IMAGE RECOLORIZATION FOR THE COLORBLIND

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ABSTRACT

In this paper, we propose a new re-coloring algorithm to enhance the accessibility for the color vision deficient (or colorblind). Compared to people with normal color vision, people with color vision deficiency (CVD) have difficulty in distinguishing between certain combinations of colors. This may hinder visual communication owing to the increasing use of colors in recent years. To address this problem, we re-color the image to preserve visual detail when perceived by people with CVD. We first extract the representing colors in an image. Then we find the optimal mapping to maintain the contrast between each pair of these representing colors. The proposed algorithm is image content dependent and completely automatic. Experimental results on natural images are illustrated to demonstrate the effectiveness of the proposed re-coloring algorithm.

Index Terms— Assistive technology, Image enhancement, Color vision deficiency.

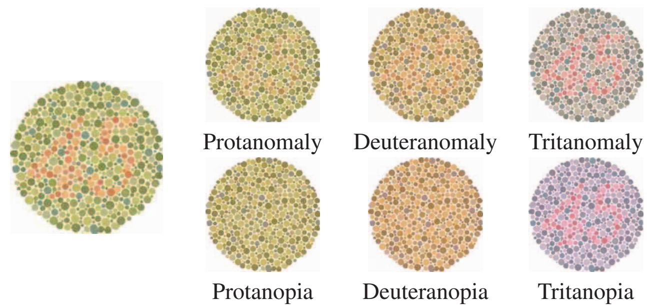

Fig. 1. Original color image and the simulation results for various types of color blindness. Image in the left is the original color image perceived by people with normal vision, while the six images in the right are the simulation results.

1. INTRODUCTION

In recent years, due to the availability of color printers and display devices, the use of colors in multimedia contents to convey rich visual information has significantly increased. It becomes more important to utilize colors for effective visual communication. However, people with color vision deficiency (CVD) have difficulty in distinguishing between some colors that are contrasting and perceptible to people with normal vision. We show in Fig. 1 an example of how CVD people perceived colors. The image in the left is the original image perceived by people with normal vision, and the visual information can be easily interpreted. On the other hand, critical color information may disappear or become indistinct in the six images in the right, which are the simulation results for people with various types of color vision deficiency.

To understand CVD, we must understand how the human color vision works. Normal color vision is based on the absorption of photons by three different types of fundamental photoreceptor cells, the *cone* cells. The three classes of cones have different spectral sensitivities with peak responses lying in the long- (L), middle-(M), and short-(S) wavelength regions of the spectrum, respectively. The energy received by the L, M, and S cones can be computed by a numerical integration over the wavelength λ:

$$[L, M, S] = \int E(\lambda)[\bar{l}(\lambda), \overline{m}(\lambda), \overline{s}(\lambda)]d\lambda, \tag{1}$$

where $E(\lambda)$ is the spectral power distribution of the light and $\bar{l}(\lambda), \overline{m}(\lambda), \overline{s}(\lambda)$ are the fundamental spectral sensitivity functions for L-, M-, and S-cones.

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CVD results from partial or complete loss of function of one or more types of cone cells. There are three major types of CVD: anomalous trichromacy, dichromacy, and monochromacy. Anomalous trichromacy, a mild color deficiency, is often characterized by the defect of one of the three cones. The three types belonging to this category are protanomaly, deuteranomaly, and tritanomaly, depending on deficiency in L-, M-, or S- cones, respectively. Dichromacy, a more severe color deficiency, is present when one of the three cone types is absent. Protanopia, deuteranopia, or tritanopia has no L-, M-, or S- cone, respectively. Monochromacy is the severest but rarest type of CVD, lacking all types of cone cells and perceiving brightness variation only. In this paper, we focus on dichromacy.

There have been several works that attempt to simulate color deficient vision. Among them, the computational model of CVD proposed by Brettel et al. [1] was widely adopted. In [1], the computational model of CVD was formulated in the three dimensional LMS space, where three orthogonal axes L, M, and S represent the responses of the three different cones. Based on the success in simulating the color perception of people with CVD, one can attempt to provide a better color representation for the colorblind.

Many works have been devoted to addressing CVD accessibility. We classify them into two main categories: 1) tools that provide guidelines for designers to avoid ambiguous color combinations, and 2) methods that (semi-)automatically reproduce colors suitable for CVD viewers. Methods in the first category assist designers in color reproduction by providing guidelines, or using a restricted CVD palette, or verifying color schemes. However, it still takes a lot of effort to select colors that are visually friendly for CVD viewers. Moreover, these methods cannot be applied to existing natural images.Methods that semiautomatically re-color images for accommodating the colorblind provide a few parameters for users to adjust the color mapping [2–4]. However, the results are sensitive to the selection of the parameters and improper parameters may result in unnatural images.

Recently, automatic re-coloring algorithms for CVD viewers have been proposed [5–10]. Believing that the differentiation of colors is more important than the identification of colors, these approaches aimed at preserving color contrast in the image for CVD people. They have similar process flow: 1) Describe the color information in the original image through color sampling to alleviate the computational burden. These representing colors are called "key colors". 2) Define the target distance. The Euclidean distance between two key colors in the color space is usually used. 3) Obtain the optimal mapping of these key colors through minimizing the difference between the original distances and the perceived distances by CVD viewers for every pair of key colors. 4) Interpolate between the corrected key colors through a distance-weighted nearest neighbor interpolation to compute the final CVD corrected image.

Although these approaches can automatically re-color an image into a suitable form for people with CVD, two significant problems remain. The first problem is that representing color information in the original image using color quantization may not be depictive enough. Yet, using too many (e.g. 256) key colors may result in pretty unnatural color images to both people with normal vision and people with CVD. For example, the colors of one object may be quantized into a few key colors. However, after computing the optimal mapping of the whole set of key colors, these key colors may be separated far apart even though originally they are near in the color space. In this case, artifacts may appear in the re-colored image (see the unnatural color on the blue pencil in Fig. 4 (e)).

The second problem with existing approaches is that the recoloring process is excruciatingly slow, which prohibits itself from many applications. As noted in [6], solving the optimal mapping over a quantized set of 256 key colors requires more than 20 seconds, and the interpolation step takes a few minutes. In [8, 9], only a small number (less than 25) of key colors can be used due to the expensive computational complexity of the algorithm.

In this paper, we present an efficient and effective re-coloring algorithm for people with CVD. We propose to represent the color information using the Gaussian Mixture Model (GMM), which is more depictive than color sampling strategy used by previous works. The center (i.e. the mean vector) of each Gaussian is analogous to the key colors used by previous approaches. The main difference is that the GMM also encodes the range information (i.e. the covariance matrix) of the key colors. We use the Expectation-Maximization (EM) algorithm to estimate the parameters of the GMM. The optimal number of Gaussians in the mixture is determined by applying the Minimum Description Length (MDL) principle [11]. Since we represent each key color using a Gaussian distribution, the "distance" between a pair of Gaussians can be computed by the symmetric Kullback-Leibler (KL) divergence. In previous works, every key colors are of the same importance.We introduce a new weighting method of colors and incorporate their importance for people with CVD into our optimization process. In the interpolation stage, we interpolate colors according to their posterior probabilities of each Gaussian and the corresponding mapping to ensure the local color smoothness in the re-colored image.

The remainder of this paper is structured as follows. The detail procedures of the proposed re-coloring algorithm are introduced in Section 2. Section 3 presents the experimental results. Section 4 concludes this paper.

2. THE PROPOSED COLOR REPRODUCTION ALGORITHM

Re-coloring an input color image involves four steps: (1) Extract the L*a*b* value in the CIEL*a*b* color space for each pixel as the color feature; (2) Group these color features into clusters by modeling the distribution using the GMM-EM approach; (3) Relocate the mean vector of every Gaussian component for a specific type of CVD through an optimization procedure; and (4) Perform Gaussian mapping for interpolation.

2.1. Image Representation via Gaussian Mixture Modeling

For each pixel in the image, we extract the color feature in the CIEL*a*b* color space, where the perceptual difference between any two colors can be approximated by the Euclidean distance between them. To model the underlying color distribution, we assume that the distribution can be well approximated by K Gaussians. The probability density is of the form:

$$p(x|\Theta) = \sum_{i=1}^{K} \omega_i G_i(x|\theta_i), \tag{2}$$

where x is the color feature vector, ω_i represents the mixing weight of the i_{th} Gaussian, Θ is the parameter set $(\omega_1 \ldots \omega_K, \theta_1 \ldots \theta_K)$, and G_i is a 3D normal distribution with parameter $\theta_i = (\mu_i, \Sigma_i)$. We initialize the values of the K mean vectors and covariance matrix by the K-means algorithm. Then, the EM algorithm can be used for GMM estimation.

E-step: Given the parameter set Θ^{old}, the probability of color feature x_j belonging to the i_{th} Gaussian is calculated as:

$$p(i|x_j, \Theta^{old}) = \frac{\omega_i G_i(x_j|\theta_i)}{\sum_{k=1}^{K} \omega_k G_i(x_j|\theta_k)}. \tag{3}$$

M-step: The parameters of the model (i.e. mean vectors, covariance matrix, and mixing weights) are re-estimated by the following update equations:

$$\omega_i^{new} = \frac{\sum_{j=1}^{N} p(i|x_j, \Theta^{old})}{\sum_{i=1}^{K}\sum_{j=1}^{N} p(i|x_j, \Theta^{old})}, \tag{4}$$

$$\mu_i^{new} = \frac{\sum_{j=1}^{N} p(i|x_j, \Theta^{old}) x_j}{\sum_{j=1}^{N} p(i|x_j, \Theta^{old})}, \tag{5}$$

$$\Sigma_i^{new} = \frac{\sum_{j=1}^{N} p(i|x_j, \Theta^{old})(x_j - \mu_i^{new})(x_j - \mu_i^{new})^T}{\sum_{j=1}^{N} p(i|x_j, \Theta^{old})} \tag{6}$$

where N is the number of pixels in the image. This update scheme allows for full covariance matrices. However, for computational efficiency, we restrict the the covariance to be diagonal matrix. While this is certainly not the case, the assumption allows us to avoid a costly matrix inversion at the expense of accuracy. The E-step and M-step are iterated until convergence or after 10 iterations.

We select the optimal value of K by applying the MDL principle [11], which suggests that the best hypothesis for a set of data is the one that achieves the largest degree of compression. We choose K to maximize $\log \mathcal{L}(\Theta|\mathcal{X}) - \frac{m_K}{2} \log N$, where $\log \mathcal{L}(\Theta|\mathcal{X})$ is the log likelihood, and m_K is the number of parameters of the model with K Gaussians. In this paper, we have $m_K = 7K - 1$ ($K - 1$ for weights, $3K$ for means, and $3K$ for variances). For our experiments, K ranges from 2 to 6.

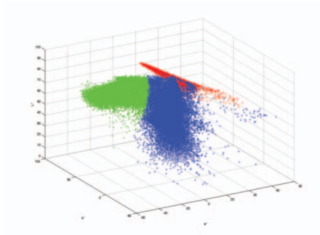

Fig. 2. Color distributions in the CIEL*a*b* color space in the image "flower" (see the second row of Fig. 3 (a)).

2.2. Target Distance

In the previous approaches, the distance between each pair of key colors is computed using Euclidean distance in the color space. As described in the previous subsection, we generalize the concept of key color from "point" to "cluster". Hence, the distance between two key colors is generalized from "point to point" to "distribution to distribution". We show in Fig. 2 the distributions in the CIEL*a*b* color space, where each color is assigned to the most probable Gaussian in the mixture. We can see that the variances vary from cluster to cluster. In this case, Euclidean distance between key colors is not informative since the variance information is completely ignored. For example, the distance between two highly compact (i.e. small variance) clusters should be larger than the distance between two less compact (i.e. larger variance) clusters with the same means. To overcome the insufficiency of the Euclidean distance, we measure the distance between each pair of clusters by the symmetric KL divergence.

The KL divergence (or relative entropy) is a measure of the dissimilarity between two probability distributions. Given two probability distributions G_i and G_j, the symmetric KL divergence $D_{sKL}(G_i, G_j)$ can be written as:

$$D_{sKL}(G_i, G_j) = D_{KL}(G_i||G_j) + D_{KL}(G_j||G_i), \quad (7)$$

where $D_{KL}(\cdot||\cdot)$ represents the KL divergence.

Since each cluster is modeled as a multivariate Gaussian distribution, the analytical solution exists and can be computed efficiently:

$$D_{sKL}(G_i, G_j) = (\mu_i - \mu_j)^T(\Sigma_i^{-1} + \Sigma_j^{-1})(\mu_i - \mu_j) + tr(\Sigma_i\Sigma_j^{-1} + \Sigma_i^{-1}\Sigma_j - 2I), \quad (8)$$

where $tr(\cdot)$ stands for the trace and I is a 3×3 identity matrix.

2.3. Solving the Optimization

The goal of the proposed re-coloring algorithm is that the symmetric KL divergence between each pair of Gaussians in the original image will be preserved in the recolored image when perceived by people with CVD. In other words, the original color contrasts which may disappear due to CVD will be preserved in the corrected image for CVD people.

We define the color mapping functions $M_i(\cdot), i = 1, \ldots, K$ for each Gaussian distribution. The mapping function $M_i(\cdot)$ relocates the mean vector while maintaining the covariance matrix of the i_{th} Gaussian distribution. In the case of re-coloring natural images, our goal is to maintain, not to enhance, the original contrast in the image. To avoid producing an unnatural corrected image, we restrict the mapping functions to be rotation operators in the a*b* plane. Therefore, each mapping function can be parameterized by only one angle variable.

The error introduced by the i_{th} and j_{th} key colors is defined as:

$$E_{i,j} = [D_{sKL}(G_i, G_j) - D_{sKL}(Sim(M_i(G_i)), Sim(M_j(G_j)))]^2, \quad (9)$$

where $Sim(\cdot)$ represents the simulation function of CVD perception [1]. Note that the covariance matrix after applying the function $Sim(\cdot)$ is approximated by clustering the colors in the simulated image using the same class probability $p(i|x, \Theta)$ as in the original image.

The objective function can be computed by summing all errors introduced by each pair of key colors. However, the key colors are assumed to be of the same importance. This may introduce unexpected effect to the optimization process if the image is rich in colors. Hence, we make a minor modification by assigning weights to the key colors. We emphasize those colors under significant color shift when perceived by people with CVD. In other words, colors that are similar with the corresponding simulated colors (e.g. colors with little chromaticity) will be assigned small weights and thus need not be corrected, and vice versa. We denote the weight of the j_{th} color feature as α_j:

$$\alpha_j = ||x_j - Sim(x_j)||, \quad (10)$$

where $||\cdot||$ is the Euclidean norm.

With the weights of the color features, we can then compute the weight of each key colors (denoted as λ_i for the i_{th} cluster) as:

$$\lambda_i = \frac{\sum_{j=1}^{N} \alpha_j p(i|x_j, \Theta)}{\sum_{i=1}^{K}\sum_{j=1}^{N} \alpha_j p(i|x_j, \Theta)}. \quad (11)$$

Therefore, the objective function can be written as:

$$E = \sum_{i=1}^{i=K}\sum_{j=i+1}^{j=K} (\lambda_i + \lambda_j)E_{i,j}. \quad (12)$$

In this way, the optimization will focus more on those colors that suffer greater changes when perceived by people with CVD , while leave insignificant colors unchanged.

Here, we have a multi-variant non-linear function. It is difficult to solve the minimization problem using analytical techniques due to the irregularity of the simulation function $Sim(\cdot)$. We thus adopt the direct search optimization method [12]. We set various initial changes to the variables and run the optimization process many times to avoid being trapped in local minima. The result with the lowest error is chosen for re-coloring.

2.4. Gaussian mapping for Interpolation

Our mapping is restricted to a rotation in the a*b* plane. Hence, the mapping works in the CIE LCH color space, where L is lightness (equal to L^* in CIE LAB), C is chroma, and H is hue. The lightness L* and the chroma C is unchanged: $T(x_j)^{L^*} = x_j^{L^*}$ and $T(x_j)^C = x_j^C$, where $T(x_j)$ denotes the transformed color. After obtaining the optimal mapping function $M_i(\cdot), i \in \{1, \ldots, K\}$, we can compute the hue of the transformed color as:

$$T(x_j)^H = x_j^H + \sum_{i=1}^{K} p(i|x_j, \Theta)(M_i(\mu_i)^H - \mu_i^H). \quad (13)$$

The hue shift of a color depends on the posterior probability of each Gaussian and the corresponding mapping function. This ensures the smoothness after the re-coloring process, especially in regions rich in colors.

3. EXPERIMENTAL RESULTS

We have implemented and tested our algorithm using C++ on a Pentium 4 3.4GHz PC. It takes $O(KN)$ for key color extraction using GMM, $O(K^2)$ for optimization process, and $O(KN)$ for interpolation, where K represents the number of Gaussian in the mixture, and N is the number of pixels in the image. By generalizing the concept of key colors, we show the image color distribution can be modeled using a small number of Gaussians. Re-coloring an image with 300×300 pixels takes less than 5 second without spending any effort on improving the speed of optimization. The computation time is significantly faster than previously published works [6–9] (a few minutes or more).

Since it is difficult to gather various types of color-deficient viewers to evaluate our method, we use the computational model to simulate color perception of people with CVD in [1]. We show in Fig. 3 some sample results on re-coloring natural images for accommodating the colorblind. Fig. 3 (a) present three original color images. The simulated views of protanopia (first row), deuteranopia (second row), and trianopia (third row) are shown in Fig. 3 (b). We can see that important visual details in the original color image are lost in the simulated view of people with CVD. Fig. 3 (c) shows the simulation results of our re-colored images. Note that the contrast information in the original images can be well preserved and the recolored images are natural.

In Fig. 4, we demonstrate comparison with the method proposed by Jefferson et al. [9]. Fig. 4 (a)(b) show the original color image and its simulation result of people with tritanopic deficiency. The re-colored result by our method and its simulated view are present in Fig. 4 (c) and (d). Fig. 4 (e)(f) show the re-colored results by Jefferson et al [9]. We can see that in Fig. 4 (d) and (f) both approaches provide a better information content for the tritanopia. However, the colors in the re-colored image are pretty unnatural and the luminance of the re-colored images are inconsistent with the original one. Compared with their method, our re-coloring algorithm produces more perceptually pleasing images.

(a) (b) (c)

Fig. 3. Sample results of the proposed re-coloring algorithm. (a) The original images. (b) The simulated views of the original image for protanopia (first row), deuteranopia (second row), and tritanopia (third row) (c) The simulation results of the re-colored images.

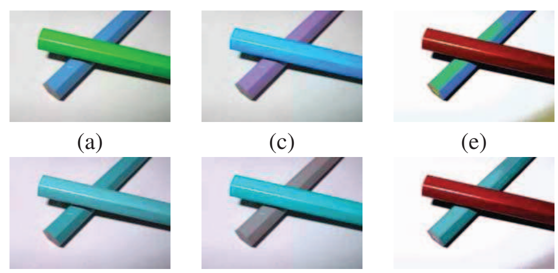

Fig. 4. Comparison with [9]. (a) The original image. (b) The simulated view of (a) for tritanopia. (c)(d) The re-colored result by the proposed method and its simulated view. (e)(f) The re-colored result by [9] and its simulated view.

4. CONCLUSIONS

In this paper, we propose a novel re-coloring algorithm for people with CVD. We have contributed to the state-of-the-art in three issues: 1) we have generalized the concept of key colors in the image; 2) we have proposed to measure the contrast between two key colors by computing the KL divergence; and 3) we have shown that our method can interpolate colors to ensure local smoothness with a few key colors. We have demonstrated the effectiveness of the proposed algorithm by re-coloring some natural images.

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