A Hue Correction Scheme Based on Constant-Hue Plane for Color Image Enhancement

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***Abstract*—In this paper, we propose a novel hue correction scheme based on constant-hue plane in the RGB color space for color image enhancement. A number of hue-preserving image enhancement methods have already been proposed. Although these methods can preserve hue, these methods cannot be applied to the state-of-the-art enhancement methods such as deep-learning based ones. We therefore generalize a hue-preserving method based on the constant-hue plane in this paper. This generalization derives our novel hue correction scheme. In the proposed scheme, any existing image enhancement method including deep-learning based ones can be used to enhance images. The hue distortion due to the enhancement is then removed by replacing the maximally saturated colors of an enhanced image with those of the corresponding input one. Experimental results show that the proposed scheme is effective to suppress the hue distortion due to two color enhancement methods including a deep-learning based one. Furthermore, objective quality evaluations demonstrate that the proposed scheme can maintain the performance of image enhancement methods.**

I. Introduction

Single-image enhancement is one of the most typical image processing techniques. The purpose of enhancing images is to show hidden details in such images. Various kinds of research on single-image enhancement have so far been reported [1]–[6]. Among methods for enhancing images, histogram equalization (HE) has received the most attention because of its intuitive implementation quality and high efficiency. It aims to derive a mapping function such that the entropy of a distribution of output luminance values can be maximized. Another way for enhancing images is to use the Retinex theory [7]. Retinex-based methods [4], [5] decompose images into reflectance and illumination, and then enhance images by manipulating illumination. However, Most HE- and Retinex-based only focus on enhancing the luminance contrast, so color contrasts will not be improved.

To enhance color contrasts, numerous color image enhancement methods have been developed [8]–[15]. A traditional approach for enhancing color images is 3-D HE that is an extension of normal 1-D HE [8], [10], [11]. In this approach, an image is enhanced so that a 3-D histogram defined on RGB color space is uniformly distributed. Recent work has demonstrated great progress by using a data-driven approach in preference to analytical approaches such as HE [13]–[15]. Those data-driven approaches utilize pairs of high- and low-quality images to train deep neural networks, and the trained networks can be used to enhance color images. However, enhancing color images will cause colors to be distorted. Although hue-preserving image enhancement methods have also been studied to avoid the color distortion [9], [10], [12], [16], these methods cannot be applied to the state-of-the-art enhancement algorithms such as deep-learning based ones since they were designed for specific enhancement algorithms.

Thus, in this paper, we generalize a hue-preserving method [12], which is based on constant-hue plane in the RGB color space, to any image enhancement method. This generalization derives our novel hue correction scheme for color image enhancement. The proposed scheme can remove hue difference between an input image and the corresponding enhanced image by replacing the maximally saturated colors on the constant-hue planes of the enhanced image with those of the input image. In addition, the hue correction can be carried out without color gamut problems. The proposed scheme is applicable to any image processing method including deep-learning based ones.

We evaluate the effectiveness of the proposed hue correction scheme in terms of the hue distortion and the quality of enhanced images, by a number of simulations. In the simulations, four objective metrics, the maximally saturated color similarity, the hue difference in CIEDE2000, discrete entropy and statistical naturalness, are utilized for the evaluation. Experimental results show that the proposed scheme can correct hue distortion due to image enhancement methods including a deep-learning based one. Furthermore, it is also confirmed that the proposed scheme can maintain the performance of image enhancement methods.

II. Background

In this paper, we generalize a hue-preserving method that is on the basis of constant-hue plane in the RGB color space [12]. For this reason, the constant-hue plane and the enhanced method is summarized here.

A. Constant-Hue Plane

Each pixel of RGB color image can be represented as $\boldsymbol{x} \in [0,1]^3$, where the R, G, and B components of the pixel $\boldsymbol{x}$ are written as x_r, x_g and x_b, respectively. In the RGB color space, a set of pixels which has the same hue forms a plane, called constant-hue plane, as shown in Fig. 1. The shape of each constant-hue plane is a triangle whose vertices correspond to white $\boldsymbol{w} = (1,1,1)$, black $\boldsymbol{k} = (0,0,0)$, and a maximally saturated color $\boldsymbol{c}$ [12], [17]. The maximally saturated color $\boldsymbol{c} = (c_r, c_g, c_b)$, which has the same hue as that of $\boldsymbol{x}$, is calculated

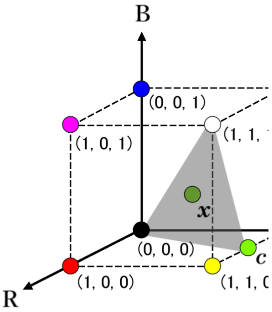


Fig. 1. Conceptual diagram of RGB color space. (
hue plane for pixel value $\boldsymbol{x}$

by

$$c_r = \frac{x_r - \min(\boldsymbol{x})}{\max(\boldsymbol{x}) - \min(\boldsymbol{x})},$$
$$c_g = \frac{x_g - \min(\boldsymbol{x})}{\max(\boldsymbol{x}) - \min(\boldsymbol{x})},$$
$$c_b = \frac{x_b - \min(\boldsymbol{x})}{\max(\boldsymbol{x}) - \min(\boldsymbol{x})},$$

where $\max(\cdot)$ and $\min(\cdot)$ are functions that return the maximum and minimum elements of the pixel $\boldsymbol{x}$, respectively.

On the constant hue plane, the pixel $\boldsymbol{x}$ can be represented as a linear combination as

$$\boldsymbol{x} = a_w \boldsymbol{w} + a_k \boldsymbol{k} + a_c \boldsymbol{c}, \tag{2}$$

where

$$\begin{aligned} a_w &= \min(\boldsymbol{x}), \\ a_c &= \max(\boldsymbol{x}) - \min(\boldsymbol{x}), \\ a_k &= 1 - \max(\boldsymbol{x}). \end{aligned} \tag{3}$$

Since $\boldsymbol{x}$ is an interior point on the plane spanned by $\boldsymbol{w}, \boldsymbol{k}$ and $\boldsymbol{c}$, the following equations hold.

$$a_w + a_k + a_c = 1, \tag{4}$$

$$0 \leq a_w, a_k, a_c \leq 1. \tag{5}$$

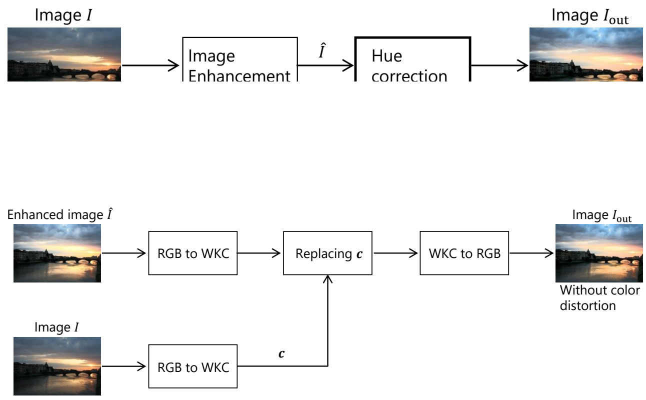
Hereinafter, we call this color space, which is described by using (a_w, a_k, a_c) and $(\boldsymbol{w}, \boldsymbol{k}, \boldsymbol{c})$, "WKC color space."

B. Image Enhancement Based on Constant-Hue Plane

After mapping RGB pixel values into the WKC color space, the method [12] independently enhance coefficients a_w, a_k, and a_c by an HE based algorithm:

$$\begin{aligned} a'_w &= G^{-1}_{w,\sigma_w}(F_w(a_w)), \\ a'_k &= G^{-1}_{k,\sigma_k}(F_k(a_k)), \\ a'_c &= G^{-1}_{c,\sigma_c}(F_c(a_c)), \end{aligned} \tag{6}$$

F_w, F_k and F_c denote cumulative distribution functions of a_w, a_k, and a_c, respectively. Also, $G^{-1}_{w,\sigma_W}, G^{-1}_{k,\sigma_k}$ and G^{-1}_{c,σ_c} indicate the inverse of smoothed cumulative distribution functions of a_w, a_k, and a_c, respectively. This enhancement does not cause hue distortion since the maximally saturated colors $\boldsymbol{c}$ are unchanged. However, this method have a limited application due to its specific enhancement algorithm in eq. (6). For this reason, we make the method applicable to any existing image enhancement method including deep-learning based ones.



(b) Hue correction procedure

Fig. 2. Proposed hue correction scheme

III. Proposed Hue Correction Scheme

Figure 2 shows an overview of our hue correction scheme for color image enhancement.

In the proposed scheme, we first enhance an input image I by using any existing image enhancement method. This enhancement will cause hue-distortion in the enhanced image $\hat{I}$ and change the maximally saturated colors $\hat{\boldsymbol{c}}$ of $\hat{I}$. For this reason, hue correction is then carried out by replacing $\hat{\boldsymbol{c}}$ with $\boldsymbol{c}$ of I. The use of the hue correction enables us to match the maximally saturated colors before and after the enhancement. In addition, because coefficients (a_w, a_k, a_c) are preserved in the hue-correction, the performance of image enhancement is maintained.

A. Proposed Procedure

The procedure of out hue correction scheme is shown as follows.

1) Obtain image $\hat{I}$ by applying an image processing method to input image I.
2) Map pixel values in I and $\hat{I}$ into the WKC color space, in accordance with eqs. (1) and (3). Then, obtain (a_w, a_k, a_c) and $(\boldsymbol{w}, \boldsymbol{k}, \boldsymbol{c})$ for I, and $(\hat{a}_w, \hat{a}_k, \hat{a}_c)$ and $(\boldsymbol{w}, \boldsymbol{k}, \hat{\boldsymbol{c}})$ for $\hat{I}$.
3) Replace $\hat{\boldsymbol{c}}$ with $\boldsymbol{c}$.
4) Calculate output RGB colors by using $(\hat{a}_w, \hat{a}_k, \hat{a}_c)$ and $(\boldsymbol{w}, \boldsymbol{k}, \boldsymbol{c})$, in accordance with eq. (2), and obtain output image I_{out}.

IV. Simulation

We evaluated the effectiveness of the proposed scheme by using four objective metrics including two color difference formulae.

A. Simulation Conditions

In this simulation, we applied the proposed scheme to two color image enhancement methods, in order to confirm that the proposed scheme is applicable to various color image enhancement methods. The two methods are shown as follows:

1) A method that applying HE to R, G, and B components,independently (Channel-wise HE).
2) Deep-learning based image enhancement method proposed by Kinoshita et al. [15].

In addition, the proposed scheme was compared with two hue-perserving image enhancement methods: Naik's method [9] and Ueda's method [12].

Eight input images selected from the dataset [18] were used for the simulation. The hue distortion after enhancement was evaluated by using the cosine similarity between maximally saturated colors and the hue difference $\Delta H'$ of the CIEDE2000 [19], where corresponding input images were utilized as reference images. Furthermore, the quality of enhanced images was also evaluated by using two objective metrics: Statistical naturalness used in tone mapped image quality index (TMQI) [20] and discrete entropy.

TMQI represents the quality of an image tone-mapped from a high dynamic range (HDR) image; the index incorporates structural fidelity and statistical naturalness. Statistical naturalness is calculated without any reference images, although structural fidelity needs an HDR image as a reference. Since the process of photographing is similar to tone mapping, TMQI is also useful for evaluating photographs. In this simulation, we used only statistical naturalness for the evaluation because structural fidelity cannot be calculated without HDR images. Discrete entropy represents the amount of information in an image.

B. Results

Tables I and II show the similarity of maximally saturated colors and the hue difference $\Delta H'$, between input and enhanced images. Here, the similarity and the hue difference were calculated as the absolute average of the cosine similarity and $\Delta H'$ for all pixels. For the similarity $\in [0, 1]$, a larger value means higher hue-similarity. In contrast, a lower value means a less hue difference for the $\Delta H'$. A comparison between traditional methods and corresponding proposed schemes illustrates that the use of the proposed method suppressed the hue distortion for all cases. Under the use of the channel-wise HE, the similarities between maximally saturated colors were not 1. This is because the channel-wise HE often maps colored pixels into gray ones. Once colored pixels become gray, the propose scheme cannot correct those color since a_c in eq. (3) for a gray pixel is 0.

Tables III and IV illustrate scores for discrete entropy and statistical naturalness, respectively. For each score (discrete entropy $\in [0, 8]$ and statistical naturalness $\in [0, 1]$), a larger value means higher quality. As shown in Tables III and IV, the proposed scheme provided almost the same scores as corresponding enhancement methods for the two metrics. Therefore, the proposed scheme can maintain the performance of image enhancement. This result is also confirmed from hue-corrected images as shown in Fig. 3.

TABLE I
COSINE SIMILARITY BETWEEN MAXIMALLY SATURATED COLORS

Scene	Input	Naik [9]	Ueda [12]	Channel-wise HE		Kinoshita [15]	
				Conv.	Prop.	Conv.	Prop.
Arno	1	1.000	1.000	0.753	**0.939**	0.945	**1.000**
Cave	1	1.000	1.000	0.260	**0.836**	0.469	**1.000**
Chinese garden	1	1.000	1.000	0.586	**0.972**	0.918	**1.000**
Estate rsa	1	1.000	1.000	0.828	**0.955**	0.949	**1.000**
Kluki	1	1.000	1.000	0.715	**0.956**	0.863	**1.000**
Laurenziana	1	1.000	1.000	0.643	**0.980**	0.907	**1.000**
Mountains	1	1.000	1.000	0.684	**0.956**	0.977	**1.000**
Ostrow tumski	1	1.000	1.000	0.719	**0.914**	0.891	**1.000**
Average	1	1.000	1.000	0.648	**0.938**	0.865	**1.000**

TABLE II
HUE DIFFERENCE $\Delta H'$

Scene	Input	Naik [9]	Ueda [12]	Channel-wise HE		Kinoshita [15]	
				Conv.	Prop.	Conv.	Prop.
Arno	0	0.144	0.726	6.699	**0.256**	1.384	**0.201**
Cave	0	0.041	0.238	0.532	**0.047**	0.734	**0.076**
Chinese garden	0	0.355	0.719	6.755	**0.484**	1.406	**0.354**
Estate rsa	0	0.441	0.607	7.007	**0.548**	1.252	**0.362**
Kluki	0	0.476	0.590	9.186	**0.664**	1.455	**0.669**
Laurenziana	0	0.200	0.609	6.875	**0.265**	1.412	**0.220**
Mountains	0	0.006	1.375	6.347	**0.344**	1.354	**0.150**
Ostrow tumski	0	0.082	0.786	3.899	**0.214**	1.288	**0.215**
Average	0	0.218	0.706	5.913	**0.353**	1.286	**0.281**

TABLE III
DISCRETE ENTROPY

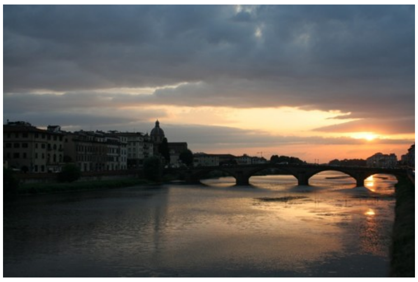
Scene	Input	Naik [9]	Ueda [12]	Channel-wise HE		Kinoshita [15]	
				Conv.	Prop.	Conv.	Prop.
Arno	6.441	6.844	6.955	**7.390**	7.372	6.561	**6.598**
Cave	2.656	4.416	5.157	5.083	**5.141**	**6.686**	6.551
Chinese garden	5.767	7.262	7.094	7.344	**7.462**	**6.768**	6.729
Estate rsa	5.898	6.931	6.756	7.310	**7.378**	**6.389**	6.383
Kluki	7.104	7.335	7.290	6.989	**7.192**	**6.878**	6.843
Laurenziana	6.706	7.318	7.276	7.185	**7.211**	**6.792**	6.714
Mountains	7.295	6.889	7.579	7.394	**7.404**	5.636	**5.691**
Ostrow tumski	6.517	6.869	7.211	7.371	**7.438**	6.855	**6.922**
Average	6.048	6.733	6.915	7.008	**7.075**	**6.570**	6.554

TABLE IV
STATISTICAL NATURALNESS

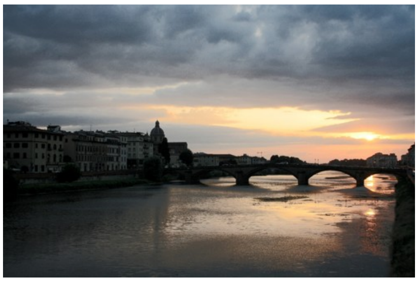
Scene	Input	Naik [9]	Ueda [12]	Channel-wise HE		Kinoshita [15]	
				Conv.	Prop.	Conv.	Prop.
Arno	0.200	0.419	0.373	**0.560**	0.526	0.153	**0.167**
Cave	0.005	0.146	0.480	**0.650**	0.648	**0.938**	**0.938**
Chinese garden	0.479	0.520	0.893	**0.489**	0.433	**0.987**	0.985
Estate rsa	0.352	0.961	0.866	0.725	**0.726**	**0.427**	0.426
Kluki	0.815	0.738	0.716	**0.894**	0.857	**0.464**	0.453
Laurenziana	0.988	0.720	0.863	**0.905**	0.875	0.677	**0.687**
Mountains	0.249	0.849	0.738	0.909	**0.921**	0.103	**0.105**
Ostrow tumski	0.207	0.281	0.329	**0.395**	0.381	0.209	**0.231**
Average	0.412	0.579	0.657	**0.691**	0.671	0.495	**0.499**

V. CONCLUSIONS

In this paper, we have proposed a novel hue correction scheme based on constant-hue plane in the RGB color space, for color image enhancement. To derive the proposed scheme,

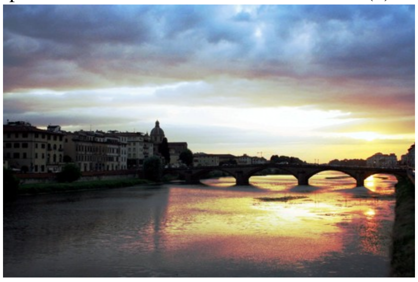


(a) Input

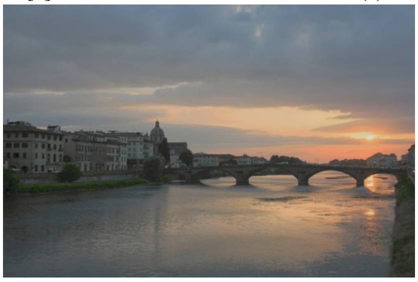


(b) Naik [9]

(c) Ueda [12]

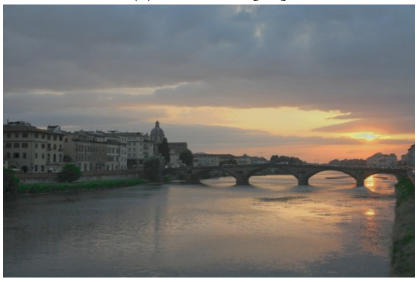


(d) HE



(e) Kinoshita [15]

(f) Proposed (Channel-wise HE)



(g) Proposed (Kinoshita)

Fig. 3. Results of hue correction (Arno)

we have generalized a hue-preserving method based on the constant-hue plane. In the proposed scheme, any existing image enhancement method including deep-learning based ones can be used to enhance images. The hue distortion due to the enhancement is then removed by replacing the maximally saturated colors of an enhanced image with those of the corresponding input one. Experimental results showed that the proposed scheme can suppress the hue distortion due to two color enhancement methods including a deep-learning based one, by using the cosine similarity of maximally saturated colors and the hue difference in CIEDE2000 for the evaluation. Furthermore, objective quality evaluations by using statistical naturalness and discrete entropy demonstrated that the proposed scheme can maintain the performance of image enhancement methods. In future work, we will apply the proposed scheme to other image enhancement methods and evaluate the effectiveness of the proposed one in detail, by using a large number of test images.

ACKNOWLEDGMENT

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