

Color Image Enhancement for Dichromats by Additive Image Noise

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Abstract: We present a method for enhancing the color recognition ability of dichromats. Whereas trichromats (usual people) recognize all colors in a 3-D color space, dichromats only recognize colors on a degenerate 2-D space in it. Our method compensates for the lost information along the degenerate direction in the color space with the amount of noise in the image. Dichromats recognize the lost color information as noisy textures, while the original color information for trichromats is preserved. Our method is applicable not only to artificial figures such as graphs but also to natural photographs. We show the effectiveness of our method by experiments.

Keywords: color image enhancement, color recognition ability, dichromats, additive image noise, color universal design

1. Introduction

“Color Universal Design (CUD)” is a user-oriented design system for removing the impediment in color design [1]. For example, by designing the colors of a railway transportation map or a road map according to CUD, colorblind people can easily find their own road or line. In another case, if he/she operates the control panel of a machine with color design according to CUD, he/she can easily and rapidly find unusual and/or dangerous occurrences of the machine. However, CUD does not impede normal people. So, CUD can improve the quality of life for color-blind people.

Trichromats (normal people) have three types of cone cells, which are called L-cone, M-cone, and S-cone, in the retina of their eyes. These cone cells detect different wave lengths of light. So, they recognize colors in 3-D space by the three types of cells. On the other hand, dichromats have two types of cone cells: S- and M-cones (protanopes), S- and L-cones (deutanopes), or M- and L-cones (tritanopes). They recognize colors in 2-D space by the two types of cone cells. So, the dimension of the color space is different for trichromats and dichromats and the color space of dichromats is degenerate compared with that of trichromats. So, for example, protanopes and deutanopes cannot distinguish a red apple and green apple (the center images in Fig. 1). If we can add a new axis into the 2-D dichromatic color space, dichromats can distinguish such colors by the value in the added axis. Then, as CUD, we can improve the quality of life for dichromats.

In this paper, we present a method for enhancing the color

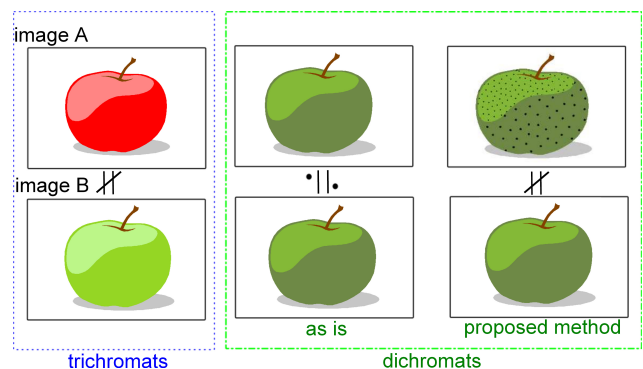


Fig. 1 Overview of the proposed method.

recognition ability of dichromats. To do this, we focus on image noise, which exists naturally in most images. Our method compensates for the lost information along the degenerate direction in the color space with the amount of noise in the image. Dichromats recognize the lost color information as noisy textures, preserving the original color information for trichromats. Our method is applicable not only to artificial figures such as graphs but also to natural photographs. We show the effectiveness of our method by experiments.

2. Related Work

Rasche et al. [4] proposed a conversion method from color images to grayscale. Their method preserves not only image information such as contrast but also important luminance gradients in the image. They formulate the conversion as an optimization problem, which is solved by constrained multiscale dimensional scaling. Their method can also be applied for re-coloring for dichromats. Gooch et al. [2] proposed an improved conversion method from color images to grayscale ones. They adopt saliency in an image and optimize luminance distances and chrominance distances between neighbor pixels. By these methods, the re-

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sultant images are in grayscale, so trichromats cannot recognize color information from them.

Nakauchi and Onouchi [3] proposed a detection and modification method of confusing color combinations for dichromats. Their method can only convert the region of confusing color combinations according to CUD. However, trichromats feel a difference because the colors of the image have been changed after the modification.

Shimamura et al. [5] proposed a method that imposes hatching into artificial figures such as graphs. Their method can improve the distinction ability in graphs, however, their method cannot be applied to natural photographs.

3. Proposed Method

3.1 Overview of the Proposed Method

We propose a new image enhancing method for dichromats to be able to recognize color changes in their lost direction. In our method, instead of re-coloring or imposing hatching into an image, we add image noise into the image. We use a noise axis as the “non-existent third axis” for enhancing the 2-D color space of dichromats. This is illustrated in Fig. 1. Whereas trichromats can easily distinguish between a red apple and a green apple (the left column), dichromats cannot distinguish between two such apples (the center column). However, if we add image noise into the red apple region, dichromats can distinguish between two apples by the noisy texture (the right column).

3.2 Viénot’s Model

First, we need a model for dichromats’ vision. Here, we use the model proposed by Viénot et al. [6]. This model is based upon their experimental result and its expression is a simple transformation in the *LMS* system. By this model, the linear transformation between the normal color and the dichromats color domains is represented by the following equations: for protanopes who have M-cone and S-cone cells, the transformation is represented by

$$\begin{pmatrix} L_p \\ M_p \\ S_p \end{pmatrix} = \begin{pmatrix} 0 & 2.02344 & -2.52581 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} L \\ M \\ S \end{pmatrix}, \quad (1)$$

and for deuteranopes who have L-cone and S-cone cells by

$$\begin{pmatrix} L_d \\ M_d \\ S_d \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0.494207 & 0 & 1.24827 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} L \\ M \\ S \end{pmatrix}. \quad (2)$$

Here, L , M , and S are the stimuli for the cone cells of trichromats; L_p , M_p , and S_p for those of protanopes; L_d , M_d , and S_d for those of deuteranopes. This model represents that protanopes feel a pseudo stimulus L_p in spite of no L-cone cells. Deuteranopes also feel a pseudo stimulus M_d in spite of no M-cone cells. We focus on the difference $L - L_p$ and $M - M_d$, which are the difference of the stimuli for trichromats and dichromats. In the following, we consider dichromats of protanopes. However, we can use the same approach for the dichromats of deuteranopes.

3.3 Models of Additive Image Noise

Generally, image noise does not depend on the position and/or

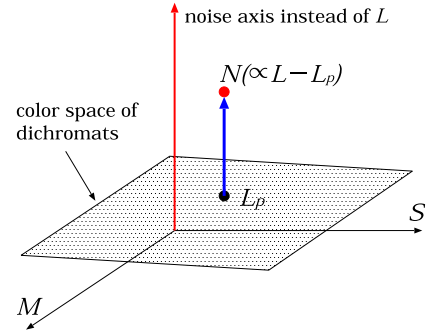


Fig. 2 Color space of dichromats and its enhancement.

values of a pixel in an image. So, we can assume that “the noise axis” is perpendicular to any axes in color space, such as (R, G, B) , (L, M, S) , and so on. Based on these characteristics of image noise, we can enhance the 2-D color space of dichromats into a 3-D space by adding the image noise axis as illustrated in Fig. 2.

In order to use image noise as an axis, we must control the image noise. In other words, we need a model of the image noise. For our purpose, the additive image noise is suitable because it is seen naturally in an image by all people. So, we generate an image noise of which the probability is according to the absolute difference $|L - L_p|$ and of which the magnitude is Gaussian with a constant mean and a constant standard deviation. By adopting such a noise model, if $|L - L_p|$ is large in a pixel, the noise at the pixel occurs with a high probability.

In this paper, we use the following two types of probabilities of noise generation.

$$p = \frac{|L - L_p - c|}{s}, \quad (3)$$

$$p_{\text{off}} = \frac{|L - L_p|}{s_{\text{off}}}. \quad (4)$$

Here, c , s , s_{off} are constants for normalizing the range of p and p_{off} into $[0, 1]$. In this paper, we use $c = 0.1477$, $s = 0.255$, and $s_{\text{off}} = 0.1478$, respectively. These parameters are obtained by computing the range of the color space. In the above equations, the probability p is without the consideration about the offset in L , while p_{off} is with the consideration about the offset. If we use the offset values, no image noise is added when $|L - L_p| = 0$. There are many models for representing a color space, we use the *HSI* model and consider to adding noise into the intensity and the hue in the color space. We can represent the “salt and pepper” noise in the image by using the intensity noise. We also think the hue noise is effective for dichromats because hue noise addition means color changes in the pixel. These noise models are represented by

$$\Delta I \sim N(0, \sigma_I), \quad (5)$$

$$\Delta H \sim N(0, \sigma_H), \quad (6)$$

where σ_I and σ_H are the standard deviations for the intensity and hue values, respectively. Once, at a pixel, ΔI or ΔH is generated by Eq. (5) or (6), with probability p or p_{off} represented by Eq. (3) or (4), then, the new intensity I and hue H of the pixel are computed by

$$I = I_o + \Delta I + I_{\text{off}}, \quad (7)$$

$$H = (H_o + \Delta H + H_{\text{off}}) \bmod 360, \quad (8)$$

where, I_o and H_o are the original intensity and hue in the pixel. In this paper, we use either intensity noise or hue noise. Here, I_{off} and H_{off} are 0 when the probability (3) is used, while they are constant offsets ($\neq 0$) when the probability (4) is used. Consequently, we use two types of noise probability models and two types of noise models.

The advantage of using such noise models is as follows:

- We can represent smooth color change regions like gradation. This means our method can be applied to natural photographs.
- Dichromats can distinguish colors by noisy textures, while trichromats do not feel the loss of color information.

4. Experiments

We conducted two experiments to show the effectiveness of the proposed method: subjective evaluation for gradation image; application to natural photographs.

4.1 Subjective Evaluation

We first conducted subjective evaluation of the images enhanced by the proposed method. The condition and environment of the experiment are shown in **Table 1**. The subjects evaluate whether they can recognize gradually changes in an image by Absolute Category Rating (ACR): Excellent(5), Good(4), Fair(3), Poor(2), and Bad(1). Then, we calculate the average of the evaluation values in each image from all subjects. In this experiment, all subjects are trichromats because we want to evaluate not only the effect of noise addition for dichromats but also that for trichro-

mati. Here, we use five types of gradation shown in **Fig. 3**, in which it is hard for dichromats to find color change. Using these gradation images, we added four noise patterns, which are intensity noise with/without offset and hue noise with/without offset, into the original gradation. The samples are shown in **Fig. 4** (a), which are obtained from the top image in Fig. 3. Figure 4 (b) shows simulated dichromatic images from Fig. 4 (a). The subjects look at an image among the original and noise added images (Fig. 4 (a)) and the dichromatic simulated images (Fig. 4 (b)). The dichromatic simulated images are computed using the Viénot

Table 1 Condition and environment.

term	spec. or value
monitor	EIZO Flexscan EV2335W
environment illuminance	840 [lx]
distance to the monitor	60 [cm]
# of subjects	21
evaluation	ACR 5
# of test images	50
	(5 gradations × 5 noise patterns × 2 color visions)

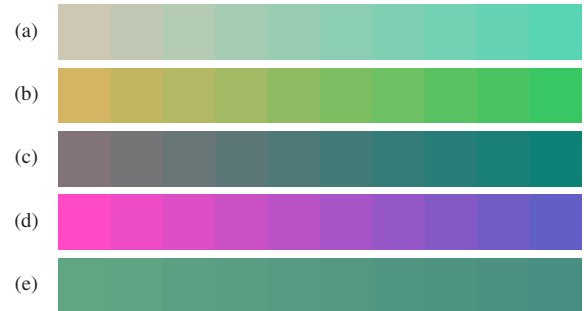


Fig. 3 Original five gradation images.

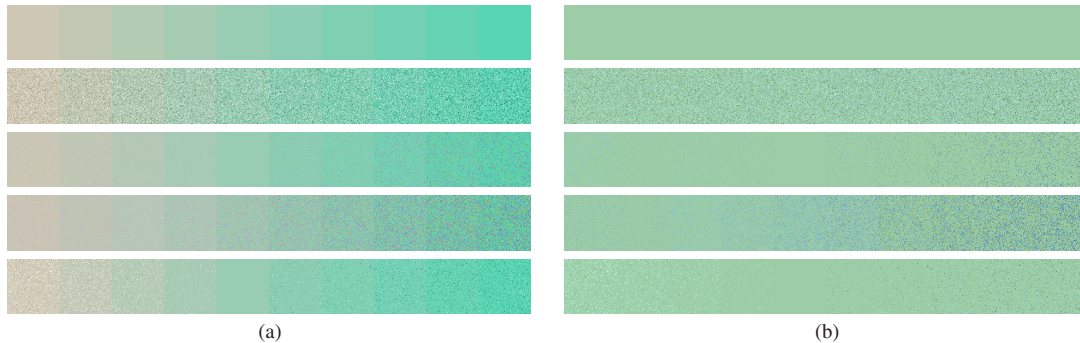


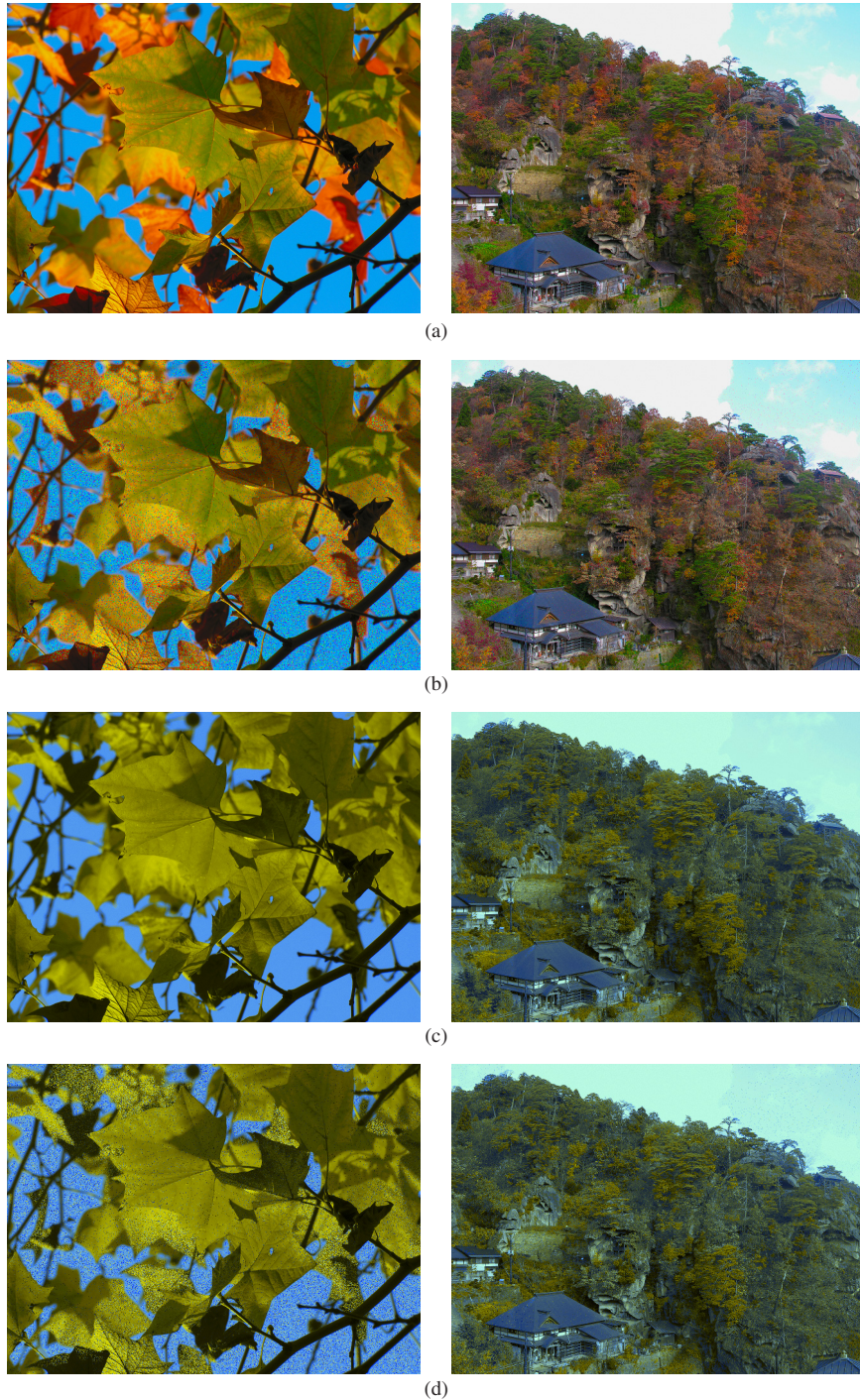
Fig. 4 Samples of gradation image with noise. (a) non-simulated images (trichromatic image). (b) dichromatic simulated images. From the top, original, noise in intensity without offset, noise in intensity with offset, noise in hue without offset, noise in hue with offset.

Table 2 Evaluation result.

image	dichromatic simulation	noise in intensity		noise in hue		noise-free (original)
		w/o offset	w offset	w/o offset	w offset	
(a)	no (=normal)	4.38	4.47	4.47	4.57	3.95
	yes	1.24	2.52	3.71	2.67	1.05
(b)	no (=normal)	4.33	4.28	4.29	4.57	4.71
	yes	2.00	2.67	1.86	2.85	1.04
(c)	no (=normal)	4.04	4.33	4.09	4.38	4.42
	yes	1.47	3.14	3.85	3.00	1.00
(d)	no (=normal)	4.85	4.71	4.38	4.66	4.70
	yes	1.33	3.04	2.24	4.42	1.00
(e)	no (=normal)	2.52	3.47	3.09	3.14	4.28
	yes	2.01	3.62	3.52	3.90	4.00

Table 3 Evaluation result (average).

dichromatic simulation	noise in intensity		noise in hue		noise-free (original)
	w/o offset	w offset	w/o offset	w offset	
no (normal)	4.02	4.25	4.06	4.26	4.41
yes	1.61	3.00	3.00	3.37	1.62


Fig. 5 Examples of natural photographs. (a) original images. (b) images with hue noise for trichromats. (c) original images for dichromats (dichromatic simulated images). (d) images with hue noise for dichromats (dichromatic simulated images).

model of Eq. (1).

In these experiments, we used the following standard deviation and offset values:

$$\sigma_I = \frac{40}{255}, \quad I_{\text{off}} = \begin{cases} +\frac{40}{255}, & \text{if } L < L_p, \\ -\frac{40}{255}, & \text{if } L > L_p, \end{cases}$$

$$\sigma_H = 80, \quad H_{\text{off}} = \begin{cases} +80, & \text{if } L < L_p, \\ -80, & \text{if } L > L_p, \end{cases}$$

which values were experimentally determined.

Figure 4 shows image examples for the subjective evaluation. The left column is the trichromatic images and the right column

is the simulated dichromatic images. The images in each row are

- first (top): original images,
- second: add the noise in intensity without offset value,
- third: add the noise in intensity with offset value,
- forth: add the noise in hue without offset value,
- fifth (bottom): add the noise in hue with offset value.

As we can see in Fig. 4, in the top image of column (a), a gradual change in color can be found, while in the top of column (b), a gradual change in color cannot be found. However, in the images from the second to fifth row, gradual changes can be found by noise texture. So, dichromats can recognize such color changes in the original images by the proposed image enhancing method.

The result of the evaluation is shown in **Table 2**. As we can see, via dichromatic simulation, while the scores of most of the original images are very low, the scores of the images enhanced by our method are mostly higher than those. This shows that the proposed method is effective. The total result of the evaluation is shown in **Table 3**. In the table, the noise in intensity without offset is the worst case in both, with and without dichromatic simulation cases. However, the scores of other noise models are higher than that of the noise-free original image with dichromatic simulation. This means that our method can improve the color distinction ability of dichromats. We can see the model “noise in hue with offset” is the best from these experiments. This result is very credible from the following:

- The intensity noise cannot change colors while the hue noise can change colors;
- Whereas the noise is always added even if $|L - L_p| = 0$ in the no offset models, the noise is suppressed in the offset models when $|L - L_p| = 0$.

4.2 Application to Natural Photographs

We next show several results of natural photographs. The image samples are shown in **Fig. 5**. In this figure, (a) shows original images, (b) shows images with additive image noise, (c) shows dichromatic simulated images of the original images, (d) shows dichromatic simulated images with additive image noise. In this case, we use the model of noise in hue with offset. From the example at the right column in Fig. 5, we can observe that the high noise density regions in the noise added images are the red regions in the original image. So, by comparison with the left images of (c) and (d), dichromats can see that noisy regions indicate a red coloring of leaves. However, we can also see this effect is dependent on the spacial frequency in the image and the resolution of the image. For example, in the right column in Fig. 5, we cannot find any difference between the right images of (c) and (d). So, we must improve the noise model for coping with this problem.

5. Conclusions

We have presented a method for enhancing the color recognition ability of dichromats by adding image noise. The proposed method imposes image noise into confusing color regions. Dichromats can distinguish colors by image noise in the confusing regions and trichromats feel almost the same as with the original image. So, our method is applicable not only to artificial

figures such as graphs but also to natural photographs. We have shown the effectiveness of our method by experiments. However, the proposed method is dependent on the resolution of the image and the spacial frequency in it.

In this paper, we assumed that the difference of cone response and the difference of color appearance have a linear relation. However, in reality, it is not true in general. So, we need to investigate this problem in the future. We also need to explore further better noise models for our purpose.

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