A content-dependent Daltonization algorithm for colour vision deficiencies based on lightness and chroma information

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Abstract
To help CVD (colour vision deficiency) observers distinguish among different colours in digital images, this study proposes a content-dependent Daltonization algorithm based on lightness and chroma information. This improves the trade-offs in contrast, naturalness, and colour consistency deficiencies found in existing methods. Chroma remapping and brightness adjustments on image content are utilized to increase contrast and maximize the preservation of the original hue. In a quantitative study, the proposed method proved more useful for dichromats than did existing methods. The evaluation by research subjects showed that the method was superior to the current methods in balancing contrast, naturalness, and colour consistency.

1 | INTRODUCTION

Colour plays a key role in the process by which humans gain information from media. However, in everyday life, CVD sufferers can easily confuse certain colours, and this problem is faced by 8.002% of men and 0.44% of women [1]. Modern anatomy studies have verified the existence of three types of cones in the human eye: L cones (sensitive to long-wavelength light), M cones (sensitive to medium-wavelength light), and S cones (sensitive to short-wavelength light). CVD is often caused by cone abnormalities. Partial dysfunction in a single cone is called anomalous trichromacy; if the cone is fully dysfunctional, the condition is called dichromacy. In cases of the total malfunction of two or three types of cone cells, the impairment is known as monochromacy [2].

Most CVD sufferers are either dichromats or anomalous trichromats. Depending on the type of cones exhibiting malfunction, dichromats can be divided into protanopes (lacking L cone function), deuteranopes (lacking M cone function), or tritanopes (lacking S cone function). Dichromacy due to abnormalities in L cones or M cones is the most common form of CVD and is known as red-green blindness. This is caused by changes in the opsin gene array in the X chromosome [3], and dichromacy corresponds to anomalous trichromacy with a 100% severity [4].

Enhancing the visibility of colour images for dichromats is an important research field [5]. In the colour enhancement of digital images, the challenge lies in improving the colour difference in the perception by the two-colour viewer while also maintaining the naturalness of the image and preventing the colour of the enhanced image from causing a cognitive conflict for dichromats. Many complicated problems are difficult to express using mathematical formulas. Therefore, enhancing the viewer’s perception of dichroic colour images is an important research area.

2 | RELATED WORK

2.1 | Simulation of dichromatic perspective

A colour stimulus consists of three-dimensional information for trichromats, but for dichromats, one dimension is lost from the colour information received. If two different colours only exhibit a significant difference in the missing dimension, the pair of colours that can be easily distinguished by trichromats will be confused by dichromats. Therefore, the simulated viewing angle of dichromats can be regarded as a dimensionality reduction problem in which colours in a three-dimensional space are projected onto a low-dimensional plane, as shown in Figure 1.
In order to understand the visual world perceived by CVD patients, results from research on unilateral dichromats (for whom one eye has normal vision, and the other has a dichromatic vision) have been used to propose a simulation algorithm [6, 7]. Meyer et al. [8] and Brettel et al. [9] used projections to simulate the perception of a given colour by CVD patients. Brettel et al. [9] established a dichromatic simulation model in the LMS colour space; the LMS space is defined based on the response of L, M, and S cones. Using research on unilateral dichromats, the author defines the colour gamut of each type of dichromatic vision and proposes a method of projecting the colours perceived by normal vision individuals into the CVD colour gamut (the visible colour gamut of dichromats can be represented as two half-planes); this is demonstrated in Figure 1. Viénot et al. [10] described the specific process and developed a method for simulating dichromatic colour vision on a monitor. Machado et al. [11] used a two-stage model [12] to translate the response curves of L, M, and S three-colour cones by using different distances to simulate the colour perception of two-colour viewers for the benefit of three-colour viewers. In this paper, we use the model in [9] and the process in [10] to simulate images perceived by CVD individuals.

This colour adaptation is called Daltonization, and is a complex problem of mapping the image gamut onto a reduced one [13]. Daltonization methods can be divided into two categories—content-independent and content-dependent.

Content-independent methods, such as colour remapping [14–16], cannot ensure colour contrast for CVD observers because the methods use pixel-based global processing and operate without reference to the image content or the spatial location of the confused colours. The entire image is processed in a uniform way, and new pixel values can be represented as a function of their original values. Generally, colour remapping can improve the contrast between the originally confused colours, but previously distinguishable colours may be remapped to indistinguishable combinations; this will have a negative impact on colour perception and learning in CVD patients.

The addition of texture [17] or noise [18] to different colours represents a special content-independent method. Adding noise or texture to the image as an information dimension can help CVD observers distinguish between different colours. However, it is difficult for the observer to distinguish whether the texture is added in the original image or to aid colour discrimination. The addition of noise will obviously reduce the quality and visual experience conveyed by the image.

Ribeiro et al. [19] considered the effects of Daltonization methods and investigated and compared the CVD-oriented Daltonization methods proposed in the past 20 years. When designing a new Daltonization method, it is extremely important to retain the three elements of perceptual learning; these are colour contrast, colour consistency, and colour naturalness.

The focus of recent research is on Daltonization based on image content. Content-dependent categories include histogram-based [5], neighbourhood-based [20, 21], and clustering-based [22–24] methods; optimization [13, 25–30],

![Figure 1](image-url)  
**Figure 1** Colour blindness perspective simulation model in LMS colour space. The grey area is the dichromatic colour gamut represented by the LMS colour space (a) projected along the L axis to the protanope gamut (grey area), (b) projected along the M axis to the deuteranope colour gamut (grey area), and (c) projected along the S axis to the tritanope colour gamut (grey area).
attention mechanism [31, 32], and feature vector-based [33] methods can more effectively analyse image colour information. In content-dependent methods, the final pixel colour value depends on the initial colour area of the image, the histogram, or the spatial location of the pixels. This type of method is complicated and requires considerable computation, and there remain difficulties in achieving the proper balance of contrast, naturalness, and colour consistency.

In a study of clustering-based Daltonization, Milic [22] proposed a re-colouring algorithm based on colour clustering, the algorithm clusters colours and remaps the image colour centres to be located on different confusion lines of the \( u'v' \) chromaticity diagram. Meguro [23] proposed the colour conversion method to improve colour perception for dichromats. This included three procedures—image segmentation based on K-means, detection of the confusion colours in images by the confusion loci on an \( xy \) diagram, and converting the confused colour to one perceptible by dichromats. Nakauchi [24] designed a method to detect confusing colours based on colour clusters for dichromats, then modified confusing colour combinations.

There is a common problem among the three clustering-based methods mentioned above that the algorithm will fail if the confusing colours are in the same cluster, because they all assume that the confusing colours are in different clusters. However, in image segmentation, different results may be obtained due to different clustering parameters, so it is completely possible that confusing colours exist in the same cluster.

The present study is focused on providing support for dichromats and anomalous trichromats. To address the problems in existing Daltonization algorithms, we propose a Daltonization algorithm based on chroma and lightness information. Existing methods can generally achieve significant contrast and maintain image naturalness, but the proposed method also has the following main advantages: (1) it can maintain global colour consistency, that is, the hue in observer perception; (2) it has little impact on the visual experience for viewers with normal colour vision; (3) it exhibits low dependence on clustering results, that is, better robustness; and (4) it can consider defect type and severity and achieve easy-to-understand control of parameters, providing optimal results for CVD individuals.

**FIGURE 2** Confusion line and confusion point in \( L\alpha\nu' \) colour space. (a) For protanopes, the red line represents the confusion line, and \((0.678, 0.501)\) is the confusion point. (b) For deuteranopes, the green line represents the confusion line and \((-1.217, 0.782)\) is the confusion point. (c) For tritanopes, the blue line represents the confusion line, and \((0.257, 0.0)\) is the confusion point.

**FIGURE 3** Steps in the proposed algorithm.

### 3 | PROPOSED METHOD

#### 3.1 | Overview of the proposed method

There is an ongoing search for an “ideal” Daltonization method. On one hand, it should consider the three elements of perceptual learning, and on the other, we hope to minimize the impact on the visual experience of three-colour viewers. Studies have shown that the breadth of the colour range visible for CVD observers is much smaller than that of tricolour viewers. In \( u'v' \) space, the colours confused by dichromats lie approximately on a straight line, and these lines intersect [34], as shown in Figure 2. Based on the research in [34], we propose a Daltonization algorithm based on chroma and lightness. The biggest innovation of this algorithm is an adaptive brightness adjustment method (Section 3.4) that can improve the lightness difference between different tones that are confused by CVD patients. In addition, the method improves the Daltonization of chrominance information in the mapping order of the clustering centres and the remapping of clustered centres.

The proposed algorithm has four steps, as shown in Figure 3. The specific steps are:

1. Transform the image from RGB colour space to \( L\alpha\nu' \) colour space and carry out colour clustering on the \( u'v' \) plane.
Then, the most representative colour centre in each cluster is obtained by calculating the average colour value of each cluster:

2. Obtain the cluster centre that is converted into polar coordinates \((R, \theta)\) according to the intersection point of the confusion line corresponding to the dichromatic type, and the cluster centre with the largest Adjacent Colour Centre Confusion Priority \(M_k\) and no unmapped centre remap until all cluster centres have been remapped. The calculation method and the idea of colour centre remapping will be described in Section 3.2. The calculation method for the Adjacent Centre Colour Confusion Priority \(M_k\) will be given in Section 3.3.

3. For each pixel, and based on the remapping of its cluster centre, perform the same angle \((\theta_k' - \theta)\) mapping as that for the cluster centre in the polar coordinates.

4. Convert \((R, \theta)\) back to \((u', v')\) and calculate the remapped radius \(R'\) based on \((u', v')\). Using the pixel \(R_{ij}\) polar coordinates, the original lightness \(L_{ij}\), the average \(R\) value of the cluster centre colour radius \(R_k\), and the maximum radius difference of the cluster centre colour \(|R_{max} - R_{min}|\), adjust the brightness to obtain \(L'_{ij}\) for each pixel \((i, j)\). The method is given in Section 3.4.

The proposed method is suitable for any type of dichromatic vision. In the following article, we will provide a Daltonization example for protanopes and explain the principles and ideas of the algorithm in detail. Because clustering and colour space conversion are not the focus of our innovation, we will not discuss them in detail in this paper.

The conversion from XYZ colour space to \(u'v'\) chromaticity space is as follows [35]:

\[
\begin{align*}
  u' &= \frac{4X}{X + 15Y + 3Z} \\
  v' &= \frac{9Y}{X + 15Y + 3Z}
\end{align*}
\]  

(1)

where \(X\), \(Y\), and \(Z\) represent the three-channel values in XYZ colour space.

### 3.2 | Colour centre remapping

We transform the pixel’s chroma \((u', v')\) into polar form \((R, \theta)\), and \((u', v') = (u'_{conf}, v'_{conf} + R)\) is set at 0 angle by the following equation:

\[
\begin{align*}
  R &= \sqrt{(u' - u'_{conf})^2 + (v' - v'_{conf})^2} \\
  \theta &= \arcsin \left( \frac{u' - u'_{conf}}{R} \right) = \arccos \left( \frac{v' - v'_{conf}}{R} \right)
\end{align*}
\]  

(2)

where \((u'_{conf}, v'_{conf})\) represents the coordinates of the confused intersection lines in \(u', v'\) space; for protanopia, \((u'_{conf}, v'_{conf}) = (0.678, 0.501)\) [34]. When colours confused by CVD patients are grouped in different clusters, it is efficient to measure whether there are confused colours by using the difference of \(\theta\) in the centre of the cluster and then, improve the contrast by remapping \(\theta\) to achieve chromaticity adjustment.

When remapping the cluster centre, for the colour corresponding to the middle of the confusion line in the three clusters \(\theta_k\), the following equation [22] can place the cluster centre map in the middle position (direction of \((\theta_{k-1} + \theta_{k+1})/2\) of the adjacent cluster \(\theta_{k-1}\) and \(\theta_{k+1}\)):

\[
\theta_k' = \begin{cases} 
  \theta_k - m, & \text{if } \frac{1}{2} \left( \theta_{k+1} + \theta_{k-1} \right) \geq \theta_k + m \\
  \theta_k - m, & \text{if } \frac{1}{2} \left( \theta_{k+1} + \theta_{k-1} \right) \leq \theta_k + m \\
  \frac{1}{2} \left( \theta_{k+1} + \theta_{k-1} \right), & \text{else}
\end{cases}
\]  

(3)

where \(m\) represents a constant that limits the maximum movement distance of the remap, depending on the type of dichromacy. To ensure that the image maintains a largely natural appearance, the value of \(m\) should be as small as possible; however, a larger value of \(m\) can improve the colour difference effect.

However, for protanopes and deuteranopes, the calculation with this remapping method is not the most balanced, as shown in Figure 4. When rotating by the same angle \(\theta\), the change in colour difference (length of \(l\)) in the perspectives of protanopes and deuteranopes becomes more unbalanced as the angle moves away from the vertical point P. To achieve the optimal colour centre remapping, Equation (4) can be established as follows:

\[
\tan \left( \theta_{k+1}' - \theta_k \right) - \tan \left( \theta_k' - \theta_{k-1} \right) = \tan \left( \theta_{k-1}' - \theta_{k-1} \right) - \tan \left( \theta_{k+1}' - \theta_{k+1} \right)
\]

(4)
where $\theta_0$ represents the angle corresponding to the intersection of perpendicular lines through a confusion point in the dichromatic gamut. For protanopes, $\theta_0 = -1.4988$ and for deuteranopes, $\theta_0 = 1.6428$.

To ensure a more balanced chromatic aberration of colour contrast for dichromatic vision, the remapping for protanopes and deuteranopes is as Equation (5) (use of Equation (3) is sufficient for tritanopes).

$$
\begin{align*}
\theta'_k & = \begin{cases} 
\theta_k - m, & if \arctan(\tan(\theta'_{k+1} - \theta_0) + \tan(\theta'_{k-1} - \theta_0)) \\
\quad + \theta_0 \geq \theta_k + m & \\
\theta_k - m, & if \arctan(\tan(\theta'_{k+1} - \theta_0) + \tan(\theta'_{k-1} - \theta_0)) \\
\quad + \theta_0 \leq \theta_k + m & \\
\arctan\left(\frac{1}{2}(\tan(\theta'_{k+1} - \theta_0) + \tan(\theta'_{k-1} - \theta_0))\right) + \theta_0, & else
\end{cases}
\end{align*}
$$

(5)

where $\theta'_{0}$ and $\theta'_{K+1}$ represent the approximate angles of the two boundaries in $u'v'$ colour space. For protanopes $\theta'_0 = -2.1698$ and $\theta'_{K+1} = -1.4600$; for deuteranopes $\theta_0 = 1.6428$, $\theta'_0 = 1.7329$ and $\theta'_{K+1} = 1.9922$; for tritanopes $\theta'_0 = -0.4749$ and $\theta'_{K+1} = 0.3548$.

### 3.3 Adjacent colour centre confusion priority

In the second step, we use the calculation of the adjacent colour centre confusion priority $M_k$ as follows:

$$M_k = (\theta'_k - \theta'_{k-1})^2 + (\theta'_{k+1} - \theta_k)^2, \quad k = 1, 2, K$$

(6)

When the $k$th colour centre has not been remapped (when $\theta'_{0}$ does not exist), $\theta'_k (\theta'_{k-1} and \theta'_{k+1}$ are the same) must be replaced by the value of $\theta_{k-1}$.

In colour centre remapping, the adjacent colour centre confusion with the highest priority takes precedence, and it can be ensured that, in the extreme case where the difference between $\theta$ values of multiple colour centres is small, the obvious chroma enhancement result can still be realized.

### 3.4 Lightness modification based on $R$ information

In an image, the colour occupying the main colour information area is affected by the brightness of the light source and the illuminance on the object, and there is not a large difference in its lightness. Based on the assumption that the lightness difference between the main colours of the image is small, we propose a novel lightness modification method based on $R$ information. The lightness modification method is shown in detail in Figure 5.

In the first step, coordinates $(u', v')$ are transformed into polar coordinate form $(R, \theta)$ and it can be directly determined from the difference in $\theta$ whether the two different hue colours are easily confused with this type of dichromacy. However, the information in $R$ is not used for remapping, and lightness modification using the information in $R$ can effectively enhance the contrast in different colours confused by CVD patients without affecting the colour consistency.

Without considering the difference in lightness, the distinguishing feature for two colours of different tones that would otherwise be confused is that their $\theta$ information is similar but their $R$ information is quite different. Therefore, combining the information in $R$ to affect a difference in lightness is an effective method in Daltonization.

The dichromatic observer is sensitive to changes in $\theta$ and not sensitive to changes in $R$. Therefore, we can increase (or decrease) the brightness of the colour with a higher $R$ value, leave the brightness of the colour with a medium $R$ value basically unchanged, and reduce (or increase) the brightness of the colour with a lower $R$ value, as follows:

$$L'_{ij} = \frac{b (R_{ij} - \bar{R})}{R_{max} - R_{min}} + L_{ij}$$

(7)

where $b$ is a constant selected through experiment.
where \( R_{\text{max}}, R_{\text{min}}, \) and \( \bar{R} \) represent maximum, minimum, and average \( R \) values for the clustering centre colour, respectively. Parameter \( b \) is a constant; note that a larger value of \( b \) can make the lightness difference between colours more obvious, but it cannot maintain the natural character of the image. Therefore, the value of \( b \) should be chosen appropriately.

With the use of Equation (7), easily confused colours with different tones and small differences in lightness can be assigned a significant difference in lightness, allowing dichromats to distinguish the different colours.

4 RESULTS AND EVALUATION

To establish the superiority of the proposed method over recently proposed methods, including some exhibiting excellent performance, we compared the results of this study with the results of literature studies [22, 28] using quantitative and subjective evaluation methods. We used virtual images (e.g., colour blocks images) and real images; Protection Images 1–4 are Ishihara colour blindness maps, Test Image 5 is a colour blocks image, and Test Images 6–8 are real images. In the numerical simulations, we chose the parameters for the proposed method as follows—the number of K-means clusters \( K \) ranges from 3 to 6, the constant \( b \) is 25, and \( m \) is 0.1 rad. The parameter selection in Milic’s method is as follows—the number of K-means clusters \( K \) is 3 to 6, and \( m \) is 0.1 rad (based on the experimental parameter selection of the author in [22]). For Hira’s Hue Blending method, the parameter rotation angle \( \theta = -20^\circ \), and the blending coefficient \( \alpha = -2.0 \). To enable readers with normal colour vision to perceive the original image and the resulting image seen by the dichromatic viewer, this paper uses the Vienot and Brettel methods [9, 10] to simulate the image of the red blind viewing angle. For each example, the first line shows the recoloured results of the original images in (a), the Hira images [16] in (b), the Milic images [22] in (c), and the images from the proposed method in (d). The corresponding simulation images for protanopes’ vision are aligned in the second row.

Figure 6 shows the results of the Daltonization of the protanope virtual image effected by the existing methods and the proposed method. For the simulation of the original image [Figure 6(a)] and the results of the method in [22] [Figure 6(c)], the contrast between the number and the background in Example 1 is lost and the colour blocks image in Example 2 will be mistakenly read by protanopes as regular colour blocks; similar results are seen in Figure 6(e). For the results of the method in [16], the number 5 that is observed by CVD patients in Example 1 obviously changes from green to blue; this indicates a certain degree of colour cognitive conflict. The proposed method retains the contrast between the number 5 and the background in Example 1 and maintains the contrast discrimination for adjacent colour patches in Example 2. In Figure 6(d), the discrimination between adjacent colour patches in Example 2 is greater, and, in the evaluation experiment, the proposed method receives the highest evaluation of the three methods.

Figure 7 shows the results of the existing method and the results of Daltonization in the real image for protanopes. The results of Hira et al. [16] in Figure 7(b) are more vivid, but a protanomal subject in the evaluation experiment pointed out that the colour of the green pepper in Example 1 was modified to blue; this did not constitute colour recognition under normal circumstances. Similarly, trichromatic subjects pointed out that the grassland in Example 2 had lost the original green colour after processing with the Hira method, and thus, received a lower score in the
evaluation experiment. Milic’s method can effectively maintain the naturalness of the image, as shown in the result and the simulation of Example 1 in Figure 7(c). Comparing the two processing results of Figure 7(b) and 7(d), the result of the Milic method is the most similar to the original image, whether it is with a perspective of normal people or protanopes, which are considered the most natural, academically, as Kuhn et al. [27] and Hassan et al. [36] used the color similarity between the daltonized image and the original image as a measure of color naturalness. However, the contrast improvement of Milic’s method is not sufficient. In Example 1 and Example 2 in Figure 7, the colour combination that confused protanopes are red and green in the original image, which can be felt more intuitively in the simulation of Figure 7(a). It is obvious that Milic’s results did not make the confusing colours have more intuitively in the simulation of Figure 7(a). It is obvious that Milic’s results did not make the confusing colours have significant contrast, because in the perspective of simulation, the colours of red and green are transformed into colours with similar tones, and there is no great colour difference between them. Because the proposed method creates brightness differences in the colours located on the confusing line in the u’ v’ chromaticity diagram, colours that were previously confused by CVD have greater colour difference in the result of the simulation. The proposed re-colouring method has similar colour consistency with the Milic method, but has a more significant contrast, which is the advantage of the proposed method. While maintaining the colour consistency, the difference between red pepper and green pepper in Example 1 of Figure 7(d) is more evident for protanopes. In Example 2, the proposed method also exhibits a better performance with the red and green jerseys.

The three elements of perceptual learning (colour contrast, naturalness, and colour consistency) are the three most important considerations in the evaluation of Daltonization. To evaluate the performance of the proposed method, we performed quantitative evaluations and user studies of the Daltonization for protanopia and compared them with the results reported in [16] and [22].

**4.1 Quantitative evaluation**

Because the confusion of image colour and colour vision disorder usually affects a specific area of an image, there are currently no truly uniform and efficient quantitative evaluation standards, and more subjective evaluation methods are preferred. Therefore, for the purposes of quantitative evaluation, we calculated u’ v’ average chromaticity and chromatic aberration with the two-colour viewing angle. Although u’ v’ average chromaticity and chromatic aberration only represent the average chromaticity differences before and after the Daltonization of the image, they can reflect the degree with which the method maintains colour consistency.

The u’ v’ average chromatic difference is a calculation method for colour chromaticity similarity that best represents human colour perception. The definitions of the average chromatic difference $\Delta F_{u,v}$, and average colour difference $\Delta F_{u,v}$, for an image are shown as follows:

$$\Delta F_{u,v} = \sqrt{\sum_{i,j} (\Delta u_{ij}^2 + \Delta v_{ij}^2)}$$

$$\Delta F_{u,v} = \sqrt{\sum_{i,j} (\Delta L_{ij}^2 + \Delta u_{ij}^2 + \Delta v_{ij}^2)}$$

where $\Delta L$, $\Delta u$, and $\Delta v$ are the differences between the two colours on the three channels in $L^*u^*v^*$ colour space, and $m$ and $n$ are the number of pixels in the horizontal and vertical directions of the image, respectively.

We randomly selected eight images containing natural scenes and computer graphics. The $\Delta F_{u,v}$ metric is applied to CVD simulation images, and the results generated by methods reported in [16] and [22] are compared with those from the proposed method. Table 1 shows the average chromatic differences for each method. The lower the value of the average chromatic differences, the more consistent is the colour recognition. Among the three methods, the average chromatic difference for the proposed method is slightly smaller than that of Milic’s method and much smaller than that of Hira’s method and this shows that the proposed method outperforms the two comparison methods.

Kuhn et al. [27] observed that they should minimize the deviation from the original image to maintain the naturalness of the image. Hassan et al. [36] used the colour difference between the generated image and the original image as a measure of naturalness. In this study, we apply this metric to CVD simulation images. The CVD simulation of the recoloured image is matched with the CVD simulation of the original image, and the colour difference is calculated. When calculating the chromatic aberration, we randomly selected eight images, containing some real images and some virtual images, for colour difference calculation. The average chromaticity and chromatic aberration of the eight images and the average values are shown in Table 2. The performance of the proposed method is significantly better than that of Hira et al. [16].

**TABLE 1 Results for the average chromatic differences for protanopes**

| Column heading | Hira’s method | Milic’s method | Proposed method |
|----------------|---------------|----------------|-----------------|
| Test Image1    | 14.0529       | 15.9200        | 13.6233         |
| Test Image2    | 25.1933       | 6.3883         | 6.6834          |
| Test Image3    | 9.3967        | 10.5284        | 9.9781          |
| Test Image4    | 16.4337       | 10.2641        | 10.5867         |
| Test Image5    | 31.967        | 18.4212        | 19.8132         |
| Test Image6    | 34.7777       | 19.7074        | 21.4403         |
| Test Image7    | 27.0292       | 13.7577        | 12.2220         |
| Test Image8    | 9.7868        | 11.6470        | 10.3872         |
| AVERAGE        | 21.0383       | 13.32926       | 13.09178        |
Similarly, we calculated the average chromatic differences and average colour differences of the resulting images and the original images, and the results are presented in Tables 3 and 4, respectively. For the calculation of trichromatic vision, Milic’s method performs the best, achieving the best evaluations for colour consistency and naturalness. The proposed method is not as good as is Milic’s in terms of naturalness and colour consistency, but both are better than Hira’s. Nevertheless, it is necessary to point out that the performance of Milic’s method with the images does not provide sufficient colour contrast (parameter selection is based on experiments reported in [22]).

### 4.2 Robustness comparison

The proposed method has a lower dependence of the clustering results on the clustering method adopted and the number of clusters obtained during clustering, and it can still perform well in the case of unsatisfactory clustering results and numbers of clusters. We probed the robustness (low dependency) of the proposed method on the clustering results by using a test image containing 12 colour patches and different clustering results. Although K-means is the most commonly used clustering method in image segmentation, in this section, in order to prove that the proposed method is not only within the limits of K-means, we applied three different clustering algorithms (K-means, K-medoids, and Fuzzy C-means) to determine the validity of the clustering results. If verified, the proposed method can play a greater role in improving the colour visibility of people with CVD. The colour remapping with the proposed method and Milic’s method are shown in Figure 8, and it can be seen that the primary colours in the image that are confounded by Milic’s method are eliminated when they are in the same cluster.

Clustering in this method is a means of obtaining chrominance information for the image when combined with R to adjust image brightness; even with poor choices for clustering and clustering number (deliberately designed to hinder good performance), the proposed method was still able to distinguish between 12 colours in three different cases. Conversely, Milic’s method performed poorly when the clustering result was bad. The example shows that the proposed method is robust and stable.

In addition, in the experiment, an interesting phenomenon has arisen that when the best clustering parameter is adopted (the resulting clustering number is set to 3), in every 20 times of clustering, FCM only achieved good results seven times. Thus, there were 13 bad results, which means that after the Milic algorithm is executed based on these clustering results, there will still be colour blocks that are indistinguishable by protanopes in the test image. In contrast, K-means had 19 acceptable results and K-medoids had 20. This may indicate that K-medoids and K-means are better suited than FCM to be used as clustering algorithms for Daltonization methods, but a larger sample size is required to prove this more rigorously. Owing to the limited number of experimental clustering times, K-medoids did not achieve bad clustering results in the case of K = 3, so we used the additional case of K = 4 to replace it in the comparison of K = 3.

### 4.3 Subjective evaluation

For subjective evaluation, 10 subjects (6 trichromats, 2 deuteranomals, 1 deuteranope, and 1 protanope) participated in the experiment. They evaluated the three Daltonization methods with respect to the three aspects of colour contrast, naturalness, and consistency.
In the subjective evaluation, the proposed method was also compared with the methods reported in [16] and [22]. The experiment consisted of three parts—subjects evaluated the colour contrast and naturalness for each image, and also evaluated the colour consistency of the methods (subjects were not informed of the method used to generate the recoloured images, but they knew which image was the original). Details are presented below.

Part I, colour comparison evaluation: Eight sets of images used in the quantitative assessment were presented to the subjects, one at a time. Each group contained the original image and the recoloured images using the methods of [16] and [22] and the proposed method, respectively. The trichromatic vision group was asked to compare the recoloured simulation images with the original images, while the CVD group was required to compare the recoloured image with the original image and use scores “1″, “2″, “3″, “4″, and “5″ to indicate “completely indistinguishable”, “barely contrasting”, “ordinary”, “significant contrast”, and “very significant contrast”, respectively.

Figures 9 and 10 provide detailed results for the distinction between CVD and tricolour vision subjects, respectively. From the results of the subjects’ evaluations of Hira’s method, we conclude that test images processed with Hira’s method generally exhibited good contrast. All subjects in the CVD group gave the highest evaluation of contrast for the test images processed with the Hira method (Figure 9) while, in the trichromats group, the contrast of the colour-blind images processed with the proposed method was rated above that of Hira’s method. In the real image, Hira’s method was rated highly by the trichromats group, and the evaluation results for the proposed method were similar to those of Hira’s. For images processed with Milic’s method, the scores for Test Images 1 and 2 in the trichromatic and CVD groups suggest that Milic’s method provides insufficient image contrast and fails to perform as well as Hira’s method or the proposed method with almost all test images.

Part II, naturalness evaluation: The relative naturalness of three groups of real scene images (Test Image 6–8) used in the quantitative naturalness evaluation was evaluated. Subjects were asked to rate the naturalness of the original image as a reference, and mark it as “1″, “2″, “3″, “4″, or “5″ to indicate “completely unnatural”, “unnatural”, “ordinary”, “natural”, or "very natural", respectively.
Figures 11 and 12 show the results for the evaluation of the processed image naturalness by the CVD group and trichromatic group, respectively. A virtual image (e.g. Test Images 1–5) is challenging to evaluate for its degree of naturalness, so the evaluation of naturalness was performed for the real images only (Test Images 6–8). In the evaluation of naturalness, Hira’s method with the best contrast performance was basically seen to be unnatural in the test image. Based on this result, we have reason to think that the main reason for the disharmony in colour cognition is that the difference before and after the chroma is too large, and the lightness effect has less influence. At the same time, the disharmony in colour cognition will have a deleterious effect on the evaluation of image naturalness. However, Milic’s method, with which the contrast performance is not ideal, received the highest evaluations among the three methods here. The evaluations of the proposed method fall in the middle of the three, and this result is consistent with that in Section 4.1. It can be concluded that it is reasonable to take the difference between the processed image and the original image as a measure of naturalness.

Part III, the assessment of colour cognitive conflict (colour consistency): Eight groups of images used in the quantitative study were evaluated for colour cognitive conflict. The subjects were asked to browse eight groups of images used in the previous test, and to mark the colour cognitive conflict of the images processed by a certain method as “1″, “2″, “3″, “4″, or “5″ to indicate “no conflict at all”, “slight conflict”, “ordinary”, “significant conflict”, and ”very significant conflict”, respectively.
Figures 13 and 14 show the evaluations of the CVD group and trichromats group for colour cognitive conflict in the processed images. Hira’s method is generally considered by the trichromats group to be common and has more conflicts, but, for the CVD group, it is considered to have more conflicts and, specifically, more significant conflicts. In contrast, most of the subjects considered Milic’s method to give only slightly conflicting results, and the ratings of the proposed method were between those of the other two methods. One noteworthy result is that the evaluation results for colour cognitive conflict are quite similar to those for naturalness. It can be inferred that colour consistency and naturalness are related factors.

At the end of the experiment, the subjects were asked to: (a) indicate which is the preferred method of blind selection and (b) rank the importance of the three elements of perceptual learning.

The results regarding the blind selection of subjects are shown in Figure 15. Half of the tricolour subjects (3 persons) and half of the bicolour subjects (2 persons) thought that the proposed method is the best after careful consideration, and only one of the 10 subjects chose Hira’s method. It is worth noting that, although there are only four subjects in the colour disorder group, none of them thought Hira’s method exhibited the best contrast effect; this shows that contrast is not the most important factor in Daltonization. Further, the results for the second question also support that contention. The second question asked the subjects to rank the importance of contrast, naturalness, and colour consistency. In the CVD group, three people (1 protanomal, 1 deuteranomal, and 1 deuteranope) gave the same responses—colour cognitive harmony is most important, naturalness is second, and contrast is least important—and it is interesting that another person (protanomal) rated contrast as most important, naturalness as second, and colour consistency as least important. In the trichromats group, the situation is different. Five out of six people ranked colour consistency in one of the first two positions, four placed naturalness there, and three placed contrast in one of the top two positions. The most interesting conclusion is that colour consistency is the most important factor, naturalness is second, and contrast is the least important; although this is very consistent with the results of current research on the Dalton method, a bigger sample is needed to prove it.

However, as introduced in Sections 2.2, Daltonization is a type of method to serve for individuals with CVD; therefore, meeting the colour discrimination needs of people with colour disorders is the most basic requirement, which means that sufficient contrast of the Daltonized image is necessary. Otherwise, why not directly provide the original image to the user, because the original image has the best colour naturalness and colour consistency? Therefore, although the subjects have greater reference value for the results of the importance of the three elements, meeting the contrast requirements of CVD users is the most basic requirement for designing Daltonization algorithms. Then, on this basis, we try to consider the user’s preference for the importance ranking of the three elements so as to meet their requirements. In other words, before the subjects’ preference ranking results, there is an implicit requirement to satisfy the colour contrast of CVDs. Milic’s method did not meet this requirement according to the subjective evaluation and the direct visual experience of Figures 6, 7, and the Figures 16 and 17 in the Appendix. Compared to Hira’s method, the proposed method performed far better in both colour naturalness and colour consistency of the quantitative and the subjective evaluation, although not as good as Hira’s in contrast, the subjects are satisfied with the contrast of both. In conclusion, the proposed method best balances the three factors of perceptual learning appropriately in subjective evaluations.
In the subjective experiment evaluation, the subjects were also asked to rank the three factors of colour naturalness, colour contrast and colour consistency in preference, and the results were shown in Table 5. In the results, 3 of the 4 trichromats believe colour consistency is the most important factor, while 3 of the 6 in the trichromats group believe naturalness is the most important.

5 | DISCUSSION AND LIMITATIONS

The proposed clustering-based method was designed to ensure that the Daltonized image enables users with CVD to distinguish the original confusing colours and reduce the dependence of existing clustering-based methods on the clustering results. Colour changes in brightness will have a negative impact on the colour naturalness of the subjective evaluation of the result, although the results of subjective evaluations and robustness comparison demonstrated that the proposed method satisfied the requirements for providing enough colour contrast for CVDs and overcomes the limitation of confusing colours in the same cluster in the clustering-based method in the cases of protanopes. Another limitation is that the lightness modification may cause some unexpected colour changes, although it
is the key to overcome the dependence of clustering results, as shown in Figure 16 Test Image2 and Figure 18 Test Image6. The original white background (Test Image2) turned grey after brightness adjustment, and the original black shadow (Test Image6) under the fruit stand also turned grey after adjustment; this seems to be unavoidable when using brightness adjustment, nevertheless, it is not obvious in other test images. As has been seen with other recolouring-based techniques, the subjective evaluation results could have been affected by the colour properties of the display device [13]. In addition, the results of test images 7 and 8 used in the evaluation experiment are shown in Figure 19.

In addition, because the method is based on clustering and adjusts the chroma and brightness based on the results of the clustering, this method is not suitable for video processing, because the processing result cannot be achieved in real time during the clustering step. Moreover, processing results are adjusted differently owing to the different clustering results; therefore, the image colour in the video time series is not continuous, that is, the colour of the pixels at the same position will be significantly different in different time frames.

6 | CONCLUSION

In this paper, we propose a content-dependent Daltonization algorithm based on lightness and chroma information, and we demonstrate its implementation for protanopes. The proposed method can maintain colour consistency, naturalness, and contrast enhancement to a significant degree. A quantitative evaluation shows that the proposed method can better maintain colour consistency for CVD patients. In subjective evaluations, the proposed method achieves the performance that best balances the three factors of perceptual learning appropriately. CVD observers consider colour consistency and naturalness to be more important than contrast, and this is consistent with the results of current research. In addition, the proposed method can accurately and easily modify parameters to account for the type and severity of CVD defects and can, therefore, provide the best personalized results for each CVD individual.

This study did not focus on improvements of the proposed method for image segmentation, such as how to extract continuous image regions more effectively and improve the computing efficiency of clustering, but these constitute important avenues for future research. It would also be valuable to determine how to weigh the relationship between the three elements of perceptual learning and to gather large sample statistics indicating CVD users’ rankings for the three.

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APPENDIX A
The test images involved in Section 4 (Results and Evaluation) are presented below, and their serial numbers correspond to the text.