An Interface to Support Color Blind Computer Users

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ABSTRACT
A new method for adapting digital images so that they are suitable for color blind viewers is presented. In contrast to earlier automatic methods which formulate the problem of adapting images for color blind observers as one of optimization, we demonstrate how it is possible to allow a user to compute a very wide range of adaptations in reasonable time under the control of a single variable. We demonstrate how the algorithm can be delivered as an adaptive technology via a simple interface, and evaluate the efficacy of our method using psychovisual experiments with simulated color blind users and a standard color vision test.

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H5.2 Information interfaces and presentation: User interfaces – *Graphical user interfaces.*

General Terms
Algorithms, Design, Human Factors.

Author Keywords
Adaptive Technology, Color Blindness, Interface Support.

INTRODUCTION
Color blindness, or color vision deficiency (CVD), is known to be a significant barrier to effective computer use. A recent usability study conducted by the UK Disability Rights Commission [3] reported color accessibility to be the second most recurrent accessibility barrier to the Web for disabled users. Therefore a need exists to model CVD, simulate its effects and correct for them. This need is challenging because there are different types of CVD and the degree of CVD can vary from person to person. Table 1 summarizes the main types of CVD, giving the technical names for the various forms of abnormal color vision systems and the prevalence rates in North America and Western Europe, adapted from [1].

The three main types of abnormal color vision system are called *anomalous trichromatism*, *dichromatism* and *monochromatism*. Anomalous trichromatism results when one of the fundamental cones has had its peak sensitivity shifted [7]. The types are classified as protanomaly and deuteranomaly depending on whether the L or M cones have been affected[1]. Anomalous trichromats' perception of color ranges from almost normal to dichromatic depending on the extent to which the defective cone has had its peak sensitivity shifted. Dichromatism is a severe form of CVD that results when one of the fundamental cones is missing. Dichromats are classified as protanopes, deuteranopes or tritanopes, depending on whether the L, M or S cones are missing. Monochromatism is the severest form of CVD and is characterized by a total inability to distinguish colors. Monochromats typically have a complete lack of cone receptors in the retina.

Name	Cause	Prevalence
Dichromacies		
Protanopia	Missing L cone	♂: 1.0% ♀: 0.02%
Deuteranopia	Missing M cone	♂: 1.1% ♀: 0.1%
Tritanopia	Missing S cone	Very rare
Anomalous Trichromacies		
Protanomaly	Abnormal L cone	♂: 1.0% ♀: 0.02%
Deuteranomaly	Abnormal M cone	♂: 4.9% ♀: 0.04%

Table 1. Major genetic color deficiencies.

The most common forms of CVD are genetic photoreceptor disorders, for which the incidence rates among populations vary. 8% of Caucasian males, 5% of Asiatic males, and 3% of African-American and Native-American males are color deficient [1]. In addition to the common congenital disorders, it is also possible to acquire CVD through damage to the retina, optic nerve, or higher brain areas.

SIMULATING COLOR BLINDNESS
Methods for simulating CVD date back to the beginning of the 19th century, when Goethe produced a water-color landscape painting in colors intended to demonstrate the view as seen by a blue-blind CVD observer [7]. More recently, it is possible to map colors in digital images to permit a normal color viewer to experience color as seen by a CVD viewer. In such models [2, 8], the energy received by the L, M and S cones is

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

where $E(\lambda)$ is the power spectral density of light as a function of wavelength and $\bar{l}(\lambda)$, $\bar{m}(\lambda)$ and $\bar{s}(\lambda)$ are the cones'

[1] A normal color observer has three types of cone cells, called long- (L), middle- (M) or short- (S) wavelength cones depending on where their peak sensitivities lie in the visible spectrum. The colors humans are able to perceive are the consequence of unequal stimulation of these three types of cone.

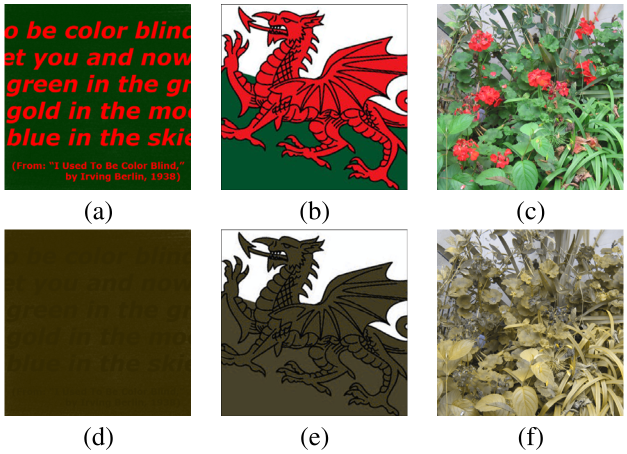

Figure 1. Computerized simulations depicting red-green color blindness. (a-c) Color images as seen by a normal color viewer; and (d-f) computerized simulations depicting how the images are perceived by a protanopic CVD viewer [2].

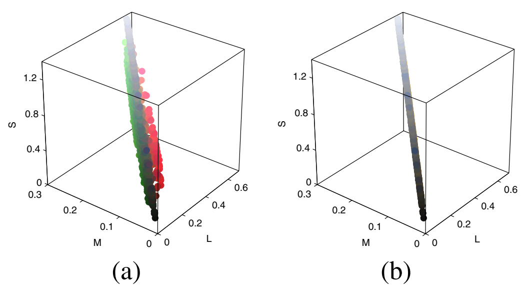

Figure 2. The effect of the protanopic projection in the LMS color space. (a) Original color points taken from the image in Figure 1(c); and (b) the same points following the protanopic projection.

fundamental response functions over the wavelength of visible light for long, medium, and short wavelengths.

In [2] the algorithm is expressed in the LMS color space as three piecewise projections, one for each type of dichromacy. The algorithm has three parts: 1) compute the LMS tristimulus values from RGB data; 2) apply the projection; and 3) compute the RGB color values from the resulting LMS coordinates. The effect of the protanopic transformation is shown in Figure 1[2].

The images in Figures 1(a-c) are easily interpreted by a normal color viewer. The text in (a) is legible; the dragon in (b) is distinct from the background; and the flowers in (c) are easily distinguished. However, the protanopic simulated versions, shown in Figures 1(d-f), contain less information and detail is lost. The effect of this transformation in the LMS color space is shown in Figure 2. The colors seen by a normal color viewer are, as shown in Figure 2(a), encapsulated in a three-dimensional color space, whereas the colors perceptible by a dichromat collapse to a two-dimensional plane, as shown in Figure 2(b).

[2]Figures in this paper are difficult to interpret in grayscale. Color versions are available here: http://www.cmp.uea.ac.uk/˜laj/chi07.

In [2] with the aid of a color calibrated monitor it is shown that, for colors within the gamut of the device, dichromats cannot distinguish the original from the dichromat version; thus there exist models for accurately simulating CVD. The challenge is to use these models to improve images for CVD viewers, which we now review.

RELATED WORK

Recently, a number of automatic adaptation algorithms have been proposed that modify content for CVD viewers [6, 9, 10]. These methods, termed *post-publication* methods in [6], formulate the problem of recoloring images for CVD viewers as one of optimization. The goal is to modulate colors in the image so that when they are viewed by a CVD person, the perceived difference between any pair of colors is of the same magnitude as that perceived by a normal color viewer. In [10], a framework is proposed in which the mapping error has three components. The first measures the squared difference between the color differences between colors. The second is the error between colors in the original image that are maximally different and the difference between the mapped versions of those colors. The third is a punishment for mapping certain special colors to new positions. Parameters are introduced for each component of error and their respective weightings so that the “author’s intention” with regard to the mapping can be preserved. The optimization is complex, requiring the use of a small number of representative colors. In [9] the optimization is constrained by restricting the mapping to be a composition of two transforms containing twelve parameters, which reduces the search space. Although this method has considerable computational advantages, it has not been extended to handle common practical problems such as the desire to force certain colors to have particular mappings. The algorithm in [6] uses the World Web Consortium (W3C) accessibility evaluation criteria to recolor images for dichromatic viewers. The algorithm has four parts: 1) select a subset of key colors from the problem image; 2) compute the target differences using color and brightness differences between key colors; 3) solve an optimization to find a recoloring for the dichromatic CVD viewer; and 4) interpolate the resulting colors across the remaining colors in the image using inverse distance weighted interpolation. The speed of the algorithm and the quality of the mapping depend on the number of key colors selected; reasonable performance was achieved using 25 key colors.

The methods [6,9,10] described in this section provide algorithmic solutions to the problem of adapting images for color blind viewers, but few of them provide interface solutions. In the next section, we describe a method that permits color images to be modified interactively in a way that preserves color content for a particular class of color blind viewer.

ALGORITHM

The basis of our algorithm is to transfer the chromatic information of the defective cone across the two functioning cones. For example, the protanope has no L cone and hence perceives no variation on the L axis; color stimuli with fixed M, fixed S and varying L collapse to the same color. Transferring this chromatic variation to the M and S cones allows the protanope to perceive the variation in color. The same is true for deuteranopes and tritanopes for the M and S cones respectively. The algorithm proceeds as follows. The image data, specified as RGB tristimulus vectors $\mathbf{C}_{RGB}$, is converted to the LMS color space using $\mathbf{C}_{LMS} = \mathbf{T}\,\mathbf{C}_{RGB}$, where the elements of the matrix $\mathbf{T}$ are the LMS tristimulus values of the CRT primaries used in [2]. They represent the appropriate display mapping function. The CVD simulated color $\mathbf{C}'_{LMS}$ is calculated from the original color $\mathbf{C}_{LMS}$ using the projection rules in [2]. The difference $\Delta\mathbf{C}$ between the original color $\mathbf{C}_{LMS}$ and the CVD simulated color $\mathbf{C}'_{LMS}$ is used to modify the original color

$$\tilde{\mathbf{C}}_{LMS} = \mathbf{C}_{LMS} + \mathbf{A}_i\,\Delta\mathbf{C} \quad (i = P, D, T). \qquad (2)$$

Hence, the adapted color $\tilde{\mathbf{C}}_{LMS}$ is a combination of the columns of $\mathbf{A}$ weighted according to the difference, $\Delta\mathbf{C}$. The off-diagonal elements of the 3×3 matrix $\mathbf{A}$ that are applicable to the adaptation depend on the dichromatic form being corrected

$$\begin{aligned} A_P &= a_{21}, a_{23}, a_{31}, a_{32} \\ A_D &= a_{12}, a_{13}, a_{31}, a_{32} \\ A_T &= a_{12}, a_{13}, a_{21}, a_{23}. \end{aligned} \qquad (3)$$

The on-diagonal elements are unity. The resulting RGB values are calculated using $\tilde{\mathbf{C}}_{RGB} = \mathbf{T}^{-1}\tilde{\mathbf{C}}_{LMS}$. In the next section we present an interface that permits the applicable parameters of $\mathbf{A}$ to be modified interactively using a slider.

INTERFACE

The interface of our adaptation tool is shown in Figure 3. The transparent window can be layered over the desktop allowing the user to recolor any region of the screen. On the bottom are controls which permit the user to capture, clear, copy and save the image; select the CVD type to simulate/correct; and view the correction control window.

The user places the window over the screen region to correct and captures the image. They specify their color vision deficiency using the CVD type drop down menu and open the color correction controls window via the correction button. Using the slider, the user is able to recolor the captured image interactively in real time. The parameters vary between images and are dependent upon the color composition of the image and the type of CVD being corrected. Also, different users have different preferences and therefore select different parameters for the same image. In our implementation, satisfactory recolorings were obtained with parameters of $\mathbf{A}$ having a step size, α, of 0.25 in the range $0-5$. Whilst it is possible to compute the four parameters of $\mathbf{A}$ directly from the position of the correction slider

$$C_i = \alpha \bmod(\lfloor \beta/\phi^{4-i} \rfloor), \phi) \qquad i = 1, 2, 3, 4 \qquad (4)$$

β is the value returned from the correction slider – 58191 in Figure 3, and ϕ is the total number of steps in the range $0-5$. It is perfectly reasonable to store all of these parameter sets in an array and index the applicable row using the value associated with the position of the correction slider. Each step of the slider selects a new version of $\mathbf{A}$ that differs from the previous by a step size of one of the parameters. Thus the user has available to her, on a slider, every possible version of $\mathbf{A}$.

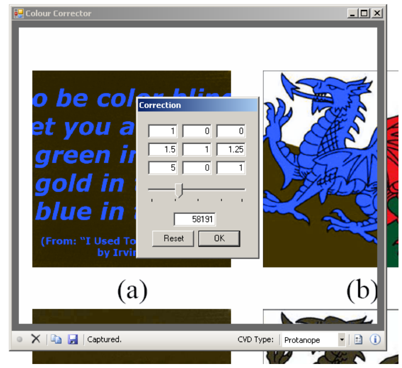

Figure 3. The interface of our color adaptation tool showing the correction controls and the adapted image.

(a) (b) (c)

Figure 4. Adaptation results. The adapted versions of the problem images from Figure 1 as viewed by a protanope. (a) Text image, $\beta = 78098, A_P = [2, 2.25, 0.25, 5]$**; (b) Flag image,** $\beta = 4594, A_P = [0, 2.5, 2, 4]$**; (c) Flower image,** $\beta = 21439, A_P = [0.5, 1.5, 3, 4.75]$**.**

EVALUATION AND RESULTS

The adapted versions of the problem images in Figures 1(a-c) as seen by a protanope are shown in Figures 4(a-c). The text in (a) can now be read easily; the dragon in (b) is noticeably different from the background; and (c) the flowers are easily distinguished from the background foliage.

We evaluated our algorithm using a computerized version of the Ishihara color vision test [5]. The Ishihara color vision test is the normal way of screening human color vision for color vision defects. For automatic color blindness correction and simulation there is no agreed evaluation methodology, so here, we attempt to replicate the Ishihara test. It is not essential to calibrate the display device to perform these tests since, as we shall see later, we are interested in changes in performance rather than absolute performance. However, to ensure consistency and repeatability we calibrated our monitor using the Gretag Macbeth Eye-one Pro with a viewing distance that was approximately 75cm under normal office illumination.

The test consisted of 15 color plates selected from the 38 plate set, including a number of vanishing, transformation and hidden digit design plates. A subset of the images used in our test is shown in Figures 5(a-c). For each image selected, we computed the protanopic version, shown in Figures 5(d-f), and the adapted version as recolored by a simulated

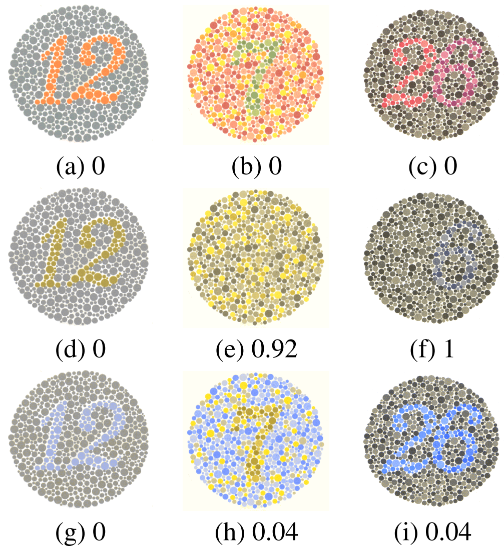

Figure 5. Ishihara test plates and the associated mean error. (a-c) Original color plates as viewed by a normal color observer; (d-f) the simulated versions showing how they are perceived by protanope; (g-i) the adapted versions as viewed by a protanope.

CVD viewer, shown in Figures 5(g-i). Hence, the complete test consisted of 45 images. The goal of the evaluation is to compare the identification rates before and after the adaptation i.e. the images in Figures 5(d-f) against the images in Figures 5(g-i).

Twenty-five subjects (7 female) with a mean age of 31.6 years (SD = 10.03) participated in our experiment. Two of the subjects were mildly red-green color blind but the rest self-reported having normal color vision. Each observer was presented with on-screen instructions and a sample question to ensure they understood the procedure. Before the test started they were asked to enter their gender and age. The observers were shown each of the images, one after the other, for a period of three seconds. After each image they were asked to type the numeral visible (if any). The images were randomly presented via a Matlab interface using the Psychophysics Toolbox extensions [4]. The monitor had a screen resolution of 1024×768 pixels and was color calibrated. The ambient light of the test room was kept as constant as possible during the tests.

The subjects' responses were transformed into error scores (0 correct, 1 incorrect). Figure 5 gives examples of error rates per Ishihara plate for all viewers. The mean error per normal viewer for the original images (standard deviations are in parentheses) is 0.024 (0.14); CVD simulated images 0.881 (0.32); and adapted images 0.014 (0.12). Thus the effect of the CVD simulation is to decrease performance (increase error) significantly and the effect of the adaptation is to increase performance (decrease error) significantly. We measured significance pairwise using McNemar's test. Comparing original with simulated gives a p-value of $p < 0.0001 \quad (n = 345, N_{01} = 297, N_{10} = 0)$, significant at the 5% level, which in terms of error performance means that the original images are significantly different from the simulated ones.

For the original images against the corrected we calculated a p-value of $p < 0.625 \quad (n = 345, N_{01} = 1, N_{10} = 3)$, not significant at the 5% level, which in terms of error performance means that the original images are indistinguishable from the corrected ones. The mean error per CVD viewer for the original images is 0.8; the CVD simulated images 0.9; and adapted images 0. The overall mean error per CVD viewer is 0.57 (SD=0.05). There are only two CVD viewers, which are too few to compute significance. Interestingly, one of our CVD viewers was unaware of his deficiency until he took this test.

CONCLUSIONS

This paper presented an adaptation algorithm for improving the accessibility to color images for CVD computer users. We demonstrated how the algorithm could form the basis of an adaptive technology via a simple interface and evaluated our adaptation algorithm using a computerized version of the Ishihara color plate test. When a CVD viewer is simulated, we see a significant increase in error rate on the Ishihara plates. Applying our new correction algorithm reduces the error rate to be comparable to the error rate of a normal color observer. The algorithm is therefore successful, at least in terms of a restricted task and a relatively small number of viewers.

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