} & \Delta I_{by} \end{bmatrix} \tag{22}$$

and our gradient matrix correlation model can be modified as:

$$g_{GMC_2} = \sum_{value\ of\ column} \frac{2\,(|{g_c}^T| \times I_c)^T}{g_{correlation} + I_{contrast}} \tag{23}$$

with the $I_{contrast}$ matrix:

$$I_{contrast} = \begin{bmatrix} \nabla {I_r}^2 + \Delta {I_{rx}}^2 + \Delta {I_{ry}}^2 & \dots & \nabla {I_r}^2 + \Delta {I_{rx}}^2 + \Delta {I_{ry}}^2 \\ \nabla {I_g}^2 + \Delta {I_{gx}}^2 + \Delta {I_{gy}}^2 & \dots & \nabla {I_g}^2 + \Delta {I_{gx}}^2 + \Delta {I_{gy}}^2 \\ \nabla {I_b}^2 + \Delta {I_{bx}}^2 + \Delta {I_{by}}^2 & \dots & \nabla {I_b}^2 + \Delta {I_{bx}}^2 + \Delta {I_{by}}^2 \end{bmatrix}_{3\times 21} \tag{24}$$

and its $g_{correlation}$ matrix can be written as:

$$g_{correlation} = \begin{bmatrix} \nabla I_r \times {w_{r1}}^2 + \nabla I_g \times {w_{g1}}^2 + \nabla I_b \times {w_{b1}}^2 & \dots & \nabla I_r \times {w_{r21}}^2 + \nabla I_g \times {w_{g21}}^2 + \nabla I_b \times {w_{b21}}^2 \\ \Delta I_{rx} \times {w_{r1}}^2 + \Delta I_{gx} \times {w_{g1}}^2 + \Delta I_{bx} \times {w_{b1}}^2 & \dots & \Delta I_{rx} \times {w_{r21}}^2 + \Delta I_{gx} \times {w_{g21}}^2 + \Delta I_{bx} \times {w_{b21}}^2 \\ \Delta I_{ry} \times {w_{r1}}^2 + \Delta I_{gy} \times {w_{g1}}^2 + \Delta I_{by} \times {w_{b1}}^2 & \dots & \Delta I_{ry} \times {w_{r21}}^2 + \Delta I_{gy} \times {w_{g21}}^2 + \Delta I_{by} \times {w_{b21}}^2 \end{bmatrix}_{3\times 21} \tag{25}$$

GMC_2 deals with both Bayer's pattern and a real-time discrete searching strategy to faithfully preserve feature discriminability and computational cost, which runs nearly two times faster than the currently fastest method.

5. EXPERIMENT RESULTS AND DISCUSSION

In this section, the performance of our proposed method is demonstrated at various image styles including synthetic and natural images, compared with different state-of-the-art algorithms. We also show the robustness of our algorithms GMC_1 and GMC_2 by testing them with conventional user experiments [11], new CSDD dataset, and the Berkeley Segmentation Dataset (BSDS) [14]. Both qualitative and quantitative experiments validate the effectiveness of our proposed algorithms.

5.1. Qualitative Evaluation

5.1.1. Cadik's decolorization dataset

We compare our method with state-of-the-art methods [Bala; Smith; Gooch; Lu [7]; Lu [10]; Liu [13]]. We evaluate our algorithm on the publicly available color-to-gray benchmark dataset [Cadik's], where results of many leading methods are available.

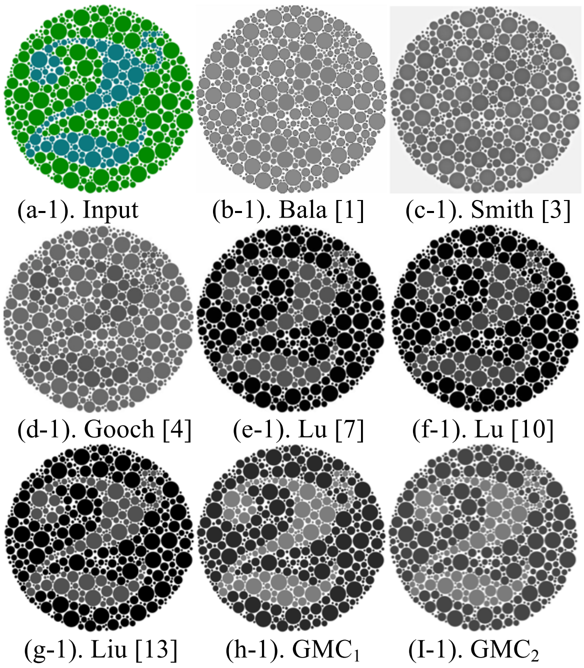
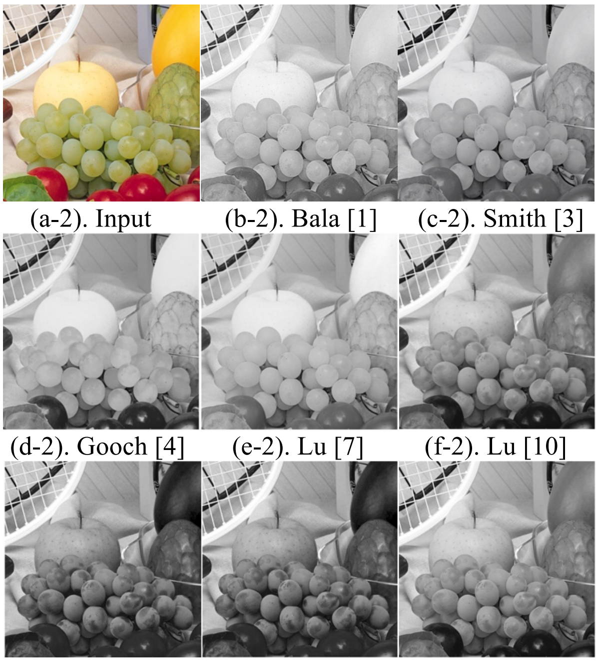
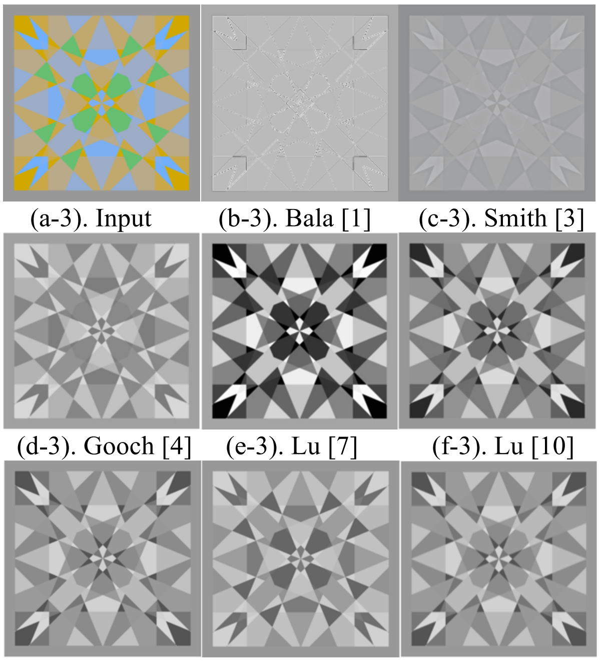


Fig. 2. Color-to-grayscale conversion comparison of ***25_color*** images from Cadik's dataset [11].



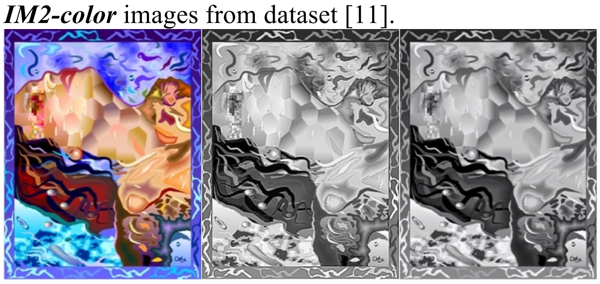
(a-2). Input (b-2). Bala [1] (c-2). Smith [3]
(d-2). Gooch [4] (e-2). Lu [7] (f-2). Lu [10]
(g-2). Liu [13] (h-2). GMC_1 (I-2). GMC_2

Fig. 3. Color-to-grayscale conversion comparison of ***fruits*** images from Cadik's dataset [11].

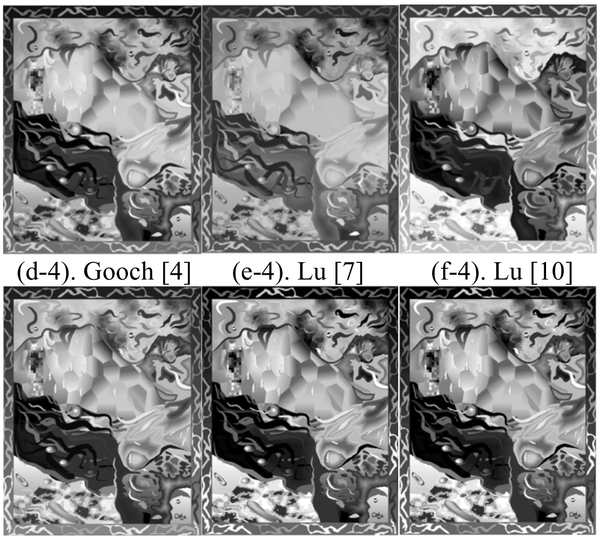


(a-3). Input (b-3). Bala [1] (c-3). Smith [3]
(d-3). Gooch [4] (e-3). Lu [7] (f-3). Lu [10]
(g-3). Liu [13] (h-3). GMC_1 (I-3). GMC_2

Fig. 4. Color-to-grayscale conversion comparison of ***IM2-color*** images from dataset [11].

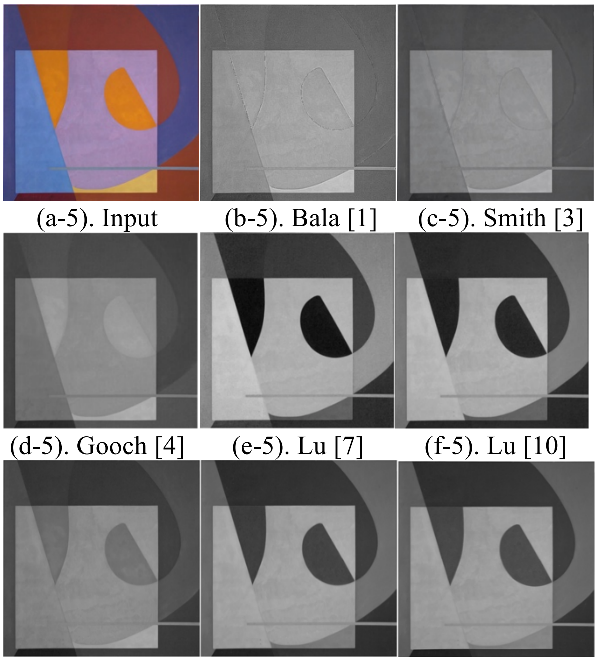


(a-4). Input (b-4). Bala [1] (c-4). Smith [3]



(d-4). Gooch [4] (e-4). Lu [7] (f-4). Lu [10]
(g-4). Liu [13] (h-4). GMC_1 (I-4). GMC_2

Fig. 5. Color-to-grayscale conversion comparison of ***serrano*** images from Cadik's dataset [11].



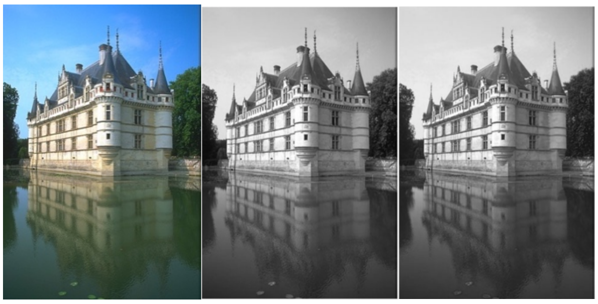
(a-5). Input (b-5). Bala [1] (c-5). Smith [3]
(d-5). Gooch [4] (e-5). Lu [7] (f-5). Lu [10]
(g-5). Liu [13] (h-5). GMC_1 (I-5). GMC_2

Fig. 6. Color-to-grayscale conversion comparison of ***C8TZ7768*** images from Cadik's dataset [11].

The comparison on the publicly available color-to-gray benchmark dataset [11] is shown in Figs. 2, 3, 4, 5 and 6. The results using our methods GMC_1 and GMC_2 locate at the last two. As can be observed, Gooch [4] doesn't consider the salient stimulus which may generate flat results. Smith [3] seems to loss part of the color contrast information which is caused by hue difference. For Lu [7] and Lu [101], the points and edges perceived in a color image cannot be seen in the converted grayscale image. Liu [13] as well as our method uses the normalized correlation to alleviate the drawbacks and preserves the salient features.

5.1.2. Berkeley Segmentation Dataset (BSDS)

We compare our method with state-of-the-art methods [Lu [7]; Lu [10]; Liu [13]]. We evaluate our algorithm on the publicly available color-to-gray benchmark dataset [BSDS], where results of many leading methods are available.

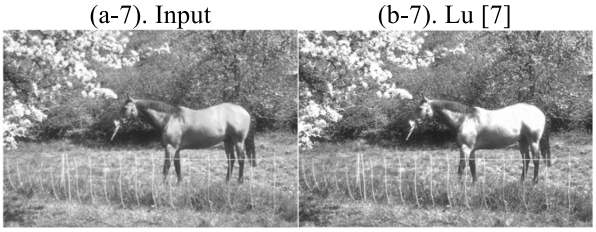


(a-6). Input (b-6). Lu [7] (c-6). Lu [10]

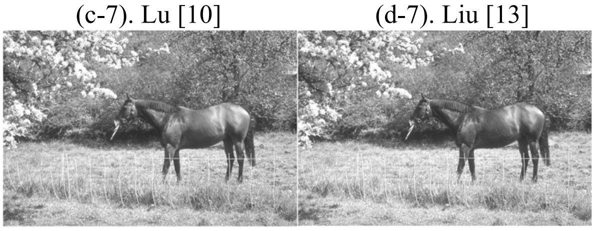
(d-6). Liu [13] (h-6). GMC_1 (I-6). GMC_2

Fig. 7. Color-to-grayscale conversion comparison of images from BSDS dataset [12].

(a-7). Input (b-7). Lu [7]



(c-7). Lu [10] (d-7). Liu [13]



(h-7). GMC_1 (I-7). GMC_2

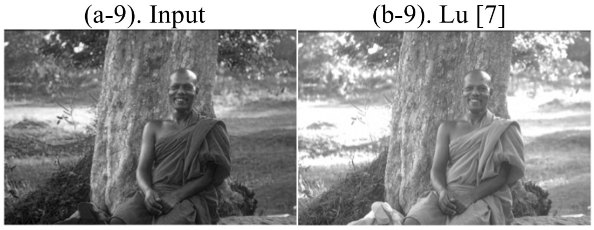
Fig. 8. Color-to-grayscale conversion comparison of images from BSDS dataset [12].

(a-8). Input (b-8). Lu [7] (c-8). Lu [10]

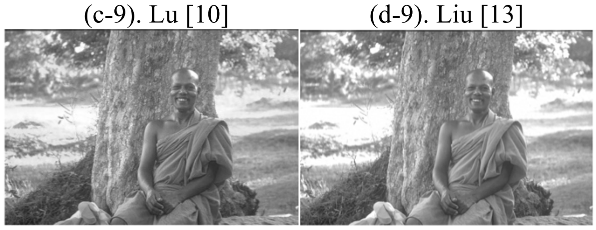
(d-8). Liu [13] (h-8). GMC_1 (I-8). GMC_2

Fig. 9. Color-to-grayscale conversion comparison of images from BSDS dataset [12].

(a-9). Input (b-9). Lu [7]



(c-9). Lu [10] (d-9). Liu [13]



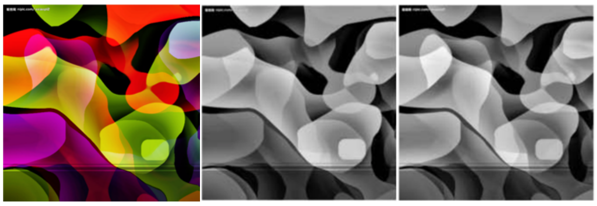
(h-9). GMC_1 (I-9). GMC_2

Fig. 10. Color-to-grayscale conversion comparison of images from BSDS dataset [12].

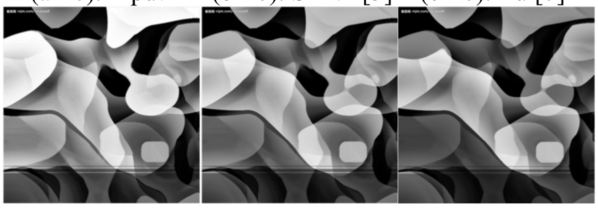
Fig. 7 - 10 show a few representative images in the BSDS dataset. Our results, shown at the last two, preserve very well color contrast presented in the input images. For the images shown in the seven, eight and nine, our method produces results with different color orders compared with others. It is also note that the running time of our algorithm is almost constant for images with different resolutions.

5.1.3. New CSDD dataset

We compare our method with state-of-the-art methods [Smith; Lu [7]; Liu [13]]. We evaluate our algorithm on the publicly available color-to-gray benchmark dataset [CSDD], where results of many leading methods are available.

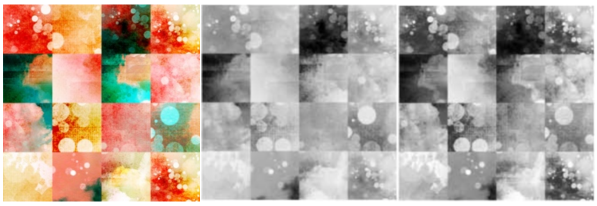


(a-10). Input (b-10). Smith [3] (c-10). Lu [7]

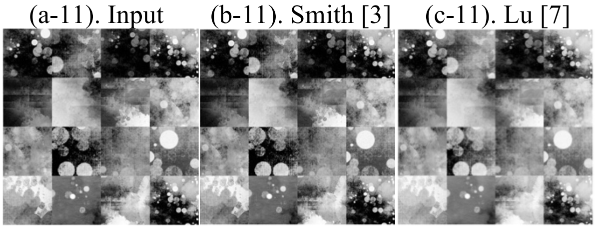


(d-10). Liu [13] (e-10). GMC_1 (f-7). GMC_2

Fig. 11. Color-to-grayscale conversion comparison of images from new CSDD dataset.



(a-11). Input (b-11). Smith [3] (c-11). Lu [7]



(d-11). Liu [13] (e-11). GMC_1 (f-11). GMC_2

Fig. 12. Color-to-grayscale conversion comparison of images from new CSDD dataset.

(a-12). Input (b-12). Smith [3] (c-12). Lu [7]

(d-12). Liu [13] (e-12). GMC_1 (f-12). GMC_2

Fig. 13. Color-to-grayscale conversion comparison of images from new CSDD dataset.

(a-13). Input (b-13). Smith [3] (c-13). Lu [7]

(d-13). GCS [13] (e-13). GMC_1 (f-13). GMC_2

Fig. 14. Color-to-grayscale conversion comparison of images from new CSDD dataset.

Fig. 11 - 14 show a few representative images in the new CSDD dataset. To sum up, the results of our approaches are impressive. It not only has good feature preservation that features in the color image still remain discriminable in the grayscale image, but also has excellent ordering preservation that can preserve a desired color ordering in color-to-gray conversion (e.g. the results shown at the last two of Fig. 12 and Fig. 13).

5.1.4. Nature Image dataset

Fig. 15. Color-to-grayscale conversion comparison of nature images [14].

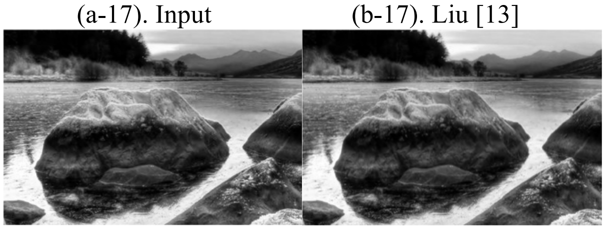
(a-15). Input (b-15). Liu [13]

(c-15). GMC_1 (d-15). GMC_2

Fig. 16. Color-to-grayscale conversion comparison of nature images [14].

Fig. 17. Color-to-grayscale conversion comparison of nature images [14].

(a-17). Input (b-17). Liu [13]



(c-17). GMC_1 (d-17). GMC_2

Fig. 18. Color-to-grayscale conversion comparison of nature images [14].

Liu [13] and our methods, reduce strict order constrain and maximally preserve the contrast existed in the source image, thus may treat all contrast equally, hence the gradient magnitude is excessively considered. To deeply compare the GCS and GMC measure, and demonstrate the advantage of GMC measure, we present the GMC mapping obtained by the four methods on the test images in Fig. 15 and Fig. 17. As can be observed, the GMC mappings obtained by our methods in Fig. 16 and Fig. 17 are more brighten, specifically for the pixels with small magnitudes, indicating higher absolute GMC values. This phenomenon indicates that our GMC model partly attenuates the influence of gradient magnitudes.

6. CONCLUSION AND FUTURE WORK

In this paper, we present a gradient matrix correlation (GMC) measure based decolorization model, which faithfully reproduces the perceived appearance of the color source image in its grayscale version. Particularly, instead of calculating the gradient error in a vector manner considering all channels, the gradient matrix correlation in a scalar manner considering each of the channels is adaptively valuated. Based on the discrete searching strategy and sensitive weighted selection, two algorithms (i.e., GMC_1 and GMC_2) are developed. The performance of the proposed methods is demonstrated through comparison study on a wide variety of images which are much faster and provide more perceptually plausible results than most of the recent algorithms.

7. REFERENCES

[1] R. Bala and R. Eschbach, "Spatial color-to-grayscale transform preserving chrominance edge information," in Proc. Color Imag. Conf., 2004, pp. 82–86.

[2] L. Neumann, M. Cadík, and A. Nemcsics, "An efficient perception-based adaptive color to gray transformation," in Proc. Comput. Aesthetics, 2007, pp. 73–80.

[3] K. Smith, P.-E. Landes, J. Thollot, and K. Myszkowski, "Apparent greyscale: A simple and fast conversion to perceptually accurate images and video," Comput. Graph. Forum, vol. 27, no. 2, pp. 193–200, Apr. 2008.

[4] A. A. Gooch, S. C. Olsen, J. Tumblin, and B. Gooch, "Color2Gray: Salience-preserving color removal," ACM Trans. Graph., vol. 24, no. 3, pp. 634–639, Jul. 2005.

[5] J. G. Kuk, J. H. Ahn, and N. I. Cho, "A color to grayscale conversion considering local and global contrast," in Proc. ACCV, vol. 4. 2010, pp. 513–524.

[6] Y. Kim, C. Jang, J. Demouth, and S. Lee, "Robust color-to-gray via nonlinear global mapping," ACM Trans. Graph., vol. 28, no. 5, pp. 1–4, Dec. 2009.

[7] C. Lu, L. Xu, and J. Jia, "Contrast preserving decolorization," in Proc. IEEE Int. Conf. Comput. Photography (ICCP), Apr. 2012, pp. 1–7.

[8] Q. Liu, J. Liu, P. Dong, and D. Liang, "SGTD: Structure gradient and texture decorrelating regularization for image decomposition," in Proc. Conf. ICCV, Dec. 2013, pp. 1081–1088.

[9] W. Xue, L. Zhang, X. Mou, and A. C. Bovik, "Gradient magnitude similarity deviation: A highly efficient perceptual image quality index," IEEE Trans. Image Process., vol. 23, no. 2, pp. 684–695, Feb. 2014.

[10] C. Lu, L. Xu, and J. Jia, "Real-time contrast preserving decolorization," in Proc. SIGGRAPH Asia Tech. Briefs, 2012, pp. 1–4.

[11] M. Cˆadík, "Perceptual evaluation of color-to-grayscale image conversions," Comput. Graph. Forum, vol. 27, no. 7, pp. 1745–1754, Oct. 2008.

[12] D. Martin, C. Fowlkes, D. Tal, and J. Malik, "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics," in Proc. IEEE Conf. ICCV, vol. 2. Jul. 2001, pp. 416–423.

[13] Q. Liu, P.X. Liu, W. Xie, Y. Wang, D. Liang, "GcsDecolor: Gradient correlation similarity for efficient contrast preserving decolorization," IEEE Trans. Image Process., vol. 24, no. 9, pp. 2889-2904, 2015.

[14] http://download-wallpaper.net/blog/images-nature.html