Color enhancement algorithm based on Daltonization and image fusion for improving the color visibility to color vision deficiencies and normal trichromats

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Abstract. In recent years, helping individuals with color vision deficiency to distinguish confusing colors in digital images, which is called Daltonization, is a hot topic. However, a number of Daltonization methods have a color reduction problem that causes unnatural image colors for normal color vision observers and those with anomalous trichromatic color vision deficiencies. A color-enhancing algorithm is proposed to make up for the shortage in color naturalness. Based on the conclusion in previous studies that colors confused in the same type of color blindness are approximately straight lines (called confusion lines) on the $u'v'$ chromaticity plane and all of the confusion lines intersect at the same point (called the confusion point), we propose a polar coordinate transformation based on intersection points of confusion lines, which can transform chromaticity information into perceptually sensitive and perceptually insensitive color blindness information. From the two color-blind sensitive information of the Daltonized image and the one color-blind insensitive information of the original image, the three-dimensional information can be combined to obtain an enhanced image. The enhanced image has a similar color appearance of the Daltonized image under the perspective of dichromats and has a more natural and colorful color appearance under the perspective of anomalous and normal trichromats. In addition, we propose a lightness modification to reduce lightness errors between the enhanced images and the Daltonized images. The quantitative evaluation shows that the method proposed is effective but sacrificing a small amount of color contrast of the Daltonized images. © *2020 SPIE and IS&T*
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1 Introduction

1.1 *Color Vision Deficiency*

Color is an important visual information and is the focus of many studies. In daily life, individuals with color vision deficiency (CVD) confuse some specific color pairs due to congenital defects. The prevalence of CVD is 8.002% in men and 0.44% in women.[1] According to the existing physiological theory, color perception in humans is related to three types of cones: L cones (sensitive to long-wavelength light), M cones (sensitive to medium-wavelength light), and S cones (sensitive to short-wavelength light). According to the different types of cone anomalies, CVD people can be divided into protanopes (protanomaly, disorder of L cones), deuteranopes (deuteranomaly, disorder of M cones), and tritanopes (tritanomaly, disorder of S cones).

1.2 *Simulation of Dichromatic Perspective*

In order to understand the perspective of dichromats, the results from the study on the unilateral dichromat (a special CVD patient with one eye having trichromatic color vision while the other has dichromatic vision) have led to an algorithm to simulate dichromatic color vision.[2,3] For a

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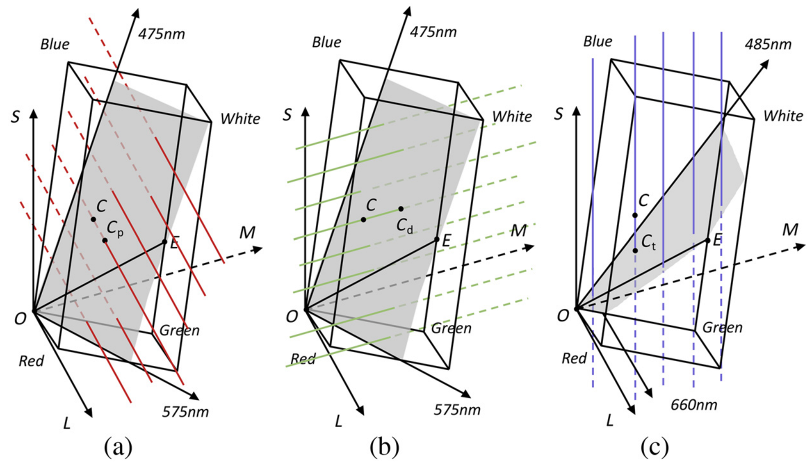


Fig. 1 Dichromatic perspective simulation model in an LMS color space. The gray area is the dichromatic color gamut represented by the LMS color space. (a) Projected along the *L* axis to the protanope gamut (gray area), (b) projected along the *M* axis to the deuteranope color gamut (gray area), and (c) projected along the *S* axis to the tritanope color gamut (gray area).

given color, Meyer and Greenberg[4] and Brettel et al.[5] simulated the dichromatic perception by projection. Based on the assumption that the appearance of neutral colors (white, gray, and black) in CVD does not change, Brettel et al.[5] proposed a model for simulating the dichromatic perspective in the LMS color space (the LMS color space is defined based on the response of L, M, and S cones). Brettel et al. define the color gamut of each type of dichromat and establishes a model of projecting the color perceived by trichromats into the dichromatic color gamut (the dichromatic color gamut can be represented as two half-planes, as shown in Fig. 1). Vienot et al.[6] proposed using the specific process presented by Brettel et al.[5] to simulate images perceived by dichromats on a monitor. Meanwhile, Machado et al.[7] used a two-stage model to translate the response curves of L, M, and S cones using different distances to simulate the color perception of dichromats or anomalous trichromats. Kotera[30] focuses on the spectral analysis and first clarified how the CVDs lose the spectral information and the reason behind the blindness and gave an optimal Daltonization solution based on "Matrix-R" theory.[32]

In this study, we use the simulation process proposed by Brettel's simulation model, and Vienot's specific process to simulate dichromatic color vision. The simulation model is shown in Fig. 1.

1.3 *Confusion Point of Dichromats*

Dichromatic viewers confuse colors that differ only in the intensity of the absent cone response.[8] In an LMS color space, confusion lines (colors considered to be the same color by color dichromats) are parallel, but in the CIE 1976 $u'v'$ chromaticity diagram (excluding the lightness dimension), they converge to a specific confusion point. Figure 2 shows the confusion lines and the confusion points for each type of dichromat.

1.4 *Daltonization*

Using existing simulations, a recoloring method adapted to the image content can be defined so that the CVD individual can see as much content as trichromatic observers. This type of method is called Daltonization, proposed for improving color visibility to CVDs mostly by enhancing confusion colors making them easier to distinguish. Daltonization methods can be divided into two categories: color gamut nonreduction Daltonization[9–15,31] and color gamut reduction Daltonization.[16–22]

The color gamut nonreduction Daltonization method does not reduce the color gamut of a display of images. Milic et al.[9] proposed a recoloring algorithm based on color clustering and the

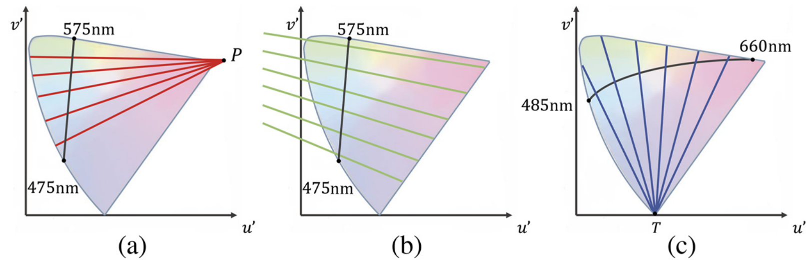


Fig. 2 Confusion lines and confusion point in a $u'v'$ chromaticity diagram. (a) For protanopes, the red lines are confusion lines, and (0.678,0.501)8 is the confusion point. (b) For deuteranopes, the green lines are confusion lines, and $(-1.217, 0.782)$ is the confusion point. (c) For tritanopes; the blue lines are confusion lines, and (0.257,0.0) is the confusion point.

confusion lines. The algorithm remaps the image color centers to be located on different confusion lines of the $u'v'$ chromaticity diagram, but the calculation amount of this clustering-based process is large, and the algorithm will fail if the confusing colors are in the same cluster. Halder[10] presented four different computationally efficient Daltonization algorithms, but the four algorithms were all based on different fixed color maps, and therefore, there was no guarantee that the Daltonized image would not produce new pairs of confusing colors. Hira et al.[11] introduced two techniques based on fixed color maps in HSV color space to offer help in distinguishing confusing colors for CVD observers, but they also had the problem of possibly producing new pairs of confusing colors. Meguro et al.[12] proposed a color conversion method based on image segmentation in $L^*a^*b^*$ color space, but had large calculations and suffered from the clustering dependence problem. Nakauchi and Onouchi[13] proposed a method to detect color combinations that will confuse dichromats based on color clusters and modified the confusing color combinations based on the minimization of an evaluation function; however, the authors did not solve the clustering dependency problem. Huang et al.[14] defined two error functions to evaluate the color contrast and the color naturalness of the image before and after the Daltonization, and took the weighted addition of the two error functions as the minimization optimization target. The problem with this is that the weight parameter selection of the sum of two error functions lacks interpretability, and there is no sufficient basis for how to choose the best weight. Lin et al.[15] presented an image recoloring algorithm based on eigenvectors in λ, Y-B, R-G color space, but the results were very unnatural, even though the color contrast was greatly improved.

The color gamut reduction Daltonization method does reduce the color gamut of images, which causes color unnaturalness and reduces the colorfulness of the Daltonized images for normal color vision observers and anomalous trichromatic observers. Rasche et al.[20] formulated Daltonization as an optimization problem and solved it using the CVD visible color gamut to maximize color contrast; however, they lost sight of color naturalness and could not capture variations alone many directions of color changes. To improve the performance of the Daltonization in color naturalness, Kuhn et al.[19] modeled the problem as a mass–spring system. Machado and Oliveira[16] improved the Daltonization calculation efficiency, orthographically projecting the original colors onto a plane aligned with the direction that maximizes contrast loss in a least-squares sense. However, this method failed in some cases. Ruminski et al.[21] proposed two procedures based on the color difference image between the original image and the simulation image; compared with Machado's method, Ruminski et al.'s method improved calculation efficiency, but it was not certain whether the process would produce new pairs of confusing colors. Zhu et al.[17] focused on the issue of naturalness preservation, formulated Daltonization as an optimization problem, and solved it by using the CVD visible color gamut to maximize color contrast and preserve color naturalness as much as possible; unfortunately, this method had poor time efficiency. Miyazaki et al.[18] proposed a method based on histogram equalization of hue values and found that the image noise caused by histogram equalization greatly reduced the image quality. In addition, Ma et al.[22] established a neural network model to remap the image color, but the image quality was degraded. Kotera[31] proposed a spectral-based Daltonization method, which solved the optimal problem to get the optimal shift wavelength for

Daltonization, then shifts the lost spectrum of CVDs into the visible wavelength region of them by the optimal shift wavelength to improved visibility for CVDs viewers, and extended the mathematical model[30] into all of CVD types, including dichromats and anomalous trichromats.

Contour enhanment[23,24] and the addition of texture[25] or noise[26] to different colors are part of a special Daltonization method. However, contour enhancement will fail if the confusing colors are not in the neighborhood of the image, and it is difficult for the observer to distinguish whether to add texture to the original image or to focus on color recognition. The addition of noise will significantly reduce the quality and visual experience conveyed by the image.

With visual sharing (allows CVD users to see the same color contrast as non-CVD users) and color naturalness as important roles in Daltonization,[17] the focus of this study is on the improvement of the color gamut reduction Daltonization method because, with the development of multimedia technology, the same multimedia information may be received by different types of observers (normal color vision observers, anomalous trichromatic observers, and dichromatic observers) at the same time. A typical application scenario is that a family has members who are colorblind and those who are not, and therefore the images on the TV should be suitable for both types of users at the same time.

Based on the fusion of the color gamut reduction Daltonized image and the original image, we could obtain an enhanced image that preserves the color appearance of the Daltonized image with dichromatic color vision while being colorful and natural to the normal color vision viewers and anomalous trichromatic viewers.

Considering the proportion of CVD individuals in the population (protanopes 1.02%, protanomaly 1.02%, deuteranope 1.11%, deuteranomaly 5.28%, tritanope 0.003%, and tritanomaly rare[1]) and the lack of the related research in tritanopes and tritanomaly, this study focuses on the improvement of the color gamut reduction Daltonization for red–green colorblindness. Unless there is a special explanation, the Daltonization referred to in this study refers to the Daltonization of gamut reduction.

2 Method

2.1 *Overview*

Our method consists of four steps. First, we convert the image from the RGB color space to the $Lu'v'$ color space. Second, we apply the prior knowledge of the confusion points of dichromats describe in Sec. 1.3, based on the coordinates of the confusion points, convert the coordinates of $Lu'v'$ to the polar coordinates of $L\rho\theta$ (the lightness information L has not changed). Dichromatic viewers of a particular type are sensitive to color changes in L and θ (θ is defined by the confusing point corresponding to the particular type of dichromats), but they are insensitive to color changes in ρ. The θ of the original image without Daltonization is not friendly to dichromats because of the difficulty in distinguishing the main colors in the image; meanwhile, the ρ of the Daltonized image is not friendly to trichromatic viewers. For the reasons mentioned above, in the third step, we achieve color enhancement based on image fusion the ρ of the original image and the θ and L of Daltonized image. Finally, the inverse transformation of the color space is performed to store and display the enhanced image.

Figure 3 shows the pipeline of our color enhancing method, and the corresponding pseudocode is given in Algorithm 1.

2.2 *Transformation from Cartesian Coordinates to Polar Coordinates in Lu′v′ Based on the Confusion Points*

Based on the prior knowledge of the confusion lines and points described in Sec. 1, we can implement a transformation of color from Cartesian coordinates to polar coordinates. Since the color changes in both chromaticity dimensions (u' and v') can be perceived by dichromatic viewers, the polar coordinate transformation based on the confusion point transforms the two-dimensional information of $u'v'$ into the dichromats-sensitive information θ and the

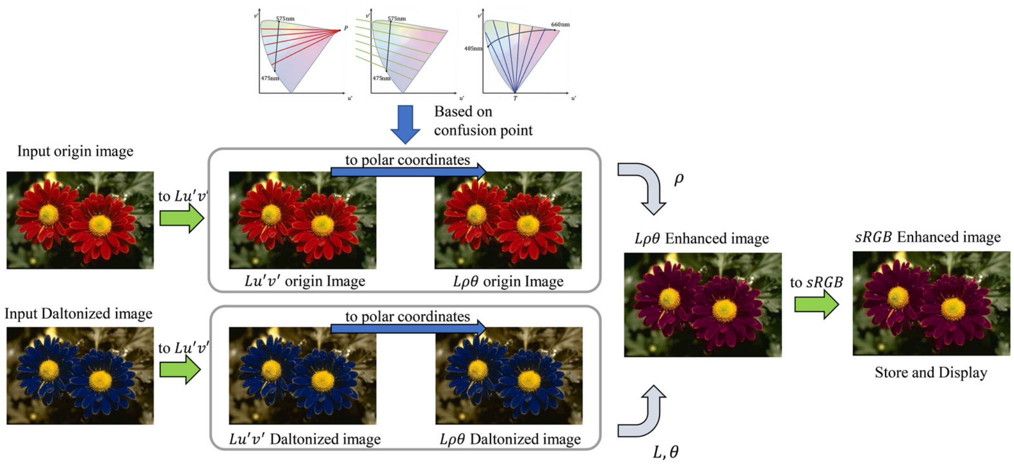


Fig. 3 Overview of the proposed method.

Algorithm 1 Color enhancement based on image fusion.

Input: The original image I, the Daltonized image D

Output: The output image O

1: Convert color space of I and D from sRGB to $Lu'v'$

2: Transformation from Cartesian coordinates (u', v') to polar coordinates (ρ, θ) based on the confusion points (Sec. 2.2)

3: Image fusion to retain the naturalness of I and the color contrast of D (Sec. 2.3)

4: Perform an inverse transform of step 1

dichromats-insensitive information ρ. The transformation is very meaningful to guide how to adjust the chroma of the image, which can minimally affect the appearance of color for CVD individuals.

The conversion method of chromaticity coordinates (u', v') to polar coordinates (ρ, θ) is as follows:

$$\begin{cases} \rho = \sqrt{(u' - u'_{\mathrm{con}})^2 + (v' - v'_{\mathrm{con}})^2} \\ \theta = \arcsin\left(\frac{u' - u'_{\mathrm{con}}}{\rho}\right) = \arccos\left(\frac{v' - v'_{\mathrm{con}}}{\rho}\right) \end{cases}, \tag{1}$$

where $(u'_{\mathrm{con}}, v'_{\mathrm{con}})$ represents the coordinates of the intersection of the confusion lines in $u'v'$ space; for protanopes, $(u'_{\mathrm{con}}, v'_{\mathrm{con}}) = (0.678, 0.501)$; for deuteranopes, $(u'_{\mathrm{con}}, v'_{\mathrm{con}}) = (-1.217, 0.782)$; and for tritanopes, $(u'_{\mathrm{con}}, v'_{\mathrm{con}}) = (0.257, 0.000)$.

2.3 *Image Information Fusion*

In Sec. 2.2, we explained the motivation of polar coordinate transformation. We found that the main reason for the unnaturalness and color gamut reduction of the Daltonized image perceived by trichromatic viewers is that the information of ρ is greatly distorted during the Daltonization of the image. This is shown in Fig. 4.

Therefore, we retain the ρ information of the original image to recover the naturalness and colorfulness of the original image for the individuals with normal color vision and preserve the θ information of the Daltonized image to maintain the appearance of color for the CVD viewers.

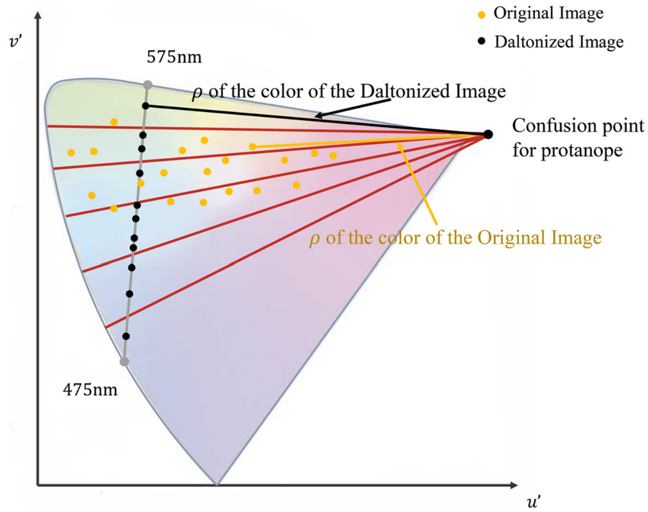


Fig. 4 Distortion of R of the Daltonized image.

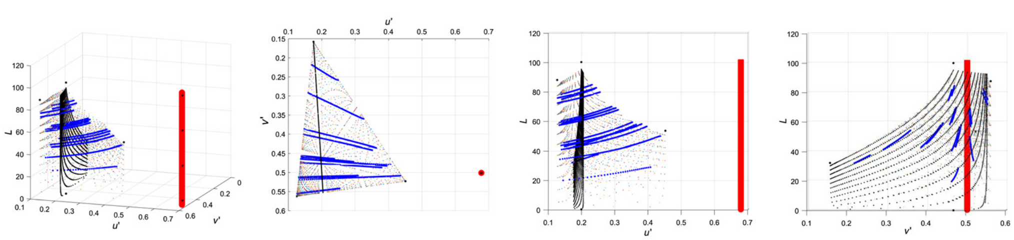
Thus, we realize color enhancement based on image fusion. In this process, we assume that the perceived luminance (L information) of the dichromats is exactly the same as that for trichromats. The fusion of image information is described as follows:

$$\begin{cases} L_{\text{fusion}}(i,j) = L_{\text{daltonized}}(i,j) \\ \rho_{\text{fusion}}(i,j) = \rho_{\text{original}}(i,j) \\ \theta_{\text{fusion}}(i,j) = \theta_{\text{daltonized}}(i,j) \end{cases}, \tag{2}$$

where $L_{\text{daltonized}}$ represents the lightness information of the Daltonized image, and ρ_{original} and $\theta_{\text{daltonized}}$ represent the ρ information and the θ information of the Daltonized image, respectively. $L_{\text{fusion}}, \rho_{\text{fusion}}, \theta_{\text{fusion}}$ represent the lightness information, the ρ information, and the θ information of the enhanced image.

We found that there is a certain lightness error in the enhanced image obtained by Eq. (2). In order to analyze the sources of bias in the quantitative evaluation experiments and taking protanopes as an example, we plotted the distribution of colors perceived by trichromatic viewers and the colors perceived by dichromatic viewers in the $Lu'v'$ color space. The result is shown in Fig. 5.

As shown in Fig. 5, it is apparent that the confusion lines are not real straight lines in three dimensional (3-D) color space, although confusion lines can be considered as straight lines in $u'v'$ chromaticity diagram, this shows that even colors with different lightness may still be



(a) (b) (c) (d)

Fig. 5 Confusion points and confusion lines in $Lu'v'$ color space. Blue lines represent the confusion lines of protanopes and the red lines represent the intersection $(u'v') = (0.678, 0.501)$ of confusion lines of protanopes. The black plane represents the color gamut of protanopes, and the color dots represent the distribution of sRGB color space in $Lu'v'$ space. (a) the 3-D view, (b) the top view of $u'v'$, (c) the view of Lu', and (d) the view of Lv'.

confused by CVD. Therefore, using Eq. (2) in image fusion is not optimal. The following formula permits an improved lightness modification for protanopes and deuteranopes:

$$L_3 = \begin{cases} \beta\sqrt{(u_1' - u_2')^2 + (v_1' - v_2')^2} + L_2, & \text{if } u_1' \geq u_2' \\ -\beta\sqrt{(u_1' - u_2')^2 + (v_1' - v_2')^2} + L_2, & \text{if } u_1' < u_2' \end{cases}, \tag{3}$$

where β represents the average slope of confusion lines in $Lu'v'$ color space, and $u_1'v_1'$, $u_2'v_2'$, $L_3u_3'v_3'$ represent the values of the original image, Daltonized image, and enhanced image in $Lu'v'$ color space, respectively.

For the determination of parameter β, if the minimum color difference between the enhanced image and the Daltonized image perceived by the CVD individuals is taken as the optimization target, then the optimal parameter β is different for different images. The amount of calculation for this problem is large. Therefore, the method of determining the parameter β in advance can be considered as abandoning the optimal solution. The mathematical description of this process is as follows:

$$\beta^* = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{m} \sum_{j=1}^{n} |\beta \Delta c(i,j) + L_s(i,j) - L_o(i,j)|. \tag{4}$$

In order to determine the optimal value of β^*, the Daltonized image at this time should be regarded as the simulation image, and the enhanced image should be regarded as the original image. Therefore, L_s, L_o represent the lightness of the simulation image and the original image, respectively. Δc represents the chromaticity difference between the simulation image and the original image:

$$\Delta c(i,j) = \begin{cases} \sqrt{[u_o(i,j) - u_s(i,j)]^2 + [v_o(i,j) - v_s(i,j)]^2} & \text{if } u_o(i,j) \geq u_s(i,j) \\ -\sqrt{[u_o(i,j) - u_s(i,j)]^2 + [v_o(i,j) - v_s(i,j)]^2} & \text{if } u_o(i,j) < u_s(i,j) \end{cases}, \tag{5}$$

where u_o, v_o represent the two channel values of the original image in the $u'v'$ space, and u_s, v_s represent the two channel values of the simulation image in the $u'v'$ space.

We generate a 4096×4096 (256^3) image that includes all discrete values of the sRGB color space and calculate the visual simulation images (deuteranope and protanope) of the generated images. We then regard the simulation image as the Daltonized image to be calculated in Eqs. (4) and (5). Next, we solve the argument of the minima using the hill-climbing algorithm; β^* steps by 0.01 for each iteration. The solution spaces of β^* for deuteranopes and protanopes are shown in Figs. 6(a) and 6(b), respectively, and some average error values of L corresponding to the parameter β^* are listed in Table 1.

For deuteranopes, the approximate optimal value of β^* is -24.21, when β^* takes this value, the average error of lightness is the smallest (1.6105); and for protanopes, the approximate

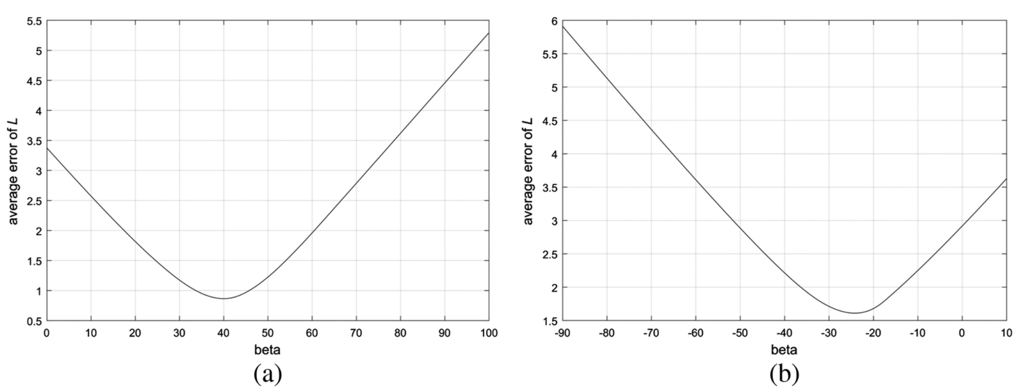


Fig. 6 Solution space of β^* (a) for deuteranopes and (b) for protanopes.

Table 1 The approximate optimal solution of β^* for deuteranopes and protanopes.

Deuteranopes							
β^*	−60	−40	−30	**−24.21**	−20	−10	10
Average errors of L	3.6093	2.2130	1.7115	**1.6105**	1.6794	2.2499	3.6290
Protanopes							
β^*	0	20	30	**39.98**	40	50	70
Average errors of L	3.3742	1.8153	1.1733	**0.8655**	0.8655	1.2253	2.7876

Note: The bold characters show the result that performed best in the quantitative assessment.

optimal value of β^* is 39.98, when β^* takes this value, the average error of lightness is the smallest (0.8655). Since the dynamic range of lightness (L) is 0 to 100, this error is acceptable.

3 Experiment and Evaluation

Figures 7 and 8 show the results of the proposed method without lightness modification based on five different Daltonization methods.[16–20,30] To enable readers with normal color vision to perceive the images seen by the dichromatic viewer, the simulation images are shown. The first row shows the original images in (a), the Daltonization[16–20,30] results in (b), the color-enhanced images without lightness modification in (c), and the color-enhanced images with lightness modification in (d). The simulation images for dichromatic vision are presented in the second row: the simulation images of the original images (e), the simulation images of the Daltonized images (f), the simulation images of the color-enhanced images with lightness modification (g), and the simulation images of the color-enhanced images without lightness modification (h).

Figure 7 shows the result of the deuteranope images affected by the existing Daltonization method and the proposed method. For the simulation of the image Fig. 7(e) example 1-6, the

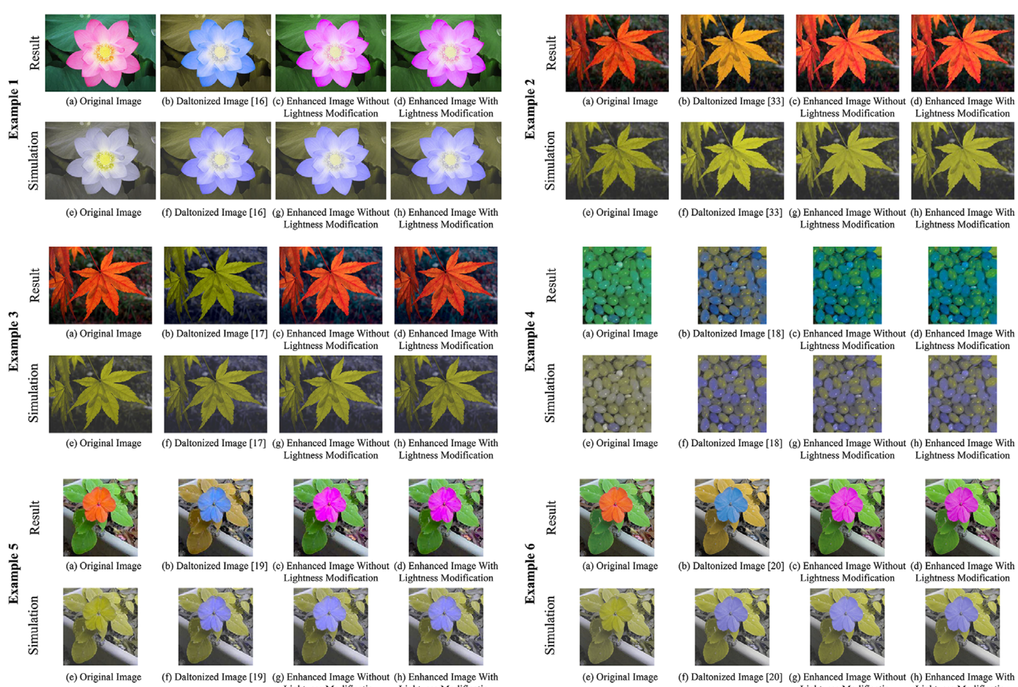


Fig. 7 Image results for five existing Daltonization methods and the proposed method (deuteranopes).

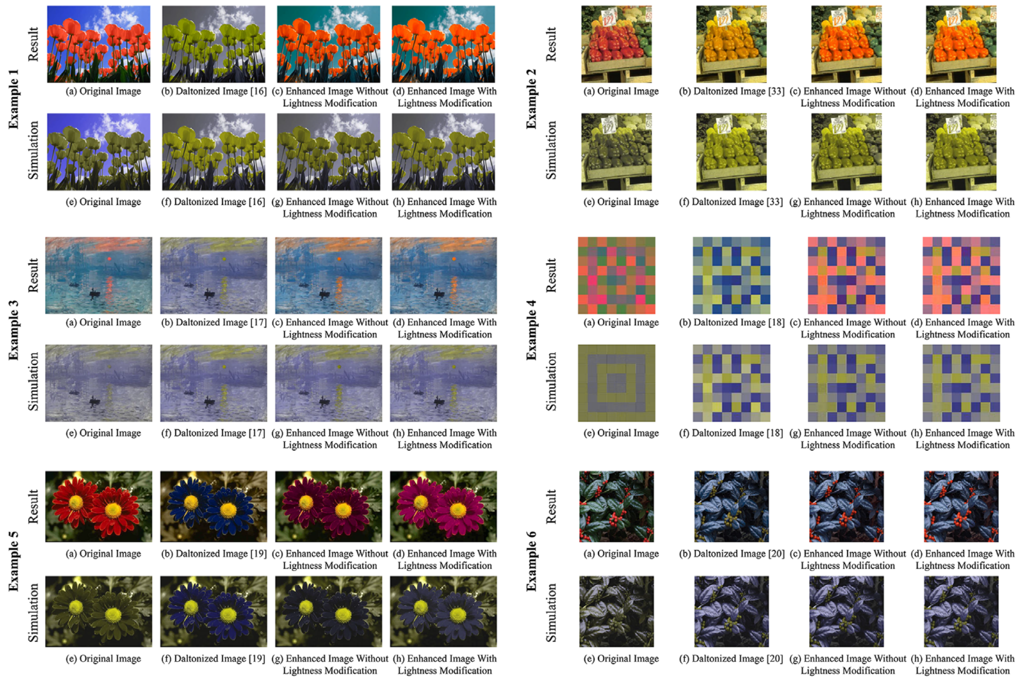


Fig. 8 Image results for five existing Daltonization methods and the proposed method (protanopes).

contrast between the main colors of images is lost, especially in examples 1e, 5e, and 6e. Most of the Daltonization methods preserve the contrast of the main colors of images for deuteranopes, but for normal and anomalous trichromats, the Daltonized images have lost naturalness and colorfulness. The proposed method has excellent performance in preserving the naturalness of the image for these viewers. It maintains the color perception of deuteranopes as much as possible while recovering the natural color of the image (see example 1cd, example 3cd, example 5cd, and example 6cd). Moreover, the lightness modification reduces the errors to a certain extent, especially in examples 3h, 5h, and 6h.

Figure 8 shows the result of the protanope images affected by the same existing Daltonization methods and the proposed method. The colors of red and green (example 5e) are lost contrast and CVD individuals have difficulty in distinguishing colors in example 5e; similar results are seen in example 6e. The color blocks image (example 4e) will be mistakenly read by protanopes as color blocks that arrange regularly. The color enhancement method presented in this paper shows a certain color bias in the enhancement from the perspective of protanopes, such as the color fading in example 5g and the color darkening in example 4g; however, there is no such phenomenon in other test images. Furthermore, the lightness modification reduces errors to a certain extent, especially in examples 1h and 5h.

Based on the discussions in Sec. 2.1, a method was proposed to recover the natural color for individuals with normal color vision as well as retain the Daltonized color for CVD individuals. In order to evaluate the color bias, and in addition to the commonly used image quality assessment variables the mean squared error (MSE), structural similarity index[27] (SSIM), and peak signal-to-noise ratio (PSNR), we also used the $L^*u^*v^*$ color difference ($L^*u^*v^*$ CD) and $L^*a^*b^*$ color difference ($L^*a^*b^*$ CD) to evaluate the similarity of Daltonized images and fused images perceived by protanope viewers. To evaluate the color colorfulness for normal and anomalous trichromatic views, the color colorfulness index[28] (CCI) and color difference was adopted. And to evaluate the color contrast, the standard deviation of the image of the $L^*u^*v^*$ and $L^*a^*b^*$ color space was adopted.

Kuhn et al.[19] and Hassan et al.[29] minimized the differences between original images and Daltonized images to preserve the naturalness of the images. Meanwhile, Zhu et al.[17] applied the color difference metric to evaluate the color naturalness.

In the following quantitative evaluation part, we will evaluate the results from 3-D of color contrast, color naturalness, and color colorfulness.

The MSE is the most commonly used metric in the quantitative evaluation of image quality. The mean square error is taken as the similarity measure between the distorted image and the original image. The calculation method is as follows:

$$\mathrm{MSE} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} [x(i,j) - y(i,j)]^2, \tag{6}$$

where m and n represent the pixels number in the length and width of the image, respectively. Meanwhile, x and y represent the Daltonized image and the enhanced image, respectively.

The MSE is actually calculating the average color difference of images in RGB color space, but the RGB color space is a nonuniform color space inconsistent with the color perception of human eyes. The $L^*u^*v^*$ color space (CIE1976 uniform color space) is a color space consistent with human visual color perception, and the distance between the two coordinate points representing the two colors in $L^*u^*v^*$ can accurately measure the visual difference of two colors. $L^*u^*v^*$ color difference is calculated as follows:

$$\Delta E_{L^*u^*v^*} = \frac{1}{m \times n} \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} (\Delta L^{*2} + \Delta u^{*2} + \Delta v^{*2})}. \tag{7}$$

The $L^*a^*b^*$ color space is also designed to approximate human vision, and $L^*a^*b^*$ color difference is the most commonly used in color difference calculation. $L^*a^*b^*$ color difference is calculated as follows:

$$\Delta E_{L^*a^*b} = \frac{1}{m \times n} \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} (\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2})}. \tag{8}$$

PSNR is an important index to measure the image quality and is the ratio of the maximum signal amount to the noise intensity. In digital images, the maximum pixel value of the image is used to replace the maximum signal amount. The calculation is as follows:

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right), \tag{9}$$

where MAX represents the maximum value of the image pixel value range.

SSIM can overcome the drawback that MSE, $L^*u^*v^*$ CD, $L^*a^*b^*$ CD and PSNR cannot measure the similarity of image structure:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}. \tag{10}$$

Here, μ_x, μ_y represent the average values of images x and y, respectively; σ_x^2, σ_y^2 represent the variances of images x and y, respectively; $c_1 = (0.01T)^2$; $c_2 = (0.03T)^2$; and T represents the dynamic range of the pixel values.

CCI assumes that the average saturation S of image and its standard deviation σ have equal influence on colorfulness judgments of human. It divides subjective colorfulness into two factors: the distance of the image colors from a neutral gray and the distance between individual image colors. The distance of the image colors from a neutral gray can be modeled as the mean of the distribution of the saturation values of all image colors. The distance between image colors can be modeled as the standard deviation of the distribution of saturation values. CCI is calculated as follows:

Table 2 Results of image similarity quantitative evaluations from the perspective of deuteranopes between Daltonized images and enhanced images (inside the brackets are the results without the lightness modification).

	MSE	$L^*u^*v^*$ CD	$L^*a^*b^*$ CD	PSNR	SSIM
Example image 1	3.0296 (6.7894)	1.2102 (2.9127)	0.4585 (1.1148)	43.2742 (36.2654)	0.9947 (0.9951)
Example image 2	13.5872 (13.3555)	3.4178 (3.8518)	1.4631 (1.6706)	30.2394 (30.3888)	0.9913 (0.9916)
Example image 3	3.4569 (8.2277)	0.9432 (3.2923)	0.4203 (1.4213)	42.1282 (34.5965)	0.9808 (0.9886)
Example image 4	5.7346 (5.6644)	2.7978 (3.4686)	1.1454 (1.3133)	37.7320 (37.8389)	0.9936 (0.9917)
Example image 5	3.4170 (9.0000)	0.7673 (2.1532)	0.3185 (0.8906)	42.2292 (33.8171)	0.9979 (0.9959)
Example image 6	2.4713 (9.1996)	0.6194 (2.0383)	0.2540 (0.8539)	45.0437 (33.6267)	0.9942 (0.9933)
Average	5.2828 (8.7061)	1.6260 (2.9528)	0.6766 (1.2108)	40.1078 (34.4222)	0.9921 (0.9927)

$$\mathrm{CCI} = S + \sigma. \tag{11}$$

We calculated the above quantitative indices. Table 2 shows the quantitative evaluations (MSE, $L^*u^*v^*$ CD, $L^*a^*b^*$ CD, PSNR, and SSIM) in test images (the same as example images in Fig. 5) for deuteranope viewers. Table 3 shows the quantitative evaluations (MSE, $L^*u^*v^*$ CD, $L^*a^*b^*$ CD PSNR, and SSIM) in test images (the same as example images in Fig. 6) for protanope viewers. Table 4 shows the quantitative evaluation of colorfulness (CCI) in test images

Table 3 Results of image similarity quantitative evaluations from the perspective of protanopes between Daltonized images and enhanced images (inside the brackets are the results without the lightness modification).

	MSE	$L^*u^*v^*$ CD	$L^*a^*b^*$ CD	PSNR	SSIM
Example image 1	12.1478 (22.3878)	3.6461 (7.3076)	1.5907 (3.0668)	31.2121 (25.9018)	0.9776 (0.9635)
Example image 2	7.9574 (11.5299)	1.9332 (3.1602)	0.8305 (1.3306)	34.8866 (31.6655)	0.9973 (0.9943)
Example image 3	1.9051 (5.4962)	0.5667 (1.2834)	0.2042 (0.5156)	47.3035 (38.1008)	0.9991 (0.9971)
Example image 4	20.5848 (29.2216)	4.5993 (6.9098)	1.7739 (2.6075)	26.6311 (23.5879)	0.9731 (0.9669)
Example image 5	15.3218 (16.8728)	4.9641 (6.1789)	2.9549 (3.2577)	29.1958 (28.3583)	0.8950 (0.8061)
Example image 6	2.1333 (5.8862)	0.4769 (0.9953)	0.2122 (0.4059)	46.3212 (37.5053)	0.9823 (0.9881)
Average	10.0084 (15.2324)	2.6977 (4.0359)	1.2611 (1.8640)	35.9251 (30.8533)	0.9707 (0.9527)

Table 4 Results of image color colorfulness quantitative evaluation from the trichromatic perspective.

	CCI		
Deuteranope	Daltonized	Without lightness modification	With lightness modification
Example image 1	0.5877	0.6535	**0.6543**
Example image 2	0.8557	0.8583	**0.8642**
Example image 3	0.9440	0.9491	**0.9545**
Example image 4	0.5563	**1.0355**	1.0353
Example image 5	0.6275	**0.7370**	0.7368
Example image 6	0.6275	**0.6928**	0.6926
Average	0.6998	0.8210	**0.8230**
	CCI		
Protanope	Daltonized	Without lightness modification	With lightness modification
Example image 1	0.8203	1.0308	**1.0315**
Example image 2	0.9288	0.9326	**0.9327**
Example image 3	0.3329	0.5319	**0.5327**
Example image 4	0.6365	**0.6398**	0.6254
Example image 5	0.9203	**1.0037**	1.0031
Example image 6	**0.5535**	0.5524	0.5433
Average	0.6987	**0.7819**	0.7781

Note: The bold characters show the result that performed best in the quantitative assessment.

from the trichromatic perspective. Table 5 presents the quantitative evaluation of naturalness ($L^*u^*v^*$ CD and $L^*a^*b^*$ CD) in test images from the trichromatic perspective.

Considering that there is no general metric of the quantitative evaluation of color contrast for CVD, we took the standard deviation of the image in $L^*u^*v^*$ and $L^*a^*b^*$ color space with the simulation perspective of the corresponding dichromats as the metric for color contrast. We applied this metric to evaluate the color contrast for dichromatic viewers in Table 6.

Table 2 presents the image similarity index calculated from the perspective of deuteranopes, with the original image set as the reference image. The smaller the MSE, the smaller $L^*u^*v^*$ CD and $L^*a^*b^*$ CD, the higher PSNR, the closer SSIM is to 1, and the higher the image similarity. For example image 2 and example image 4, the MSEs are higher than 5 and PSNRs lower than 40; these have the highest errors in the quantitative evaluations. These metrics also proved that the proposed method cannot perfectly retain the color appearance of Daltonized images from the perspective of dichromats. Table 3 shows the image similarity indices calculated from the perspective of protanopes, with the original image set as the reference image. The average value of each metric in the result is not as good as the results for protanopes. It is very interesting that in the test images for deuteranopes, the enhanced image obtained with the lightness modification method has a lower color difference, but the image SSIM obtained without lightness modification is higher; meanwhile, in the test images for protanopes, the color difference and structure similarity are both better with lightness modification in average form.

Tables 4 and 5 demonstrate the color colorfulness and naturalness quantitative evaluations from the trichromatic perspective. There is no doubt that the proposed method has an excellent performance in restoring the color colorfulness and color naturalness of the Daltonized image.

Table 5 Results of image color naturalness quantitative evaluation from the trichromatic perspective (inside the brackets are the results of the CIELAB).

	$L^*u^*v^*$ CD and $L^*a^*b^*$ CD of the original image as the reference image		
Example for Deuteranope	Daltonized	Without lightness modification	With lightness modification
Example image 1	40.9673 (14.5097)	**30.1362 (8.8527)**	30.2176 (9.4445)
Example image 2	31.6800 (11.0598)	13.9738 (5.2003)	**12.3040 (4.6657)**
Example image 3	57.0942 (15.1809)	**10.6537 (5.0913)**	14.6923 (6.2471)
Example image 4	51.0942 (21.8241)	32.6986 (12.8994)	**32.0298 (12.3258)**
Example image 5	49.3773 (14.6581)	28.2264 (9.9492)	**27.3027 (9.5045)**
Example image 6	46.4297 (13.8385)	**25.9839 (9.1106)**	26.3697 (9.3250)
Average	46.1071 (15.1785)	**23.6121 (8.5173)**	23.8194 (8.5854)
	$L^*u^*v^*$ CD and $L^*a^*b^*$ CD of the original image as the reference image		
Example for protanope	Daltonized	Without lightness modification	With lightness modification
Example image 1	73.2724 (20.0026)	**33.1578 (14.2502)**	37.6759 (15.9516)
Example image 2	19.1878 (9.0945)	**16.3131 (6.8786)**	17.8468 (7.4630)
Example image 3	17.3571 (6.7655)	**10.9775 (4.3278)**	11.0499 (4.3707)
Example image 4	80.6729 (28.0985)	**49.4909 (21.1865)**	51.4536 (22.1175)
Example image 5	44.9639 (17.2370)	25.9373 (9.3644)	**16.4150 (6.5443)**
Example image 6	20.0132 (8.0300)	**14.8967 (7.0600)**	15.5260 (7.3517)
Average	42.5779 (14.8714)	25.1289 **(10.5113)**	**24.9945** (10.6331)

Note: The bold characters show the result that performed best in the quantitative assessment.

There is no great difference in the effect with lightness modification in the colorfulness and naturalness evaluation.

Table 6 demonstrate the color contrast quantitative evaluations from the dichromatic perspective. The evaluation results of CIELUV and CIELAB did not show a significant difference, and the Daltonization results showed the best performance in average form, which is consistent with our subjective perception. It should be noted that the of the Daltonized images in the example images 1, 3, and 5 for deuteranopes is actually higher than other images, but there are some abnormalities in the evaluation of the color contrast quantitative evaluations, which is obviously inconsistent with our subjective visual experience, this also shows that there are still some cases where the standard deviation is not suitable for the evaluation of color contrast, but according to the average of the standard deviation, the result of color contrast is consistent with subjective visual perception. In the example image 1 for protanopes, the standard deviation of the original image is also higher than the standard deviation of the Daltonized image, but in this example 1, the blue sky of the Daltonized image is obviously not the same vivid as that of the original image, so this abnormal result is consistent with our subjective visual perception.

Overall, the color contrast of the Daltonized image from the perspective of dichromats is generally higher than the enhanced image processed by the proposed method, but the proposed method can sacrifice a certain color contrast from the perspective of dichromats to get better color naturalness and colorfulness from the perspective of anomalous trichromats and normal trichromats, significantly improve Daltonized images of poor color naturalness and colorfulness.

Table 6 Results of image color contrast quantitative evaluation from the dichromatic perspective (inside the brackets are the results of the CIELAB).

	The standard deviation of the image in $L^*u^*v^*$ and $L^*a^*b^*$ color space			
Deuteranope	Original	Daltonized	Without lightness modification	With lightness modification
Example image 1	20.9397 (21.2143)	20.8362 (23.6043)	**21.5687 (23.8525)**	20.9215 (23.5323)
Example image 2	16.2100 (16.8117)	**21.7347 (22.4045)**	19.9327 (20.5397)	19.5019 (20.1161)
Example image 3	16.4325 (17.0461)	15.4590 (16.6338)	**16.8041 (18.0028)**	15.1635 (16.3651)
Example image 4	9.7368 (9.9150)	**9.9823 (12.2909)**	9.5150 (11.2537)	9.6509 (11.4524)
Example image 5	**18.6683** (19.1742)	18.4608 **(20.5752)**	18.5185 (20.5373)	18.4387 (20.5260)
Example image 6	18.1265 (18.5691)	**18.7245** (20.3071)	18.6671 **(20.3193)**	18.6264 (20.2832)
Average	16.6856 (17.1217)	**17.5329 (19.3026)**	17.5010 (19.0842)	17.0505 (18.7125)
	The standard deviation of the image in $L^*u^*v^*$ and $L^*a^*b^*$ color space			
Protanope	Original	Daltonized	Without lightness modification	With lightness modification
Example image 1	**20.1518 (26.2633)**	19.9180 (20.8889)	19.2485 (20.0165)	19.3398 (20.1842)
Example image 2	21.9558 (21.9824)	**22.2981 (22.4824)**	22.1575 (22.3004)	22.0646 (22.2193)
Example image 3	8.4461 (8.7120)	**9.4692 (10.3023)**	9.1198 (9.9921)	9.3727 (10.2134)
Example image 4	5.4428 (6.4593)	**16.4258 (19.4717)**	13.4200 (16.6621)	14.0196 (17.2646)
Example image 5	17.3059 (17.3687)	**18.4409 (20.0959)**	18.4169 (18.7152)	17.4153 (17.9646)
Example image 6	17.6964 (17.7897)	**17.9218 (18.3078)**	17.7831 (18.1594)	17.7387 (18.1326)
Average	15.1665 (16.4292)	**17.4123 (18.5915)**	16.6910 (17.6410)	16.6585 (17.6631)

Note: The bold characters show the result that performed best in the quantitative assessment.

4 Conclusion

With the concept of color naturalness and visual sharing of images getting more and more attention in the field of Daltonization, in this study, we propose an enhancing algorithm based on Daltonization and image fusion for improving the color visibility to CVDs and normal tristimats. The Daltonization image perceived by dichromatic viewers is almost unchanged, while the naturalness of the Daltonized image colors perceived by normal and anomalous trichromatic users is recovered. The quantitative evaluation shows that the proposed method can effectively improve the color naturalness and color colorfulness of the image from the perspective of anomalous trichromats and normal trichromats, though sacrifice a few color contrasts from the perspective of dichromats.

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