Modification of Indistinguishable Colors for People with Color Vision Deficiency

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Abstract In this paper, we present a modification method of indistinguishable colors on the basis of the Color2Gray algorithm for people with color vision deficiency (CVD). Compared with people with normal color vision, people with CVD have difficulty in distinguishing between certain combinations of colors. To address this problem, we modify saturation and lightness components of the original image to preserve visual detail when perceived by people with CVD. The proposed method can automatically construct a transformation to maintain details for people with CVD while preserving naturalness for normal viewers. In addition, high-speed processing of recoloring is achieved by clustering on the basis of color quantization using the median cut algorithm.

Keywords: image processing, color vision deficiency

1. Introduction

Because of the increasing use of colors in multimedia contents to disseminate various visual information, it is important to perceive colors for information interpretation. However, people with color vision deficiency (CVD) have difficulty in distinguishing between several colors that have color differences. Roughly around 7% of men and 0.8% of women have a form of color deficiency [1]. Compared with people with normal color vision, people with CVD have difficulty in distinguishing between certain combinations of colors. Therefore, multimedia contents with rich colors may sometimes cause misunderstanding to people with CVD.

To address the above problem, many conventional methods have been proposed to modify color components of original images to preserve visual detail when perceived by people with CVD [2-8]. Basically, all previous methods involve the creation of images that are more comprehensible for viewers with CVD. However, recolored images may look unnatural to normal viewers. From an application viewpoint, images in a public place may be simultaneously observed by viewers with normal vision and CVD. Huang et al. preserved color informations in an original image, maintaining the recolored images as natural as possible, by optimizing the hue in each region [2]. This method, however, sometimes changes a certain color to a quite different color, such as red to blue. Tanaka et al. [3] proposed the recoloring method for converting lightness components of an original image on the basis of the Gray2Color algorithm proposed by Gooch et al. [9]. However, human visual perception is sensitive to lightness change. In addition, the modification of saturation components may not be effective when the intensity of a target color is lower than the a* axis in the a*b* color space [10]. Therefore, a novel recoloring approach based on the modification of saturation and lightness is required. Moreover, these methods require much computational time for recoloring.

In this paper, we present an efficient and effective recoloring algorithm for viewers with CVD and normal color vision. We propose a recoloring algorithm that can automatically construct a transformation to maintain details for viewers with CVD while preserving naturalness for normal viewers. To create a recolored image that looks natural to viewers with normal color vision, we propose the method of modifying saturation and lightness components using the Color2Gray algorithm. In addition, we achieve high-speed recoloring by clustering a color components using the median cut algorithm.

2. Related Work

To understand CVD, we must understand how human color vision works. The human retina has two types of photoreceptor cells: rod cells that only work in darkness, and cone cells that only work in light. Cone cells are further divided into three groups depending on which wavelength of light they mainly detect. The peak sensitivities of these three distinct types of cones lie in the long-wavelength (L), middle-wavelength (M), and short-wavelength (S) regions of the spectrum [11].

People with normal color vision have all three types of cone cells. People with protanopia (protanopes) lack the L cone cells that mainly detect red light among the three types of cone cells. On the other hand, the lack of M cone cells is referred to as deuteranopia, and the lack of
S cone cells is referred to as tritanopia. Among these three types of dichromats, those with protanopia and deuteranopia have difficulty in distinguishing red from green, whereas those with tritanopia have difficulty in discriminating blue from yellow.

To address this problem, some conventional methods have been proposed to create images that are more comprehensible for viewers with CVD. Ichikawa et al. proposed the manipulation of webpage colors for viewers with CVD [4]. They first decomposed a webpage into a hierarchy of colored regions and determined important pairs of colors that are to be modified. They later extended this technique to full color images [5]. On the other hand, Meguro proposed a color conversion method for creating perceptible color by using the combinatorial optimization method [7]. This approach realizes the perceptible images for dichromats by changing the confusion colors on the basis of simulated annealing in several regions of images. However, recolored images created by these previous methods may look very unnatural to normal viewers. Huang et al. proposed a novel recoloring algorithm that can automatically construct a transformation to maintain details for viewer with CVD while preserving naturalness for normal viewers [2]. Most of these methods, however, change color values for normal viewers and effective modification for viewers with CVD is not always achieved [8]. Moreover, gamut mapping is not considered in those methods even though the gamut problem is related to color conversion.

Tanaka et al. proposed the recoloring method of converting lightness components of original images on the basis of the Gray2Color algorithm [3]. In this method, lightness components of the original image $L^* = (L^*_1, L^*_2, \ldots, L^*_n)$ after modification are obtained by solving the following minimization problem:

$$E(L'_1, L'_2, \ldots, L'_n) = \arg\min \sum_{i=1}^{n} \sum_{j=1}^{n} ((L^*_j - L'_j)^2 - \delta L'_j^2)$$

subject to $\sum_{i=1}^{n} L'_i = \sum_{i=1}^{n} L^*_i$

where $L^*_i$ is the lightness component of the $i$-th pixel in the original image. $n$ is the number of pixels in the original image. This method preserves the mean lightness of the original image. This minimization problem is solved by the conjugate gradient method.

The signed color distance $\delta L'_j$ considering a difference in colors between the $i$-th and $j$-th pixels is defined as follows:

$$\delta L'_j = \Delta L'_j + \text{sign}(\Delta L'_j)w_{ij}\Delta BM_{ij}$$

with

$$\text{sign}(x) = \begin{cases} +1, & x > 0 \\ -1, & \text{otherwise} \end{cases}$$

$$w_{ij} = \alpha e^{-d_{ij}/h^*}$$

and

$$\hat{d}_{ij} = \min(d_{ij}, \beta d_{ij})$$

where $\Delta L'_j$ is $L^*_i - L'_j$, $\Delta a'_j$ is $a'_i - a'_j$, and $\alpha$ and $\beta$ are parameters determining the degree of modification and a nonnegative real value. $\Delta BM_{ij}$ is the basic modification value defined by

$$\Delta BM_{ij} = \sqrt{(a'_i - a'_j)^2 + (b'_i - b'_j)^2}$$

$d_{ij}$ means the degree of indistinguishable colors based on confusion loci theory. $d_{ij}$ is defined as follows:

$$d_{ij} = \left|\frac{y_i - y_j}{\sqrt{1 + u^2}}\right|$$

$$u = \frac{x_i - y_i}{x_i - y_i}$$

$$v = \frac{x_i - y_i}{x_i - y_i}$$

where $x$ and $y$ refer to the $xy$ color diagram calculated on the basis of CIE XYZ color space. Moreover, $(x_C, y_C)$ is the center of confusion in the $xy$ color diagram. For example, for protanopia, $(x_C, y_C) = (0.747, 0.253)$, and for deuteranopia, $(x_C, y_C) = (1.000, 0.000)$.

However, human visual perception is sensitive to lightness change. Moreover, these conventional methods require much computational time for re-coloring.

3. Proposed Method

In this section, we describe the modification method of saturation and lightness components based on the Color2Gray algorithm. The process of the proposed method is as follows.

1. Color quantization (clustering by the median cut algorithm)
2. Modification of saturation and lightness components
3. Correction of gamut colors

Here, we adopt the CIELAB color space as the working domain. Chroma $C'$ and hue $H'$ are calculated using $a^*$ and $b^*$ as follows:

$$C'_i = \sqrt{(a'_i)^2 + (b'_i)^2}$$

$$H'_i = \arctan(b'_i/a'_i)$$

3.1 Color quantization

In conventional methods [3,9], the processing cost is high since it is necessary to calculate signed color distances between pixels. In the proposed method, the number of colors in the original image is reduced by color quantization using the median cut algorithm [12].

First, an arbitrary number of pixels in RGB color space are sorted into a series of sets. Then, each set of data is divided at the median point on each dimension. After the color quantization, the number of color clusters in the quantized image is $k$. 

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3.2 Minimization problem for color modification

In this paper, to create recolored images for viewers with normal color vision and CVD, saturation and lightness components of the original image are modified using the Gray2Color algorithm.

Saturation components \( \hat{C}_i^* = (\hat{C}_1^*, \hat{C}_2^*, \ldots, \hat{C}_k^*) \) and lightness components \( \hat{L}_i^* = (\hat{L}_1^*, \hat{L}_2^*, \ldots, \hat{L}_k^*) \) after modification are obtained by solving the following minimization problems:

\[
E(\hat{C}_1^*, \hat{C}_2^*, \ldots, \hat{C}_k^*) = \arg\min \sum_{i=1}^{k} \sum_{j=1}^{k} ((\hat{C}_i^* - \hat{C}_j^*) - \delta_{ij})^2
\]

subject to \( \sum_{i=1}^{k} \hat{C}_i^* = \frac{1}{k} \sum_{i=1}^{k} \hat{C}_i \) \hspace{1cm} (12)

\[
E(\hat{L}_1^*, \hat{L}_2^*, \ldots, \hat{L}_k^*) = \arg\min \sum_{i=1}^{k} \sum_{j=1}^{k} ((\hat{L}_i^* - \hat{L}_j^*) - \delta_{ij})^2
\]

subject to \( \sum_{i=1}^{k} \hat{L}_i^* = \frac{1}{k} \sum_{i=1}^{k} \hat{L}_i \) \hspace{1cm} (13)

where \( \hat{C}_i^* \) and \( \hat{L}_i^* \) are a saturation and lightness component of the i-th color cluster in the quantized image, respectively. \( k \) is the number of color clusters.

The signed color distances \( \delta_{ij}^c \) and \( \delta_{ij}^l \) considering the difference in colors between i-th and j-th color clusters are defined as

\[
\delta_{ij}^c = \Delta C_{ij} + \text{sign}^c(C_i/C_j)w_{ij}\Delta BM_{ij}
\]

\[
\delta_{ij}^l = \Delta L_{ij} + \text{sign}^l(\Delta L_{ij})w_{ij}\Delta BM_{ij}
\]

where \( \Delta C_{ij} \) is \( C_i - C_j \), \( \Delta L_{ij} \) is \( L_i - L_j \), and \( \alpha \) and \( \beta \) are parameters determining the degree of modification and a nonnegative real value, respectively. \( \text{sign}^c, w_{ij}, \) and \( \Delta BM_{ij} \) are defined by Eqs. (3), (4), and (6). The sign function for a saturation component is defined by

\[
\text{sign}^c(x) = \begin{cases} +1, & x > 1 \\ -1, & \text{otherwise} \end{cases}
\]

Here, proposed minimization problems are solved by the conjugate gradient method. In order to optimize minimization problems defined by Eqs. (12) and (13), it is necessary to solve the following simultaneous equation.

\[
A_{(k)}x^w = b^w
\]

\[
A_{(k)} = \begin{pmatrix} \sum_{i=1}^{k} S_i & S_2 & \cdots & S_k \\ S_1 & \sum_{i=2}^{k} S_i & \cdots & S_k \\ \vdots & \vdots & \ddots & \vdots \\ S_1 & S_2 & \cdots & \sum_{i=2}^{k} S_i \end{pmatrix}
\]

\[
x^w = \left( BV_1^w, BV_2^w, \ldots, BV_k^w \right)^T
\]

\[
b^w = \left( \sum_{i=1}^{k} \delta_{ii}^w S_i, \sum_{i=2}^{k} \delta_{ii}^w S_i, \ldots, \sum_{i=k}^{k} \delta_{ii}^w S_i \right)^T
\]

here, \( S_i \) is the number of pixels that belong to the color cluster \( i \), \( W \) is the wild card of \( L \) or \( C \). The number of dimensions in the proposed simultaneous equation is \( k \). The mean value (\( BV_i^w \)) of each color cluster \( i \) is set to an initial value of \( x^w \). By solving the simultaneous equation, the modified saturation (\( AV_i^w \)) and modified lightness (\( AL_i^w \)) of each color cluster \( i \) are obtained. Therefore, the amount of modification of color cluster \( i \) is defined by

\[
\Delta MV_i^w = BV_i^w - AV_i^w
\]

However, human visual perception is sensitive to lightness change. In addition, the modification of saturation components may not be effective in the case of intensity \( b^* \) of a target color cluster being lower than \( a^* \), since confusion lines with viewers prone to protanopia or deutanopia are nearly parallel to the \( a^*b^* \) axis in the \( a^*b^* \) color space [10]. Therefore, \( \Delta MV_i^w \) is corrected by

\[
\Delta MV_i^c = \Delta MV_i^w \cdot \frac{|H_i^*|}{90.0}
\]

\[
\Delta MV_i^l = \Delta MV_i^w \cdot \left( 1 - \frac{|H_i^*|}{90.0} \right)
\]

where \( H_i^* \) is the hue angle of color cluster \( i \), which is in the range from \(-90.0 \) to \(+90.0 \). Then, each pixel in the original image is modified by

\[
\hat{C}_i = C_i + \Delta MV_i^c
\]

\[
\hat{L}_i = L_i + \Delta MV_i^l
\]

The proposed method enables high-speed recoloring through the calculation of the modification value of each color cluster.

3.3 Consideration of color gamut

The modified color obtained by Eqs. (24) and (25), i.e., \( (\hat{L}_i^*, \hat{C}_i^*, H_i^* ) \), is sometimes excluded from the color gamut and color correction should be carried out in such a case. First, \( \hat{L}_i^* \) is corrected so that the color is included in the color gamut as follows:

\[
\hat{L}_i = \begin{cases} 0 & \hat{L}_i < 0 \\ \hat{L}_i & 0 \leq \hat{L}_i \leq 100 \\ 100 & \text{otherwise} \end{cases}
\]

Second, \( \hat{C}_i^* \) is corrected so that the color is included in the color gamut as follows:

\[
\hat{C}_i = \begin{cases} \hat{C}_i^* & C_{\max}(\hat{L}_i^*, H_i^*) \leq C_{\max}^\ast(\hat{L}_i^*, H_i^*) \\ C_{\max}^\ast(\hat{L}_i^*, H_i^*) & \text{otherwise} \end{cases}
\]

where \( C_{\max}(\hat{L}_i^*, H_i^*) \) means the maximum chroma that can be displayed on a monitor with \( (\hat{L}_i^*, H_i^*) \) [13].
4. Experiments

4.1 Experimental conditions

In this work, we focus on protanopia and deuteranopia, which are the major types of color deficiency. In order to mimic the color perception of protanopia and deuteranopia, we adopt Bretell’s model [14] to simulate the perceived images.

In our criterion, we desire these two perceived color differences to be as similar as possible. On the other hand, we attempt not to dramatically modify the color perception of the color images since a severe modification may make the recolored image extremely unnatural for normal viewers. We use the error function

\[ E_a = \sum_{i=1}^{n} (|C_i - T(C_i)|)^2 \]

\[ E_d = \sum_{i=1}^{n} \sum_{j=1}^{n} \left( |C_i - C_j| - |SIMP(T(C_i)) - SIMP(T(C_j))| \right)^2 \]

where \( i \) and \( j \) range over the colors contained in the images, \( |-| \) is the perceptual color difference metric, \( T(\cdot) \) is recoloring function, and \( SIMP(\cdot) \) denotes the color perception simulated using Bretell’s model. \( E_a \) means the naturalness of recolored image for normal viewers, \( E_d \) means the contrast of recolored image for viewers with CVD. These functions were proposed by Huang et al. in [2].

On the other hand, Tanaka et al. proposed a novel criterion of contrast for viewers with CVD [3].

\[ E_c = \frac{\sum_{(i,j) \in \sigma_k} \left| \Delta E(C_i, C_j) - \Delta E(SIMP(T(C_i)), SIMP(T(C_j))) \right|}{\sum_{(i,j) \in \sigma_k} \left| \Delta E(C_i, C_j) - \Delta E(SIMP(C_i), SIMP(C_j)) \right|} \]

\( \Delta E(\cdot) \) is the perceptual color difference metric defined as

\[ \Delta E(i, j) = \sqrt{(L_i^* - L_j^*)^2 + (a_i^* - a_j^*)^2 + (b_i^* - b_j^*)^2} \]

\( \sigma_k \) is a set of a pair of pixels \( [i, j] \) that satisfy \( T_{ij} \leq \lambda \). Here, \( T_{ij} \) is defined by

\[ T_{ij} = \frac{|SIMP(C_i) - SIMP(C_j)|}{|C_i - C_j|} \]

Minimizing these error functions shortens the color distance between the original colors and the corresponding remapped colors.

To evaluate the performance of our method in terms of the execution time, we implemented the there-coloring scheme with the support of the Intel OpenCV library using a personal computer running on Microsoft Windows 7. The hardware platform for the experiment was a personal computer equipped with Intel Core i7 2.93 GHz CPU and 8 GB RAM.

4.2 Results and discussion

First, we evaluate the effectiveness of contrast and the naturalness of the proposed method compared with those of conventional methods. The test image for this experiment is shown in Fig. 1(a). This test image is expressed in 24-bit RGB color, and has the dimensions of 360 x 355 pixels. In our opinion, recoloring of the test image is very difficult since the test image has many colors.

The results of recoloring for deuteranopia are shown in Figs. 1(b)-(d) and Table 1. The parameter \( \lambda \) in \( E_c \) is 0.25, and the number of color clusters \( k \) is 1000. The parameters of recoloring in Figs. 1(b)-(d) are \( \alpha = 0.5 \) and \( \beta = 0.5 \). As comparable methods, we use the conventional method [3] proposed by Tanaka et al. and our previous method [10], in which lightness and saturation components are modified, respectively. From the result, contrasts \( E_a \) and \( E_d \) are found to be improved with an increase in parameters \( \alpha \) and \( \beta \) for recoloring. On the other hand, naturalness \( E_a \) declined with an increase in these parameters. Conventionally, the relationship between contrast and naturalness is a trade-off. Comparison with conventional methods using two evaluational criteria \( (E_a, E_d) \) is shown in Fig. 2. In this figure, a result with a low error value is sufficient. In other words, a result in the lower left region is favorable. When parameter \( \alpha = [0.3, 0.5] \), contrast \( E_c \) of the conventional method [3] is the lowest among all methods. However, in Fig. 1(c), the recolored image looks unnatural to normal viewers. \( E_a \) and \( E_d \) of the proposed method are satisfactory compared with other methods. Therefore, we confirmed that the proposed method can yield a transformation to maintain details for viewers with CVD while preserving naturalness for normal viewers.

Second, we evaluate the processing cost of the proposed method. Comparisons of evaluational criteria with the number of color clusters are shown in Table 2. By increasing the number of color clusters, processing cost was increased, but error rates were reduced. From this table, we confirmed that error values of the proposed method are saturated when \( k = 1000 \) or more. An example of a recolored image with parameters \( (\alpha = 0.3, \beta = 0.3) \) is shown in Fig. 3. Here, we chose the median value of each parameter for this example. From these results, recolored image with \( k = 100 \) is deemed natural for normal viewers. For the comparison of processing time, we implemented the conventional method [3]. As a result, the processing time of the conventional method [3] in the case of Fig 1(a) is 3615 s. Therefore, we achieved high-speed recoloring for viewers with CVD while preserving high naturalness and contrast.

5. Conclusions

In this paper, we presented the modification method of indistinguishable colors using the Color2Gray algorithm for people with CVD. We modified saturation and lightness components of the original image to preserve visual
Table 1. Naturalness and contrast of each method

<table>
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Fig. 1 Recoloring results by proposed and conventional methods (α = 0.5, β = 0.5)

Fig. 2 Comparison with two conventional methods

References
[1] M. Okabe and K. Ito: Color universal design (CUD) - How to make figures and presentations that are friendly to colorblind people; http://fly.is.k.u-tokyo.ac.jp/color/
Table 2  Evaluational criteria for various numbers of color clusters $k$

<table>
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Fig. 3  Recoloring results of proposed method ($\alpha = 0.3, \beta = 0.3$)


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(Received May 8, 2012; revised July 27, 2012)