Signal Processing: Image Communication 79 (2019) 1–12

Contents lists available at ScienceDirect

Signal Processing: Image Communication

journal homepage: www.elsevier.com/locate/image

Directive local color transfer based on dynamic look-up table☆

Zhijiang Li [a], Zhenshan Tan [a], Liqin Cao [a,*], Hu Chen [b], Lei Jiao [c], Yanfei Zhong [d]

[a] School of Printing and Packaging, Wuhan University, Wuhan 430072, China
[b] Morningstar (Shenzhen) Ltd, China
[c] Department of Information and Communication Technology, University of Agder, Grimstad 4879, Norway
[d] State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan 430072, China

ARTICLE INFO

Keywords:
Color transfer
Color transfer intention
Color cluster
Dynamic look-up table

ABSTRACT

Color transfer in image processing usually suffers from misleading color mapping and loss of details. This paper presents a novel directive local color transfer method based on dynamic look-up table (D-DLT) to solve these problems in two steps. First, a directive mapping between the source and the reference image is established based on the salient detection and the color clusters to obtain directive color transfer intention. Then, dynamic look-up tables are created according to the color clusters to preserve the details, which can suppress pseudo contours and avoid detail loss. Subjective and objective assessments are presented to verify the feasibility and the availability of the proposed approach. Experimental results demonstrate that our proposed method has better performance on natural color images than classical color transfer algorithms. Furthermore, the reference image can be extended to color blocks instead of images.

1. Introduction

Color transfer aims to assign colors from a reference image to a source image. Color transfer has various applications, such as image enhancement, image colorization and special effects for movies. In color transfer, two key steps are usually conducted to construct correct color mapping between images and to keep content of the source image unchanged. Color mapping directs the colors in the reference image that should be transferred to the source image. Keeping content unchanged means that texture and structure of source image should be kept consistent during the process of color transferring.

Many researchers have made efforts to address the above two issues and the approaches are divided into global methods and local methods. Global color transfer methods calculate the color statistics by taking into account all pixels in the respective images [1,2], which are very fast and convenient. However, global methods usually ignore the spatial relationships and may easily cause misleading color mapping and color distortion. To address the above issues, local color transfer methods are derived by considering the spatial relations and color correspondences. Typical local color transfer methods include conventional methods and machine learning methods. Conventional local methods include Gaussian Mixture Models (GMMs) [3,4], dominant color mapping [5], probabilistic moving least square algorithm [6], etc., while machine learning methods have a rapid development in the last decade such as colorization with SVM algorithm [7] and color style changed with neural network [8]. Comparing with the global methods, local methods have advantages in processing the texture of images. However, most of local methods still suffer from misleading color mapping and loss of details, which deserved to be researched further.

In this paper, we propose several improvements on conditional local color transfer methods. Firstly, we study the open image datasets of [4,9] and summarize the basic rules of constructing color mapping intentions in automatic color transfer. Secondly, we propose a new directive color mapping method which can be automated or via manual interaction. The automated operation is based on the rules of color mapping intentions. For manual interaction as proposed in [10], users can manually operate the color mapping relationship between the reference image and the source image. Different from [10] where intensive manual mapping needs to be carried out, D-DLT method (D-DLT) releases the manual work significantly by mapping several dominant colors between the images. Thirdly, we propose a novel method for abstracting salient regions based on the improved simple non-iterative clustering (I-SNIC) method. Finally, color look-up tables are constructed to enrich the colors of the reference images to avoid details loss. Furthermore, based on the constructed look-up tables, this algorithm can use color blocks instead of the reference images, which extends the range of the reference images.

The overall framework of D-DLT method is proposed in Fig. 1, which includes four steps. The first step is local processing, which is intended

☆ No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.image.2019.06.010.

* Correspondence to: Department of Printing and Packaging, Wuhan University, Luoyu Road 129, Wuhan, 430079, China.
E-mail address: clq@whu.edu.cn (L. Cao).

https://doi.org/10.1016/j.image.2019.06.010
Received 24 November 2018; Received in revised form 24 June 2019; Accepted 24 June 2019
Available online 22 August 2019
0923-5965/© 2019 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

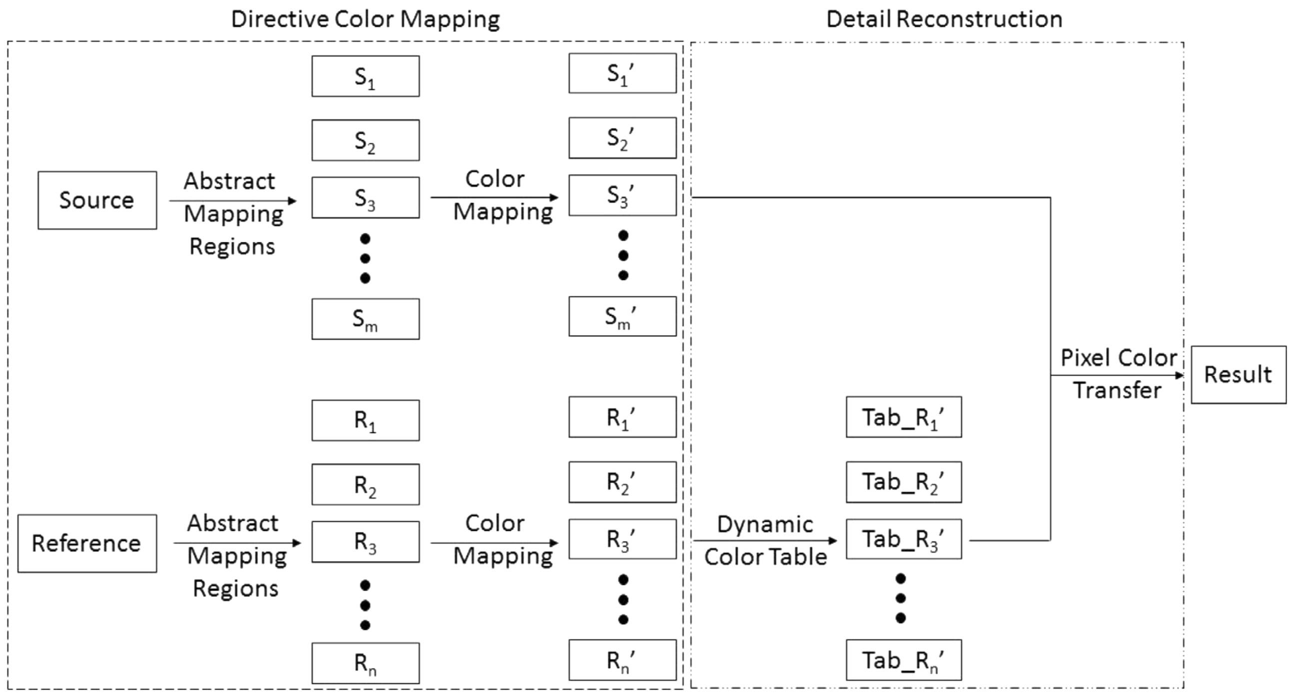


Fig. 1. Overall framework.

to abstract the dominant colors using color clustering. The second step is directive color mapping which constructs the mapping relationships of the color clustering between the source image and the reference image. The third step is to construct the dynamic color table based on mapping intention. The final step is to transfer the pixel color.

The significant contributions of this paper are summarized as follows:

- We study several open image datasets and propose a novel color mapping method based on the human vision system, which is more accurate and reasonable than the existed methods
- A novel method for abstracting salient regions is proposed based on the improved simple non-iterative clustering (I-SNIC) method. This method can detect salient regions more accurate and outperforms the classic method [11]. Furthermore, the I-SNIC method fits boundaries better than the simple non-iterative clustering (SNIC) method [12] especially for the color transfer.
- Dynamic color look-up tables are established to enrich the colors of the reference image and to prevent the appearance of the pseudo contour region.
- This paper provides a manual interaction method, which is convenient, friendly and fast to use. Furthermore, we also extend the range of the reference image, which the color blocks can also be added to the reference images.

The remaining of the paper is organized as follows. Section 2 presents a short review of relevant and recent color transfer techniques. The details of D-DLT method are presented in Section 3. Section 4 shows the experimental results before we conclude the paper in Section 5.

2. Related work

Existing color transfer approaches can mainly be divided into global methods and local methods. The global methods calculate the color statistics of every pixels and the local methods consider the spatial relations and the color correspondences. An automatic global color transfer algorithm was firstly proposed by Reinhard et al. [1]. This algorithm aims to shift the color of the source image to match the color of the reference image in the L$\alpha\beta$ color space. Although this method was simple and fast, utilizing only the means and variances may cause serious color distortion. Neumann et al. [13] proposed a 3-Dimensional histogram matching in the HSL color space to map the colors between images. However, histogram matching for each color component is independent, which ignores the relationship of the color space. Considering the correlation of three channels, Xiao et al. [2] used covariance of three channels in any color space to achieve the purpose of color transfer. However, covariance matrix transformation handled the linear color transfer, which easily losses details. In general, the global algorithms were efficient but sometimes had unwanted color mapping and detail loss. Therefore, different kinds of local color transfer methods had been proposed to solve the above two issues.

To solve the problem of misleading mapping relationships, Pitié et al. [14] proposed a method to transfer N-Dimensional probability distribution to another. The algorithm was iterative and non-linear, but can produce artifacts. Their further work [15] reduced the effect of artifacts by considering the surround pixels of pending pixel. The Probability Density Function (PDF) [15] had a low computational cost but changed the intensity of the pixels. Chang et al. [16] held on the opinion that mapping relationships should be connected with human color perception and they proposed a color category-based approach by the characteristics. Each pixel value was classified into one of the basic color categories by psychophysical experiments. Kong et al. [17] separated the foreground from the background through image analysis, and constructed the mapping in the same or similar regions of the semantics. Tai et al. [3] modeled the color distribution as Gaussian mixture models (GMMs) and solved the problems of mapping relationship by expectation maximization. Mairéad et al. [4] proceeded the work of GMMs for shape registration and they compared the results of several kernel functions. The results indicated that it was hard to confirm that all colors of the images were associated with Gauss distribution or other kernel distributions. Dong et al. [5] proposed a dominant color mapping method to reduce unrelated items. However, dominant color methods might cause misleading color mapping and details loss. In contrasted to the above mentioned automatic local methods, researches proposed several manual operation methods. Hwang et al. [6] proposed an interactive color transfer method which specified the color change style by drawing some strokes. Mairéad et al. [10] offered a fast user friendly approach to recolor of image and video materials.

To solve the problem of detail loss, Chang et al. [16] found the location of pseudo contour and proposed an approach to solve the issues by using sigmoid function. However, it was hard to find every area of pseudo contour. Similarity, Kong et al. [17] solved the problems of color distortion by using super-pixel method. Tai et al. [3] proposed the spatial smoothing methods by considering the neighborhood pixels. Since the main reason of detail loss was the insufficient colors in reference images, most researches tried to find the damaged areas in terms of the retails and reconstructed the areas by certain algorithms. Recently, some researches have begun to use deep learning to solve detail loss of color transfer. For instance, Gatys et al. [18] and Luan et al. [19] achieved the image style by using convolutional neural network of deep learning. Li et al. [20] proposed a deep learning strategy taking advantage of a stylization step and a smoothing step to solve the problems of spatially inconsistent stylizations with noticeable artifacts. However, deep learning methods usually required large numbers of original data for training. Moreover, some unpleasable colors will be migrated.

In view of the above mentioned studies, it is clear that there are still difficulties within color mapping and detail loss, especially when the human subjective cognition and the insufficient colors in the reference image are jointly considered. Therefore, in this work, we propose D-DLT method to improve the state-of-the-art by applying the reasonable color mapping intentions based on the human subjective cognation and the enriched colors in the reference image based on the constructed dynamic look-up tables. Furthermore, we improve the state-of-the-art SNIC method to fit the boundaries better and propose a novel method for abstracting salient regions in this paper.

3. Description of the proposed D-DLT approach

As mentioned in Section 2, color transfer depends on seeking the appropriate mapping relationships between the images, and constructing the color transfer function which avoids detail loss. Therefore, our process of color transfer have two main stages, i.e., the color mapping stage and the detail reconstruction stage. Color mapping determines which color in the reference image should be transferred to the source image, which is based on the color mapping intentions. We propose the general rules in color mapping intentions based on human subjective experiment and the previous papers [4,17] in Section 3.1. Then in Section 3.2, we propose the directive color mapping method based on the content in Section 3.1. Finally, in Section 3.3, we propose a detail reconstruction algorithm based on constructing dynamic color look-up table.

3.1. Color mapping intentions

Color mapping intentions determine what colors in the reference image should be transferred to the source image. In the paper [4], the authors proposed the color mapping intentions that should be based on the salient regions and the numbers of colors. In the paper [17], the authors proposed the color mapping intentions that depend on the spatial location. They both had reasonable results based on different methods. However, they only offered several possible ways to construct the color mapping intentions, which could not include all conditions and the relationships among the conditions. Moreover, reasonable intentions should be consistent to human certain general rules of human cognition based on subjective experiment, and we summarize several methods to construct the color mapping intentions based on different conditions. The results show that D-DLT methods are the most reasonable.

In the experiment, we invite 20 people to observe 20 images offered by several open image datasets [4,9] and google. The images are allocated in pairs and 190 pairs of images are combined totally. Each

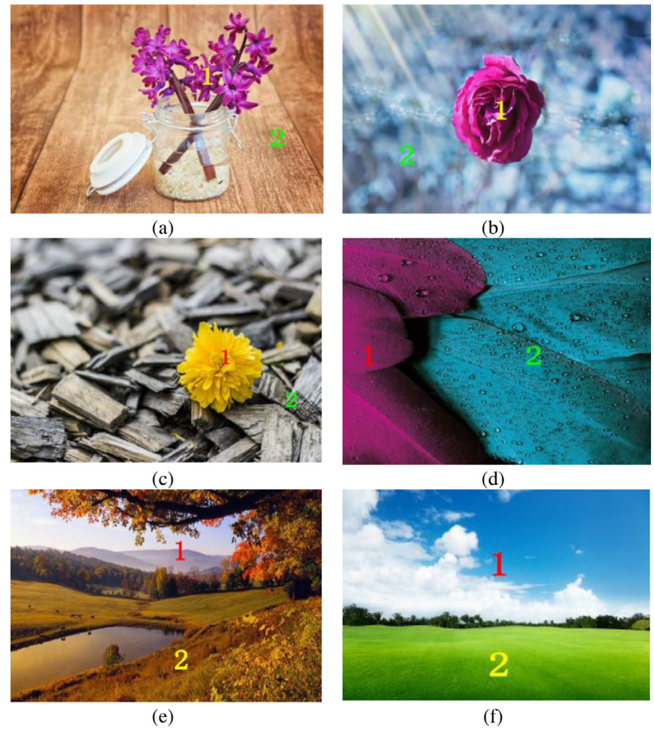


Fig. 2. Three pairs of images and their salient or cluster regions.

person has 10 s to abstract what colors in the images should be transferred. Thereafter, they have to determine what colors in the image should be transferred to another image and give their reasons why they have constructed this mapping. The reasons are offered as color similarity, the number of colors, salient regions and spatial location, which are referred to the previous papers in color transfer [3,17].

According to the results of the experiment, we find that human vision system prefers to find the salient area or the foreground in the images priority, and the images with salient area are also called salient images [21,22]. The salient images can be divided into foreground and background. If the images cannot be divided into foreground and background, which are called non-salient images [21,22], human vision system clusters the colors based on color similarity. To simplify the experiment and the subjective experiment in the paper [21], the images are only divided into two parts. Part of the image pairs and their salient or cluster region results are shown in Fig. 2. The number of people constructing the mapping relationship in Fig. 2 are shown in Table. I. Where, "Mapping" denotes the mapping relationships between the regions of images, and "Pairs" represents the images pairs to be transferred. The results denote the number of people who construct a color mapping with the pairs.

We can now summarize the insights from the experimental results shown in Table 1. Based on whether the image is a salient image or a non-salient image, the experiment can be divided into three cases. The first case is color transfer between salient image and salient image, the second is color transfer between salient image and non-salient image, and the third is color transfer between non-salient image and non-salient image.

(1) Salient Image to Salient Image
For case 1, which is that the source image and the reference image are both salient images, such as Fig. 2(a) and Fig. 2(b), human vision system prefers to color transfer between foreground and foreground (1–1) of the two images, and color transfer between background and background (2–2) of the two images. The results of Table. I have shown that all of the people construct

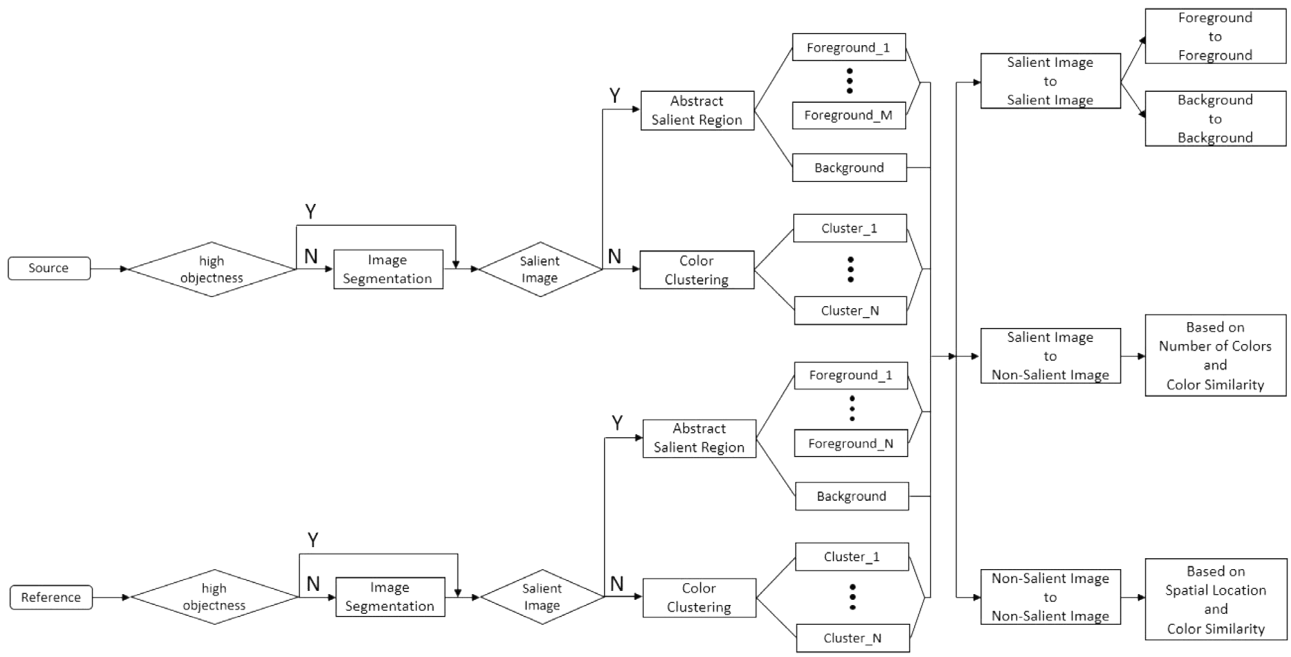


Fig. 3. Process of directive color mapping.

Table 1
The number of people constructing the mapping relationship.

Mapping		1–1	1–2	2–1	2–2
Pairs	Salient (a)-(b) salient	20	0	0	0
	Salient (c)-(d) non-salient	18	2	2	18
	Non-salient(e)-(f) non-salient	19	1	1	19
	Non-salient(d)-(f) non-salient	3	17	17	3

the mapping relationships between salient regions or non-salient regions. This rule is the same as that in [4,17].

(2) Salient Image/Non-Salient Image to Non-Salient Image/Salient Image
For case 2, i.e., one of the images is a salient image and the other is not, human vision system constructs mapping relationships based on the numbers of colors and color similarity. For example; in Fig. 2(c) and Fig. 2(d), people prefer to transferring the colors from the left part of Fig. 2(d) to the foreground of Fig. 2(c) (1–1) and transferring the colors from the right part of Fig. 2(d) to the background of Fig. 2(c) (2–2). After counting all the data, 70% people deem that color similarity is more important than the number of colors. Similar rule is also reported in the paper [4].

(3) Non-Salient Image to Non-Salient Image
For case 3, i.e., the source image and the reference image are both non-salient images, such as Fig. 2(e) and Fig. 2(f), human vision system prefers to transferring color based on spatial location and color similarity of the clustering colors. For instance, for Fig. 2(e) and Fig. 2(f), human vision system transfers colors from the upper part of Fig. 2(f) to the upper part of Fig. 2(e) (1–1), and transfers colors from the lower part of Fig. 2(f) to the lower part of Fig. 2(e) (2–2), which is based on spatial location. On the other hand, for Fig. 2(d) and Fig. 2(f), human vision system transfers colors from the left part of Fig. 2(d) to the lower part of Fig. 2(f) (1–2), and transfers colors from the right part of Fig. 2(d) to the upper part of Fig. 2(f) (2–1), which is based on color similarity. 80% people deem that spatial location is more important than color similarity. Based on the above color mapping intention experiment, we propose "directive color mapping" strategy to enhance the correctness of color mapping.

There are three cases of this strategy, salient image to salient image, salient image to non-salient image, and non-salient image to non-salient image. The detail process is shown in Fig. 3.

Referring to the paper [21,22], the foreground of salient image should have limited similar distractors, relatively clear and simple shape, and high objectness. Therefore, the foreground of the given salient images should have high objectness and fewer numbers. In this paper, we only focus on the images that contain one salient object to support the color mapping.

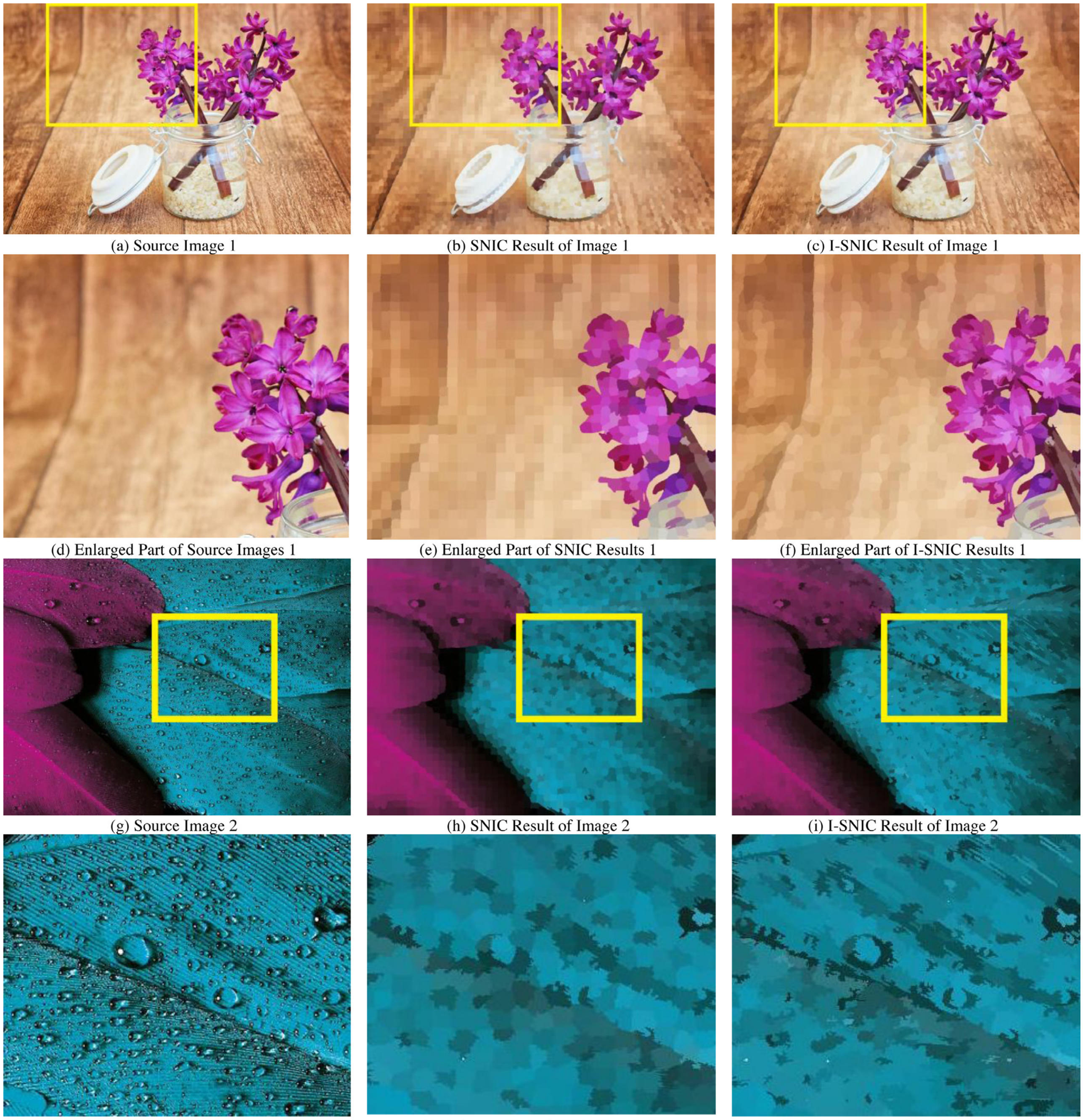
3.2. Color mapping

In this section, we proposed the color mapping strategy based on the analysis in Section 3.1. We first propose to detect salient regions in salient images and to cluster in non-salient images based on the improved SNIC method (I-SNIC) in Section 3.2.1. The improved SNIC method proposed in this paper outperforms in fitting boundaries than the original SNIC method [12]. Meanwhile, we abstract the salient regions based on the number of colors, the spatial locations, and the color of every super pixels based on the improved SNIC method, which is more reasonable than the method proposed in [11]. We also consider the super pixels on the four sides of the image as the background, which makes the results of abstracting salient regions more accurate. Then, in Section 3.2.2, we propose the directive color mapping method based on the human vision system. For different image types in color transfer, we propose distinct methods to construct the color mapping. The experiment shows that our results are the most accurate and reasonable.

3.2.1. Saliency detection and non-saliency clustering

Based on the analysis in Section 3.1, human vision system tends to abstract salient regions in salient images and cluster colors in non-salient images. Therefore, in this section, we process the salient and non-salient images separately.

We propose a saliency detection method based on super pixel method. First, SNIC [12] is adopted as the basic super pixel method, since SNIC is non-iterative, adhere well to image boundaries, and fast to compute. However, SNIC is based on CIE-Lab color space, which is non-orthogonally and non-uniform [1]. Therefore, an improvement of



(a) Source Image 1 (b) SNIC Result of Image 1 (c) I-SNIC Result of Image 1
(d) Enlarged Part of Source Images 1 (e) Enlarged Part of SNIC Results 1 (f) Enlarged Part of I-SNIC Results 1
(g) Source Image 2 (h) SNIC Result of Image 2 (i) I-SNIC Result of Image 2
(j) Enlarged Part of Source Images 2 (k) Enlarged Part of SNIC Results 2 (l) Enlarged Part of I-SNIC Results 2

Fig. 4. Results of SNIC and I-SNIC.

the SNIC algorithm is proposed in this paper. We transfer the image from RGB color space to L$\alpha\beta$ color space instead of CIE-Lab color space. L$\alpha\beta$ color space is orthogonal and uniform, which means that the three channels of L$\alpha\beta$ color space has little correlation [1], and hence, L$\alpha\beta$ color space is widely used in color transfer. The results of the I-SNIC are shown in Fig. 4. It is easy to find that the I-SNIC can fit boundaries better than SNIC. The source images are obtained from the open dataset provided by Mairéad [4].

We calculate the number of colors, the spatial location, and the color of every super pixels according to the method proposed [11]. Then we propose the formula of abstracting salient region that is based on spatially weighted region contrast is shown in Eq. (1).

$$S(r_k) = \sum_{r_k \neq r_i} exp(\frac{-D_s(r_k, r_i)}{\sigma_s})\omega_i exp(\frac{-D_c(r_k, r_i)}{\sigma_c}), \tag{1}$$

where, r_k and r_i are super pixels, k and i are the index of the super pixels, and $S(r_k)$ is the salient value of r_k. ω_i is the number of pixels in r_i. $D_s(r_k, r_i)$ is the spatial distance betweenr_k, and σ_s controls the strength of spatial weighting. $D_c(r_k, r_i)$ is color distance metric between two super pixels, and σ_c controls the strength of color weighting. In our implementation, we set the empirical parameters $\sigma_s = 0.4$ and $\sigma_c = 0.4$. Meanwhile, pixel coordinates, color values and the number of pixels are normalized to [0, 1]. The formulas of $D_s(r_k, r_i)$ and $D_c(r_k, r_i)$ are shown in (2).

$$D_s(r_k, r_i) = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2},$$
$$D_c(r_k, r_i) = \sqrt{(l_k - l_i)^2 + (\alpha_k - \alpha_i)^2 + (\beta_k - \beta_i)^2}, \tag{2}$$

where, (x_k, y_k) is the coordinate of r_k, and l_k, α_k, β_k denote the color components of r_k in L$\alpha\beta$ color space.

Fig. 5. Saliency detection.

After calculating the salient values of all super pixels, the average salient value is derived. If the salient value of super pixel is larger than the average salient value, the super pixel will be the salient region. Furthermore, the super pixels on the four sides of the image are considered as the background [23]. The formulas is shown in Eq. (3).

$$avg = \frac{\sum_{i=1}^{m} S(r_i)}{m},$$
$$avg_{four\_sides} = \frac{\sum_{i=1}^{n} S(r_i)}{n}, \tag{3}$$

where, avg is the average salient value of all super pixels, avg_{four_sides} is the average salient value of super pixels on the four sides. m is the number of all super pixels and n is the number of super pixels on the four sides. The value of the salient region should be larger than avg and avg_{four_sides}. Repeat the above steps until all super pixels are processed. The results of salient region abstracted are shown in Fig. 5.

For the non-salient image, color clustering will be applied to the image. This paper adopts the simple K-means algorithm [24] in the L$\alpha\beta$ color space to extract the dominant colors of the non-salient image. The initial value of K-means should be same as the sum of the numbers of the salient regions and non-salient regions.

3.2.2. Directive color mapping

"Base color" is defined in this paper, which is the color represented by a color region after color clustering. "Base color" also denotes the foreground or background. We determine whether the given images are salient images, and label them by "Salient" or "Non-Salient" [21].

According to the analysis in Section 3.1, we propose a directive color mapping method. There are three cases during color mapping as follow:

(1) Salient Image to Salient Image
When the two images are both salient images, abstract foreground and background first. Then transfer colors between foreground and foreground, and transfer colors between background and background of the two images. This process is shown in Fig. 6(a) as an example. In Fig. 6(a), flowers are the salient regions in the images, and thus we transfer the colors of flowers in one image to flowers in the other image.

(2) Salient Image/Non-Salient Image to Non-Salient Image/Salient Image
When one of the images is a salient image and the other is not, we abstract foreground and background of the salient image and cluster colors of the non-salient image. Thereafter we calculate the colors number and color similarity. In the end, we transfer colors between images based on the following equation (4).

$$D(R_i, R_j) = exp(\frac{-D_{dn}(R_i, R_j)}{\sigma_{dn}})exp(\frac{-D_{dc}(R_i, R_j)}{\sigma_{dc}}), \tag{4}$$

where, R_i and R_j are the color clusters of source image and reference image, $D(R_i, R_j)$ denotes the directive color mapping. $D_{dn}(R_i, R_j)$ returns the number of colors between R_i and R_j, and σ_{dn} controls the strength of number weighting. $D_{dc}(R_i, R_j)$ returns the color distance metric between two super pixels, and σ_{dc} controls the strength of color weighting. In our implementation, we use the empirical parameters $\sigma_{dn} = 0.7$ and $\sigma_{dc} = 0.3$, which are based on the rules in Section 3.1.1 that the number of colors is more important than color similarity. Meanwhile, pixel coordinates, color values and number of pixels are normalized to [0, 1]. The computing methods of $D_{dn}(r_k, r_i)$ and $D_{dc}(r_k, r_i)$ are the same to $D_s(r_k, r_i)$ and $D_c(r_k, r_i)$. The result of the process is shown in Fig. 6(b).

(3) Non-Salient Image to Non-Salient Image
When the two images are both non-salient images, cluster colors first. Then we transfer colors between images based on the Eq. (5).

$$D(R_i, R_j) = exp(\frac{-D_{ds}(R_i, R_j)}{\sigma_{ds}})exp(\frac{-D_{dc}(R_i, R_j)}{\sigma_{dc}}), \tag{5}$$

where, R_i and R_j are the color clusters of the source image and the reference image respectively, and $D(R_i, R_j)$ denotes the directive color mapping. $D_{ds}(R_i, R_j)$ is spatial distance between R_i and R_j, and σ_{ds} controls the strength of spatial weighting. Similarly, $D_{dc}(R_i, R_j)$ is the color distance metric between two super pixels, and σ_{dc} controls the strength of color weighting. In our implementation, we use the empirical parameters $\sigma_{ds} = 0.4$ and $\sigma_{dc} = 0.1$, which are based on the rules in Section 3.1 that means spatial location is more important than color similarity. The computing methods of $D_{ds}(r_k, r_i)$ and $D_{dc}(r_k, r_i)$ are the same as those for $D_s(r_k, r_i)$ and $D_c(r_k, r_i)$. This process is shown in Fig. 6(c) for example.

3.3. Color transfer based on dynamic color look-up tables

The way to preserve the color details is important in the process of color transfer. Su et al. [25] proposed several conditions, which mainly include the grain effect and the loss of details. Chang et al. [16] used super-pixels to find false contours and to solve them by using sigmoid function. However, it is hard to find every pseudo contour region. The reason is that the reference image cannot provide all the colors that the source image needs. We have to enrich the reference image colors to ensure that all colors in source image will be transferred. Therefore, we construct a look-up table to enrich the reference image colors and the associations among the look-up tables of the base colors to prevent the appearance of the pseudo contour region appearing. In addition, this paper provides a manual operation method based on the base colors.

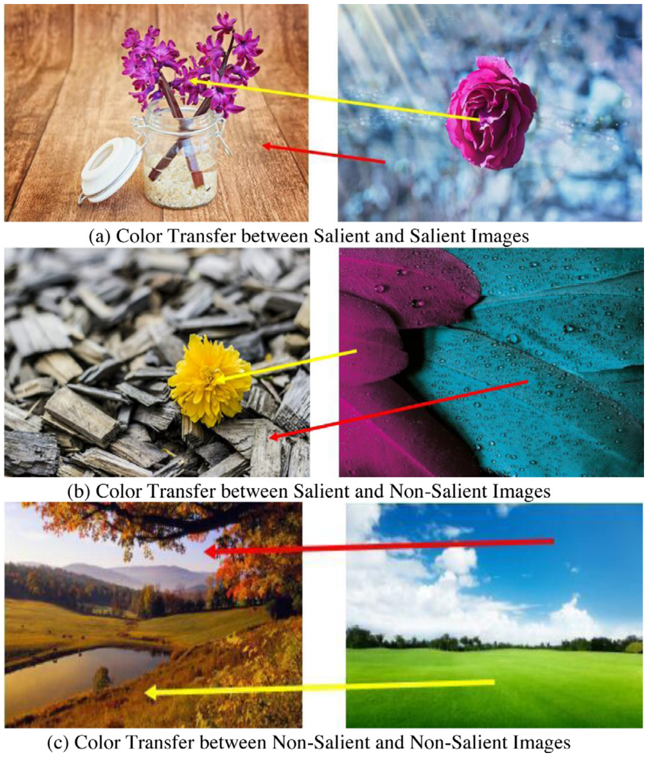


Fig. 6. Color transfer between images.

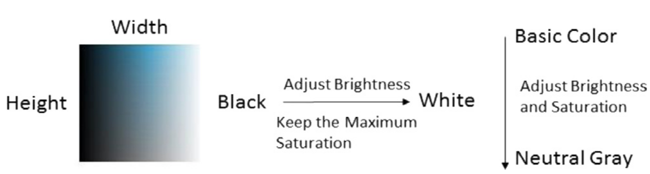


Fig. 7. Look-up table.

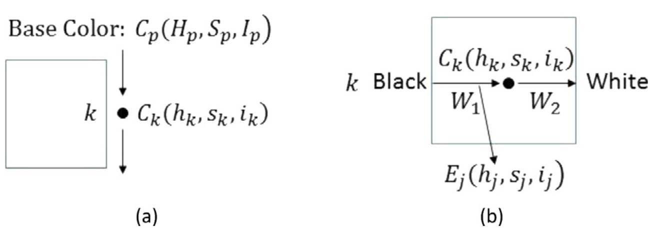


Fig. 8. The details of the look-up table. (a) Vertical Look-up Table. (b) Horizontal Look-up Table.

3.3.1. Dynamic color look-up table construction

Dynamic look-up table produces more colors than the reference image, which can help with avoiding detail loss. To suppress the pseudo contours, the association of each base color's look-up table is constructed with neutral color. In human vision system, neutral color means the balance of three channels [16]. In this paper, the neutral color is the average color of all colors in the HSI color space.

The method is proposed to keep the color tone of the base color unchanged and to adjust the saturation and brightness. Therefore, the base color needs to be transferred from the RGB color space to the HSI color space and then back to the RGB color space. As shown in Fig. 7, the base color is expended to a rectangular color table. It is proven that the results are ideal in most cases when Width and Height are configured as 80 and 20 respectively.

For the look-up table, we configure the value of the base color in the HSI color space $C_p(H_p, S_p, I_p)$, and the number of base colors $m(C_0, C_1, \ldots, C_p, \ldots, C_{m-1})$, where, C_p denotes the base color, and H_p, S_p, and I_p denote the hue, the saturation, and the intensity respectively. The intensity of neutral gray C_g in HSI space is I_g, and the saturation is 0. The process of constructing dynamic color table is as follows:

Firstly, the color between the base color and the neutral gray is generated vertically, which means that the hue is unchanged, the saturation is gradually reduced and the intensity is linear. The color $C_k(h_k, s_k, i_k)$ of vertical look-up table indexed by k can be calculated by Eq. (6):

$$\begin{aligned} h_k &= H_p, \\ s_k &= S_p + \frac{0 - S_p}{H} \times k, \\ i_k &= I - p + \frac{I_g - I_p}{H} \times k, \\ I_g &= \frac{\sum_{l=0}^{m-1} I_l}{m}, \end{aligned} \tag{6}$$

where, k is the number of rows, m is the number of base colors, H is the height of the base color block, and I_l is the intensity of each base color. The result of this process is shown in Fig. 8(a). In Fig. 8(a), the point $C_k(h_k, s_k, i_k)$ denotes the point to be calculated.

Secondly, the color between black and white is generated horizontally, which means that the hue is unchanged. While the intensity increased, the saturation should be changed linearly to avoid saturation deficiency. Assume the color of vertical H is $C_k(h_k, s_k, i_k)$ and the color of horizontal j is $E_j(h_j, s_j, i_j)$, which can be calculated by Eq. (7).

$$\begin{aligned} h_j &= h_k, \\ W_1 &= \frac{i_k}{255} \times W, \\ W_2 &= W - W_1, \end{aligned} \tag{7}$$

where, W_1 is the length of black to C_k, W_2 is the length of C_k to white, and W is the width of base color. This process is shown in Fig. 8(b).

From black to base color, the intensity changes can be described as follows.

$$i_j = i_k + \frac{0 - i_k}{W_1} \times j. \tag{8}$$

From base color to white, the intensity changes can be represented as follows.

$$i_j = i_k + \frac{255 - i_k}{W_2} \times j. \tag{9}$$

The saturation changes can be represented by

$$s_j = \frac{s_p}{s_{max}} \times s_{jmax}, \tag{10}$$

where, s_{max} is the maximum saturation of base color C_p in the hue H_p and intensity I_p. s_{jmax} is the maximum saturation of the color E_j of lateral j in the hue h_j and intensity i_j. The maximum saturation s_{max} is obtained by the procedure in the third step below.

Thirdly, we fix the hue and brightness and accumulate the saturation by a step a. For each step, we transfer the coordinates HSI is transferred to RGB until any value of R/G/B out of the range of [0,255]. Experiments show that setting a to 0.001 will help to obtain feasible results. Fig. 9 shows the process of constructing dynamic color table.

Fig. 10 demonstrates the differences between the processes with or without neutral color in color transferring. From the zoomed local regions in the red boxes, we can easily see that pseudo contours disappear when neutral color is considered.

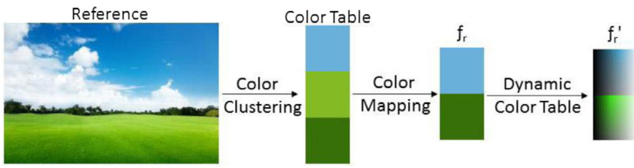


Fig. 9. Process of constructing dynamic color table.

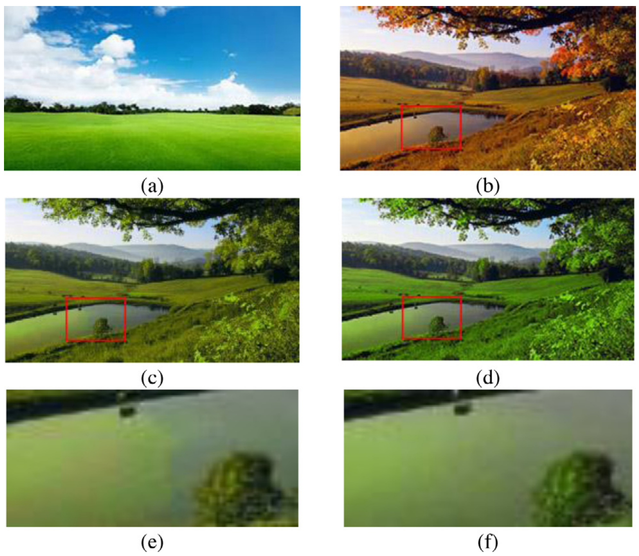


Fig. 10. Suppress pseudo contours. (a) Reference Image. (b) Source Image. (c) Result without Neutral Color. (d) Result With Neutral Color. (e) Enlarged of (c). (f) Enlarged of (d).

3.3.2. Pixel color transfer

After constructing color mapping between images and enriching the colors of the reference image by look-up tables, we should transfer colors from the look-up tables of the reference image to the source image based on the mapping. As shown in the Eq (11), C_s and C_r belong to the same mapping, where, C_s is a set of color clustering in a color cluster of the source image and C_r is a set of color clusters in a color clustering area of the reference image. d represents the color migration scheme between pixels.

$$d = \min_{\{i,j\}}\{\sqrt{\alpha_i^2+\beta_i^2} - \sqrt{\alpha_j^2+\beta_j^2}\,|(\alpha_i,\beta_i)\in C_s,(\alpha_j,\beta_j)\in C_r\}. \tag{11}$$

3.3.3. Manual operation

This paper also provides a manual operation method based on the base colors. After salient region abstracting or color clustering, users can manually select any base colors in the reference image to any base colors in the source image to construct the color mapping. Thereafter, according to the dynamic look-up table based on the base colors, the base colors are enriched to prevent the appearance of the pseudo contour region appearing. Furthermore, users can also appoint the base colors instead of the reference images to color transfer, which extends the range of the reference color. Different from [10] where complex manual mapping needs to be carried out to make. sure the correct color mapping, D-DLT method releases the manual work significantly by mapping several base colors between the images. In addition, the process of the manual operation is easy, convenient, friendly and fast to use.

4. Performance evaluations and numerical results

4.1. Results of the proposed method

The result of the pipeline between salient images is presented in Fig. 11. The pipeline includes directive color mapping and detail reconstruction. During directive color mapping, salient images are detected automatically and correct color mapping is constructed. During detail reconstruction, dynamic color table from the reference image is created and color transfer based on color mapping is executed. The result image shows that the source image obtains color information that is highly consistent with the reference image. Additionally, the pipelines of color transfer between salient and non-salient image or between non-salient images are similar to the pipeline between salient images, which are only based on the different rules described in Fig. 1 and Fig. 3.

Comparison experiments with the state-of-the-art methods [1,4,15] are shown in Fig. 12 and the original images come from the open dataset of [4,9] and google. Reinhard method was a classic global method, PDF was a classic local method, and Mairéad method was one of the most effective local methods. We compared our results with those of other methods from color mapping and detail reconstruction.

For color mapping as shown in Fig. 12, Reinhard method makes mistakes in color mappings in the four groups of images. In the groups (1) (2) of Fig. 12, Reinhard method transfers the purple colors of the salient region in the source image to the background of the source image, which causes the wrong color mapping. In the group (3), Reinhard method almost has a total wrong color mapping for background, such as the green sky.

It is easy to find that the global method may construct wrong mapping relationships accidentally. Although PDF outperforms than Reinhard method, it also brings an erroneous color mapping in the group (1) (2), which constructs a wrong color mapping from the foreground to background. Mairéad method constructs correct color mapping between salient image and salient image, and between salient image and non-salient image. However, Mairéad method still involves mistakes in color mapping relationships between non-salient image and non-salient image. For instance, although the color transferring for sky between the source image and the reference image in the group (3) is pleased, there are blue colors instead of the correct yellow colors in flowers in the source image. Incorrectly color mapping also appears for

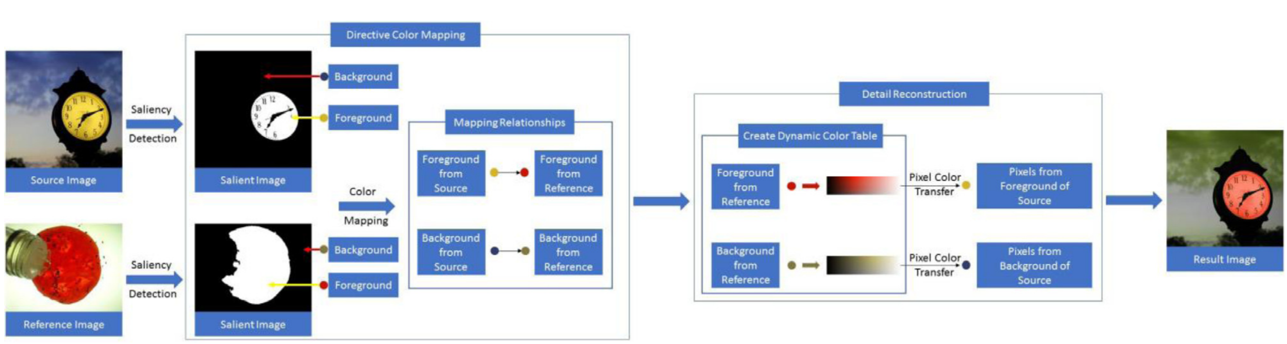


Fig. 11. Result of the pipeline between salient images.

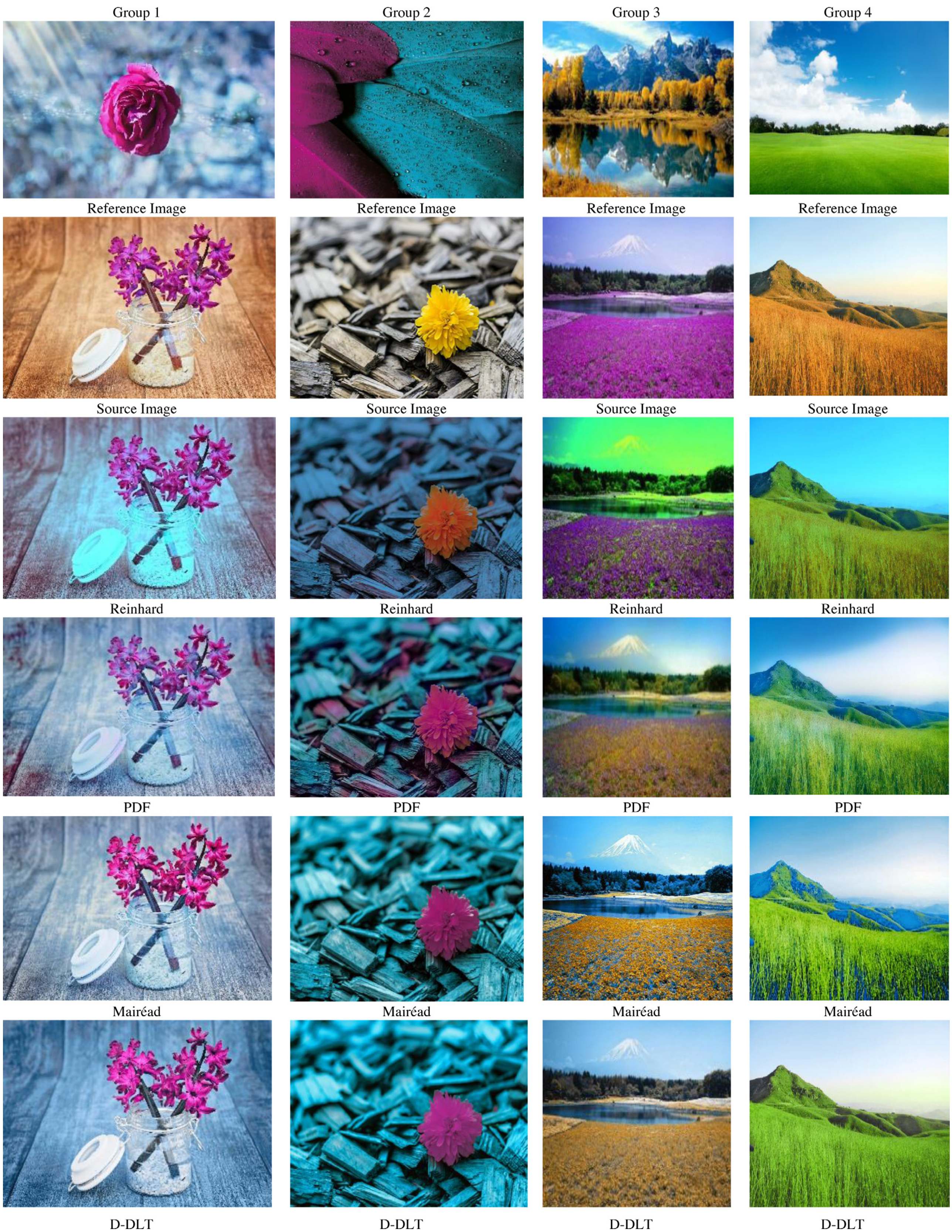


Fig. 12. Different methods' results.

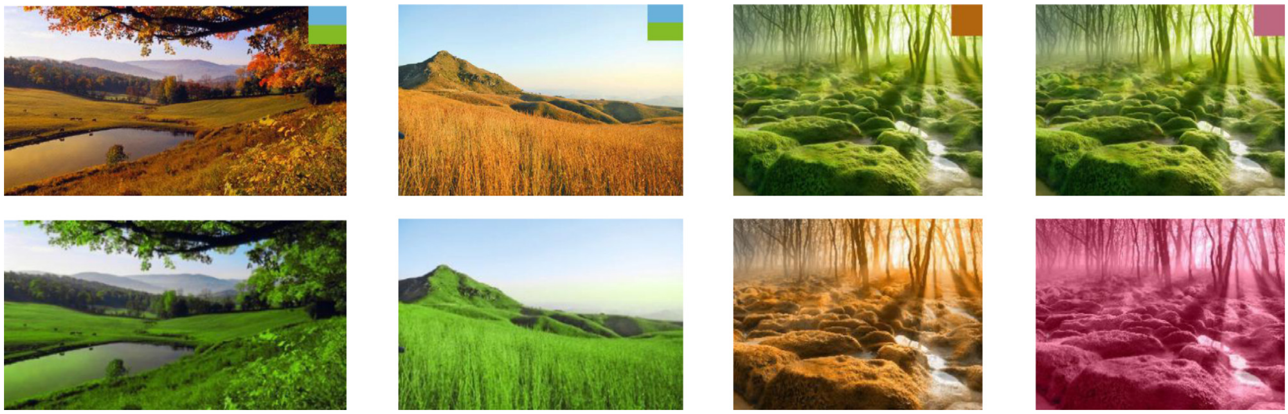


Fig. 13. Use color blocks as reference image.

the grass in the result image in the group (4). Comparing with the above methods, D-DLT method almost constructs the correct color mapping relationships between the images.

For detail reconstruction, D-DLT method also outperforms other methods. The detail reconstruction process mainly includes color reconstruction and texture reconstruction. If there is anything wrong in the process of color reconstruction, it is easy to cause color distortion [25]. The results in Fig. 12 demonstrate that Reinhard method is prone to producing color distortion and blur texture. For example, in the group (1), it is hard to distinguish the texture of all the stones in the bottle, which should be distinguished easily in the source image. Similarly, in the group (2) (3), there are color distortions with the orange flower and the green lake. In addition, the mountain of the result image in the group (3) cannot be found clearly. It produces green colors which should not exist, and the purple colors of the source image should not be transferred. PDF outperforms the global method in detail reconstruction. In the above four groups of images, PDF does not produce unexpected colors which are not included in the reference images. However, PDF loses the texture in the results. In the group (1), the texture of the stones in the bottle have been destroyed by smooth transition. In the group (3) (4), the clouds have been destroyed and the structure of the results are not consistent with the source image. Comparing with the Reinhard's method and the PDF method, Mairéad method has better performance in color transferring and texture retention. However, in the color transfer between non-salient image and non-salient image in the fourth group, there is texture reconstruction for grass and the mountain. According to the results in Fig. 12, D-DLT method has better performance in detail reconstruction especially for non-salient images.

In the above approaches, we can also consider clustering colors as the given color blocks directly. The look-up table can be constructed based on the color blocks. As shown in Fig. 13, taking color blocks instead of reference image can achieve the same results of color transfer.

Fig. 14 shows different results with various choices when manual operation is applied to color mapping. Fig. 14(c) and Fig. 14(g) indicate the results with different color mapping based on the rules in Fig. 14(d) and Fig. 14(h), respectively. In addition, users can keep some colors of the source image unchanged and transfer the other colors of the source image, as is shown in Fig. 15. In Fig. 15, it is easy to find that the colors of the sky in the Source 2 image are not changed during the process of color transfer, which means the Result 2 keeps the colors of the sky in Source 2.

4.2. Subjective assessment

To make a subjective assessment, in this paper, 20 groups of images were selected, and 70 people (40 males and 30 females) with ages

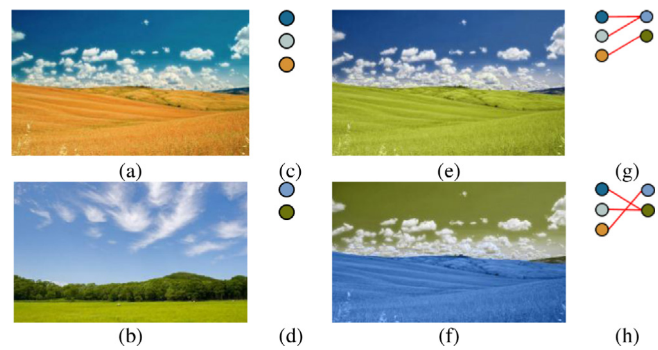


Fig. 14. Color mapping by manual operation. (a) Source image. (b) Cluster of the source image. (c) Result. 1. (d) Color mapping scheme. 1. (e) Reference image. (f) Cluster of the reference image. (g) Result.2. (h) Color mapping scheme. 2.

ranging from 17 to 40 were invited. The number of people between 17 and 30 was 50, and the number of people between 31 and 40 was 20. Similar to the subjective assessment in the paper [4], each participant was offered with images at the same time — a source image, a reference image, and two different result images. Then they had 15 to 20 s to view the images and pick the best result. Time interval for each group is configured as 30 s. Furthermore, the sequence of results on the screen was displayed randomly.

There are two approaches to evaluate the attained results. S_1 is to evaluate the detail loss of the source image, and the second S_2 is to evaluate the color distortion [26]. For the assessment of detail loss, the participants should judge the texture similarity between each group of results and source images. To assess color distortion, participants should judge the color similarity between each group of results and reference images. The degree was scored from 1.0 (not pleasing) to 5.0 (very pleasing).

Part of the results of subjective assessment are shown in Table 2. Group (1) denotes the color transfer between salient and salient images. Group (2) is for the color transfer between salient and non-salient images, and group (3) and group (4) illustrate the color transfer between non-salient and non-salient images. The representative images of groups (1)–(4) are shown in Fig. 12.

The scores of D-DLT for detail loss are higher than those of the global method and PDF. According to the experiment, the participants hold the opinions that the methods of Mairéad method and D-DLT loss less details than the Reinhard method and the PDF method, which means that the Mairéad method and D-DLT have better texture similarity than the Reinhard method and the PDF method. Comparing D-DLT method with the Mairéad method, especially in the groups (3) (4), the participants deem that D-DLT outperforms Mairéad method in structure consistency of adjacent regions.

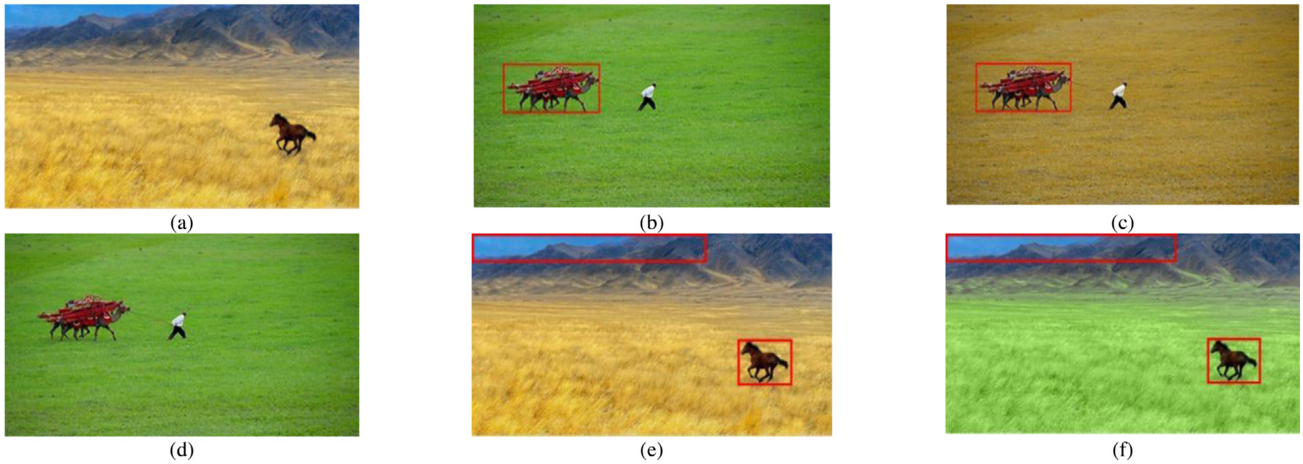


Fig. 15. Keep some colors unchanged. (a) Reference 1. (b) Source 1. (c) Result 1. (d) Reference 2. (e) Source 2. (f) Result 2.

Table 2
The result of subjective quality assessment.

Group	Detail loss				Color distortion			
	Reinhard	PDF	Mairéad	D-DLT	Reinhard	PDF	Mairéad	D-DLT
$1 Salient--Salient$	3.1	3.3	4.5	4.6	2.9	3.2	4.4	4.5
$2 Salient-NonSalient$	2.8	2.7	4.6	4.5	3.3	3.0	4.5	4.5
$3 NonSalient--NonSalient$	2.4	3.5	3.7	4.3	2.5	3.6	4.0	4.2
$4 NonSalient--NonSalient$	3.4	3.1	3.0	4.8	3.3	3.1	3.2	4.3

The scores of D-DLT for color distortion are higher than other approaches. The participants state that the color distribution of D-DLT is more natural and continuous. Comparing with other methods, D-DLT focuses more on the color consistency of adjacent regions, which benefits from the added spatial relationship parameters. In Fig. 12, pleasing results are obtained by Mairéad method if the source image or reference image includes salient image. However, Mairéad method has color distortion during non-salient images transferring, which can be found in group (4) in Fig. 12. Clearly, some grass is colored mistakenly to blue.

4.3. Objective assessment

The objective assessment includes structure similarity and color consistency. Three kinds of indicators, PSNR [27], SSIM [28], GSSIM [29] are applied to indicate the structure similarity indexes. PSNR indicates the image noise produced during the process of color transfer. Different from PSNR, SSIM focuses on image structure similarity, and GSSIM is for the image gradient structure similarity. Those indicators evaluate the structural similarity and detail consistency between the source image and the result image. The larger the value of each indicator is, the better the result will be. NIMA [30] is adopted to evaluate the global visual performance of the result image. Similarly, the larger the value, the better the results.

In Table 3, the values of PSRN, SSIM, GSSIM and NIMA of D-DLT and Mairéad method are greater than those of the global method and the PDF method. In particular, in group (4), the values of assessment indexes of D-DLT are superior to those of other methods, especially the results of PSNR and GSSIM, which means that D-DLT does better in processing the color and texture between the non-salient images. The reason is that D-DLT takes into account both the spatial relationship and color similarity rather than just color feature, which can maintain the structure similarity of adjacent regions to avoid losing details. Furthermore, D-DLT constructs the dynamic look-up tables to enrich the colors of reference image and to keep the saturation maximum to ensure the results natural. In Table 3, PSNR values of group (2) are less than those of other groups of all the methods. The reason is that the values of PSNR depend on the change of image luminance. The larger the color change before and after transferring is, the smaller the PSNR value is. In group (2), the color difference between the reference image and the source image is larger than that in other groups, which produce transferring image with a larger color change and a smaller PSNR.

The results of the objective assessment illustrate that D-DLT outperforms Reinhard method, PDF and Mairéad method. The conclusion is consistent with the subjective assessment.

5. Conclusions

In this paper, we have presented a new directive color transfer method to realize local color transfer with preferable detail. Summarizing the general rules based on the state-of-the-art approaches and subjective experiments, our algorithm has constructed automatic directive color mappings between images, which consist with human vision system. Manual operation method is also proposed in this paper, which is convenient, friendly and fast to use. Furthermore, dynamic color look-up tables are proposed by augmenting the colors of the reference image to avoid detail loss. In addition, the dynamic color look-up tables are also extend the range of the reference images, which also add the color blocks. The experimental results show that D-DLT method outperforms the traditional color transfer methods in color mapping and detail reconstruction. In our future work, we will apply D-DLT method to video color transfer and attempt to realize the better color transfer results with machine learning methods.

Acknowledgments

This work was supported by National Key Research and Development Program of China under Grant No.2018YFB10046 and No. 2017YFB0504202, the Fundamental Research Funds for the Central Universities, China under Grant No. 2042018kf0229, National Natural Science Foundation of China under Grant Nos. 41671441 and 41771385.

Table 3
The result of objective quality assessment.

Group	PSNR				SSIM			
	Reinhard	PDF	Mairéad	D-DLT	Reinhard	PDF	Mairéad	D-DLT
1 $Salient--Salient$	25.3	24.8	31.3	31.7	0.95	0.95	0.97	0.97
2 $Salient--NonSalient$	12.6	12.7	16.3	15.6	0.75	0.78	0.89	0.87
3 $NonSalient--NonSalient$	22.9	22.4	23.9	24.5	0.89	0.90	0.93	0.95
4 $NonSalient--NonSalient$	18.0	16.5	19.4	40.5	0.94	0.91	0.90	0.99
Group	GSSIM				NIMA			
	Reinhard	PDF	Mairéad	D-DLT	Reinhard	PDF	Mairéad	D-DLT
1 $Salient--Salient$	0.66	0.65	0.72	0.73	4.83	4.75	5.54	5.75
2 $Salient--NonSalient$	0.60	0.66	0.75	0.72	3.66	3.89	4.95	5.06
3 $NonSalient--NonSalient$	0.72	0.74	0.75	0.78	4.74	4.72	4.95	4.92
4 $NonSalient--NonSalient$	0.71	0.65	0.79	0.95	4.21	4.03	5.58	5.94

References

[1] E. Reinhard, M. Ashikhmin, B. Gooch, P. Shirley, Color transfer between images, IEEE Comput. Graph. Appl. (2001) 34–41, http://dx.doi.org/10.1109/38.946629.

[2] X. Xiao, L. Ma, Color transfer in correlated color space, ACM Int. Conf. Virtual Reality Contin. Appl. (2006) 305–309, http://dx.doi.org/10.1145/1128923.1128974.

[3] Y.W. Tai, J. Jia, C.K. Tang, Local color transfer via probabilistic segmentation by expectation-maximization, IEEE Conf. Comput. Vis. Pattern Recognit. (2005) 747–754, http://dx.doi.org/10.1109/CVPR.2005.215.

[4] M. Grogan, R. Dahyot, L2 divergence for robust colour transfer, Comput. Vis. Image Underst. 181 (2019) 39–49, http://dx.doi.org/10.1016/j.cviu.2019.02.002.

[5] W. Dong, G. Bao, X. Zhang, J.C. Paul, Fast local color transfer via dominant colors mapping, ACM Siggraph Asia Sketches (2010) 1–2, http://dx.doi.org/10.1145/1899950.1899996.

[6] Y. Hwang, J.Y. Lee, I.S. Kweon, S.J. Kim, Color transfer using probabilistic moving least squares, IEEE Conf. Comput. Vis. Pattern Recognit. (2014) 3342–3349, http://dx.doi.org/10.1109/CVPR.2014.427.

[7] L.Q. Cao, L. Jiao, Z.J. Li, T.T. Liu, Y.F. Zhong, Grayscale image colorization using an adaptive weighted average method, J. Imaging Sci. Technol. (2017) 60502–1–60502–10(10), http://dx.doi.org/10.2352/J.ImagingSci.Technol.2017.61.6.060502.

[8] Q.F. Chen, V.J. Xu, Fast image processing with fully-convolutional networks, IEEE Int. Conf. Comput. Vis. (2017) 2497–2506, http://dx.doi.org/10.1109/ICCV.2017.273.

[9] N. Bonneel, J. Rabin, G. Peyr, H. Pfiste, Sliced and radon wasserstein barycenters of measures, IEEE Int. Conf. Comput. Vis. 51 (2015) 22–45, http://dx.doi.org/10.1007/s10851-014-0506-3.

[10] M. Grogan, R. Dahyot, A. Smolic, User Interaction for Image Recolouring using L2, in: Proceedings of the 14th European Conference on Visual Media Production, 2017, http://dx.doi.org/10.1145/3150165.3150171.

[11] M.M. Cheng, G.X. Zhang, N.J. Mitra, Global contrast based salient region detection, IEEE Conf. Comput. Vis. Pattern Recognit. (2011) 409–416, http://dx.doi.org/10.1109/CVPR.2011.5995344.

[12] R. Achanta, S. Susstrunk, Superpixels and polygons using simple non-iterative clustering, IEEE Conf. Comput. Vis. Pattern Recognit. (2017) 500–510, http://dx.doi.org/10.1109/CVPR.2017.520.

[13] L. Neumann, A. Neumann, Color style transfer techniques using hue, lightness and saturation histogram matching, Eurographics Conf. Comput. Aesthet. Graph. Vis. Imaging (2005) 111–122, http://dx.doi.org/10.2312/COMPAESTH/COMPAESTH05/111-122.

[14] F. Pitie, A.C. Kokaram, R. Dahyot, N-dimensional probablility density function transfer and its application to color transfer, IEEE Int. Conf. Comput. Vis. (2005) 1434–1439, http://dx.doi.org/10.1109/ICCV.2005.166.

[15] F. Pitie, A.C. Kokaram, R. Dahyot, Automated color grading using color distribution transfer, IEEE Int. Conf. Comput. Vis. (2007) 123–137, http://dx.doi.org/10.1016/j.cviu.2006.11.011.

[16] Y. Chang, S. Saito, K. Uchikawa, M. Nakajima, Example-based color stylization of images, ACM Trans. Appl. Percept. (2005) 322–345, http://dx.doi.org/10.1145/1077399.1077408.

[17] F. Wu, W. Dong, Y. Kong, X. Mei, J.C. Paul, X. Zhang, Content-based colour transfer, Comput. Graph. Forum 32 (2013) 190–203, http://dx.doi.org/10.1111/cgf.12008.

[18] L. Gatys, A. Ecker, M. Bethge, A neural algorithm of artistic style, arXiv:1508.06576.

[19] F. Luan, S. Paris, E. Shechtman, K. Bala, Deep photo style transfer, IEEE Conf. Comput. Vis. Pattern Recognit. (2017) 4990–4998, http://dx.doi.org/10.1109/CVPR.2017.740.

[20] Y.J. Li, M.Y. Liu, X.T. Li, M.H. Yang, J. Kautz, A closed-form solution to photorealistic image stylization, Eur. Conf. Comput. Vis. (2018) 453–468.

[21] C.Q. Xia, J. Li, X. W, What is and what is not a salient object? learning salient object detector by ensembling linear exemplar regressors, IEEE Conf. Comput. Vis. Pattern Recognit. (2017) 4142–4150, http://dx.doi.org/10.1109/CVPR.2017.468.

[22] D.P. Fan, M.M. Cheng, J.J. Liu, Salient objects in clutter: Bringing salient object detection to the foreground, IEEE Eur. Conf. Comput. Vis. (2018) 186–202.

[23] C. Yang, L. Zhang, H. Lu. E.P, Saliency detection via graph-based manifold ranking, IEEE Conf. Comput. Vis. Pattern Recognit. (2013) 3166–3173, http://dx.doi.org/10.1109/CVPR.2013.407.

[24] M. Grogan, M. Prasad, R. Dahyot, L2 registration for colour transfer, Eur. Signal Process. Conf. (2015) http://dx.doi.org/10.1109/EUSIPCO.2015.7362799.

[25] Z. Su, K. Zeng, L. Liu, B. Li, X. Luo, Corruptive artifacts suppression for example-based color transfer, IEEE Trans. Multimed. (2014) 988–999, http://dx.doi.org/10.1109/TMM.2014.2305914.

[26] L. He, H. Qi, R. Zaretzki, Image color transfer to evoke different emotions based on color combinations, Signal, Image Video Process. (2014) 1965–1973, http://dx.doi.org/10.1007/s11760-014-0691-y.

[27] M. Carnec, P.L. Callet, D. Barba, Objective quality assessment of color images based on a generic perceptual reduced reference, Signal Process. Image Commun. (2018) 239–256, http://dx.doi.org/10.1016/j.image.2008.02.003.

[28] Z. Wang, A.C. Bovik, H.R. Sheikh, E.P. Simoncelli, Image quality assessment: From error visibility to structural similarity, IEEE Trans. Image Process. (2003) 600–612, http://dx.doi.org/10.1109/TIP.2003.819861.

[29] G.H. Chen, C.L. Yang, S.L. Xie, Gradient-based structural similarity for image quality assessment, IEEE Int. Conf. Image Process. (2006) http://dx.doi.org/10.1109/ICASSP.2006.1660497.

[30] H. Talebi, P. Milanfar, NIMA: Neural image assessment, IEEE Trans. Image Process. (2017) 3998–4011, http://dx.doi.org/10.1109/TIP.2018.2831899.