Using Patterns to Encode Color Information for Dichromats

Article *in* IEEE Transactions on Visualization and Computer Graphics · March 2012

DOI: 10.1109/TVCG.2012.93 · Source: PubMed

5 authors, including:

Aditi Majumder
University of California, Irvine

Manuel M. Oliveira
Universidade Federal do Rio Grande do Sul

Rosalia Galiazzi Schneider
KU Leuven

Ramesh Raskar
Massachusetts Institute of Technology

Using Patterns to Encode Color Information for Dichromats

Behzad Sajadi, Aditi Majumder, Manuel M. Oliveira, Rosália G. Schneider, and Ramesh Raskar

Abstract—Color is one of the most common ways to convey information in visualization applications. Color vision deficiency (CVD) affects approximately 200 million individuals worldwide and considerably degrades their performance in understanding such contents by creating red-green or blue-yellow ambiguities. While several content-specific methods have been proposed to resolve these ambiguities, they cannot achieve this effectively in many situations for contents with a large variety of colors. More importantly, they cannot facilitate color identification.

We propose a technique for *using patterns to encode color information* for individuals with CVD, in particular for dichromats. We present the *first content-independent method* to overlay patterns on colored visualization contents that not only minimizes ambiguities but also allows color identification. Further, since overlaying patterns does not compromise the underlying original colors, it does not hamper the perception of normal trichromats. We validated our method with two user studies: one including 11 subjects with CVD and 19 normal trichromats, and focused on images that use colors to represent multiple categories; and another one including 16 subjects with CVD and 22 normal trichromats, which considered a broader set of images. Our results show that overlaying patterns significantly improves the performance of dichromats in several color-based visualization tasks, making their performance almost similar to normal trichromats'. More interestingly, the patterns augment color information in a positive manner, allowing normal trichromats to perform with greater accuracy.

Index Terms—Color Vision Deficiency, Visual Aids, Patterns in Visualization, Color Visualization.

1 INTRODUCTION

HUMAN trichromatic vision requires three different kinds of photoreceptors, which are sensitive to the long (L cones), medium (M cones), and short (S cones) visible wavelengths. The spectral sensitivity of a given photoreceptor depends on the type of photopigment it contains. Some variations in the proteins that form these photopigments lead to a condition called *anomalous trichromacy* characterized by a shift in the spectral sensitivity of the photoreceptors [35]. Depending on the affected type of photoreceptor, anomalous trichromats can be classified as *protanomalous*, *deuteranomalous*, or *tritanomalous*, if the shifted sensitivity affects the L, M, or S cones, respectively. A more severe type of CVD, known as *dichromacy*, is caused by the absence of one of the S, M, or L photoreceptors. Dichromats can be classified according to the type of missing photopigment as *protanopes* (missing L photopigment), *deuteranopes* (missing M photopigment), and *tritanopes* (missing S photopigment).

Normal trichromats perceive a three-dimensional color space spanned by the three types of photoreceptors. The color gamut of a dichromat, on the other hand, is 2D and can be approximated by a plane in this 3D space (Figure 1). The color gamut of an anomalous trichromat falls in between these two. Thus, dichromats have a reduced ability to distinguish between certain colors. The same is true for anomalous thrichromats, although their restrictions are less severe. Protanomaly, deuteranomaly, protanopia, and deuteranopia are collectively known as *red-green* CVD, due to the difficulty of the affected individuals to distinguish between red and green. Red-green CVD corresponds to over 99.9% of all cases of CVD [35], affecting approximately two hundred million individuals worldwide. Tritanomaly and tritanopia are much rarer conditions and impair people's ability to distinguish between yellow and blue.

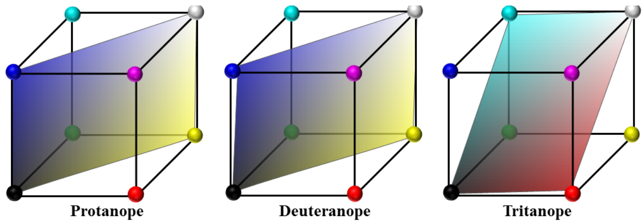

Fig. 1: The 3D cube represents the 3D color space perceived by a normal trichromat. Left to right: We show the 2D plane of perceivable colors for Protanopes, Deuteranopes, and Tritanopes in this space. Though Protanopia and Deuteranopia result from the lack of different photopigments (L and M respectively), the plane of colors visible to Protanopes and Deuteranopes are very similar.

To improve the color contrast for individuals with CVD, several recoloring techniques have been proposed based on optimization [20], [30] or projection [21] strategies. These techniques offer content-specific ways to analyze and remap the colors in an image or video, thus alleviating the red-green or blue-yellow ambiguity for these individuals.

- *B. Sajadi and A. Majumder are with the Department of Computer Science, University of California, Irvine. E-mail: bsajadi — majumder@ics.uci.edu*
- *M. M. Oliveira and R. G. Schneider are with Instituto de Informática - UFRGS. E-mails: oliveira — rgschneider@inf.ufrgs.br.*
- *R. Raskar is with Media Labs, Massachusetts Institute of Technology, Email: raskar@media.mit.edu.*

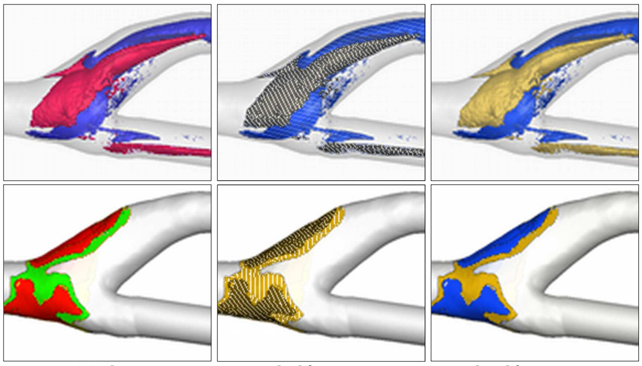

Fig. 2: Left: Visualization of the fluid dynamics in carotid bifurcation showing iso-surfaces of velocity (top) and iso-surfaces for helicity (bottom). Middle: Our pattern overlaid visualization for dichromats. Note that the interpretation of the patterns remain same across both the images due to the content-independent nature of our method. Right: Recolored visualization using [21]. Note that in both images red denotes the maximum. But it gets mapped to two different colors: yellow for the top image and blue for the bottom. This is due to the content-specific nature of the recoloring technique.

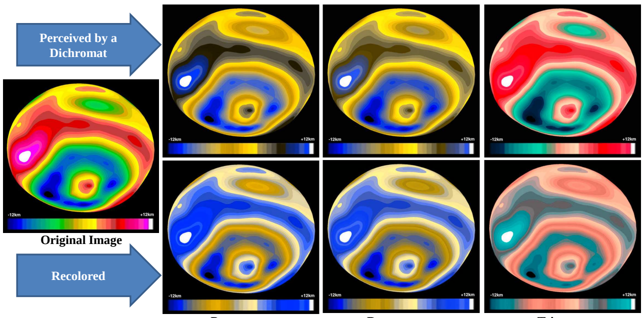

Fig. 3: The original image is the elevation diagram of 4 Vesta (determined from Hubble Telescope images of May 1996). The other six images show the simulated views of the three types of Dichromats and the result of recoloring [21] for each case. Since the image contains a large number of colors spanning the entire RGB cube, current recoloring techniques are unable to resolve the ambiguities.

However, they do not help the CVD individuals to identify the original colors (Figure 2). Further, they may not be able to resolve ambiguities effectively (Figure 3), especially for contents with a large variety of colors.

1.1 Main Contributions

We present a general technique for using patterns to encode color information into image content to allow individuals with CVD to compensate for their reduced color gamut (Section 3). This is achieved by overlaying patterns on the images, without the need to recolor them. Figure 4 shows an example of the application of our method. The most salient features of our technique are as follows:

1. Our technique overlays patterns over color images to provide content-independent mapping between the pattern-overlaid-colors in the 2D space of colors perceived by a dichromat and all colors in the 3D color space of a normal trichromat. Hence, our approach not only minimizes color ambiguities in the perceived content, but also facilitates proper color interpretation;

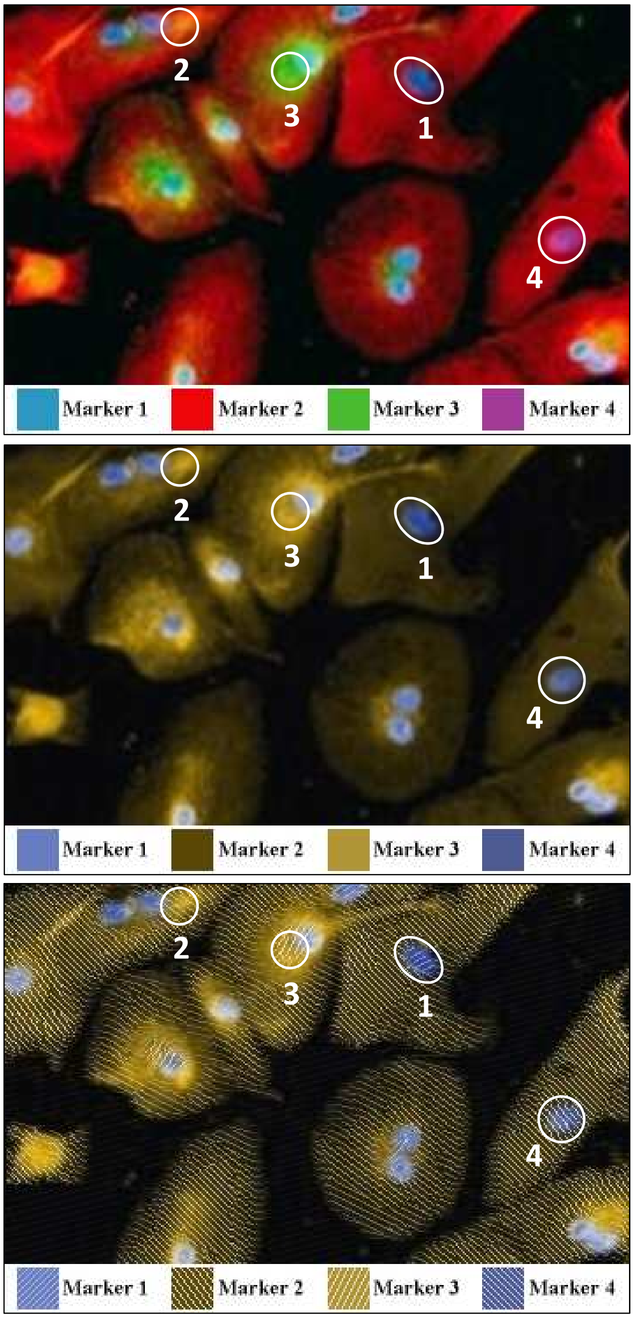

Fig. 4: Top: A picture of several cells with red, green, cyan, and magenta markers. Middle: The top picture as perceived by a deuteranope. Note that cells with marker 2 (red) and marker 3 (green) look the same to a deuteranope; the same is true for cells with marker 1 (cyan) and marker 4 (magenta). One example of each ambiguous case is marked in the image. Bottom: Result of our method with overlaid patterns as perceived by a deuteranope – hatching with positive slope indicates a share of green in the underlying color and hatching with negative slope indicates a share of red. Note that the patterns aid the deuteranopes to retrieve the color information and hence distinguish the red and green markers or cyan (*i.e.* blue+green) and magenta (*i.e.* blue+red) markers.

2. Since the underlying color information is not compromised by the overlaying patterns, they can still be used by normal trichromats;

3. Our method is amenable to interactive implementation on GPUs to allow interactive exploration of content by individuals with CVD (Section 3.5);

4. Finally, our technique is general and can support the use of different kinds of patterns to custom tailor the patterns for specific applications (Section 4).

Through two user studies (Section 5), we show that our technique allows CVD subjects to perform almost as well as normal trichromats on color visualization tasks. Moreover, when used by normal trichromats, our technique improves the consistency of the answers of these individuals.

2 Related Work

Patterns or textures have been used in visualization and graphics in the past in many ways. Healey and Enns [6] explore using patterns in combination with color to visualize large multi-variate scientific data. Gorla et al. [5] and Kim et al. [17] explore the use of patterns in visualizing and understanding 3D shapes. Interrante et al. [12] use patterns effectively to visualize multiple transparent objects when enclosing an opaque object. Patterns have also been used for flow visualization [13], [18]. Further, patterns have been used to provide shading cues in different kinds of non-photorealistic or stylized rendering. Line or stroke based patterns have been used to create the effects of pen and ink illustrations [33], [32], [38], [31], hatching [28], painting [8], [24], image guided streamline placement [36], and for stroke placement on 3D models, both parameterized or unparameterized [39], [3], [16]. Other stylized rendering techniques use the characteristics of human visual perception to improve the attractiveness of the colors in the image [2]. Dithering or stipple patterns have been used for shading [4], [27], [34]. Grain based patterns have been used for charcoal rendering [23]. Stroke based patterns have also been used for non-photorealistic visualization [7]. Our method can be considered to be supplementary to all these works. We use patterns in a completely different manner to compensate for the significantly compromised color gamut in dichromats.

There has been a significant prior work in modeling color vision deficiency as well as providing aids and tools to help color deficient individuals. Efforts have been made to model the perception of dichromats [1], [25] and of anomalous trichromats [19], [40]. The most comprehensive model is presented by Machado et al. [22] that can consistently handle normal color vision, anomalous trichromacy, and dichromacy in a unified way.

The methods designed until now to aid CVD individuals in performing visualization tasks fall in the domain of recoloring. Recoloring methods consider the specific content to map original colors of an image to a different set of colors that alleviate color ambiguities (red-green or blue-yellow) by enhancing contrast that avoids misleading the CVD individual. The recoloring method of Iaccarino et al. [9] is controlled by user defined parameters, while some other recoloring methods [10], [11], [15], [37] try to preserve naturalness in a few user specified key colors. Hence, they often produce variable results, even for the same content, based on the colors/parameters chosen by the users. Rasche et al. [29], [30] present the first automatic method that attempts to preserve perceptual differences across all pairs of colors in the image. However, often naturalness is compromised in the process. Since all these are optimization based techniques, they do not scale well with increasing size of the image taking minutes to recolor even small images.

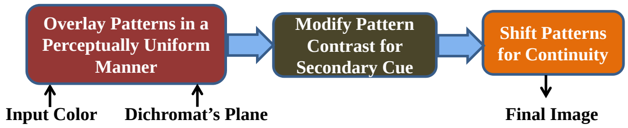

Fig. 5: Pipeline of our pattern augmentation method.

Kuhn et al. [20] and Machado and Oliveira [21] present the first interactive automatic recoloring techniques for dichromats. The technique by Kuhn et al. uses an optimization procedure and can preserve, as much as possible, the naturalness of the original colors. The approach by Machado et al. is based on projection and achieves real-time performance. Like other recoloring techniques, these are not appropriate for situations in which the colors of the original images already span most of the RGB color space. In these cases, while trying to solve some ambiguities, recoloring techniques tend to introduce new ones (Figure 3).

3 Pattern Augmentation Method

In this section, we present our technique to encode color information using patterns to compensate for the lost color dimension in dichromats. The range of perceivable colors by a dichromat forms a 2D plane instead of a 3D volume in the *RGB* space as shown in Figure 1. Let us call this plane P. Since perfect black is visible to all the dichromats similar to normal trichromats, P always passes through $(0,0,0)$ and therefore, can be simply defined by its normal vector, N. To find P, we use the comprehensive model of [22] to simulate the perception of color in dichromats. Let us consider color $C = (R,G,B)^T$ in an *RGB* space. [22] shows that the color will be approximately perceived as C', where

$$C' = \Phi_{CVD}(R,G,B)^T. \tag{1}$$

and Φ_{CVD} is a 3×3 matrix that depends on the degree and type of the CVD and the spectral response of the *RGB* channels. Φ_{CVD} is a rank deficient matrix since the dichromats have only two types of photopigments. Different Φ_{CVD} matrices are used to model the different types of dichromacy and hence the 2D planes differ for protanopes, deuteranopes, and tritanopes. Further, each column of Φ_{CVD} is a point on P and shows the perception of the RGB colors $(1,0,0)$, $(0,1,0)$, and $(0,0,1)$ by the dichromat. Therefore, N is the third eigenvector of Φ^T_{CVD} and can be found using singular value decomposition of Φ^T_{CVD}.

For any color C in the RGB space, our method finds a pattern in a content-independent manner based on the distance d of C from the plane P. The complete pipeline of our method includes the following three steps (Figure 5): (a) overlaying patterns in a perceptually uniform manner based on the distance d; (b) modifying the contrast of the overlaid patterns for secondary cue based on the difference between

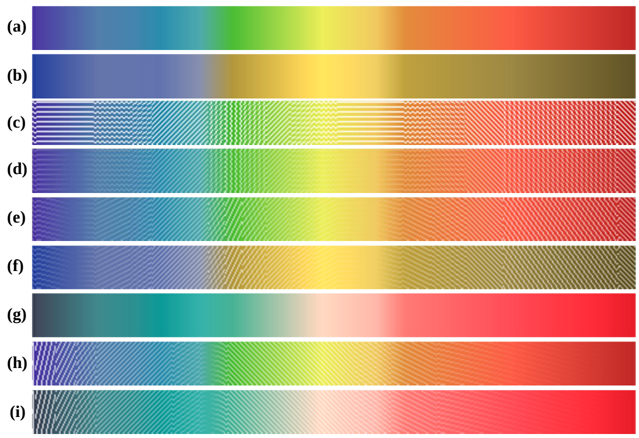

Fig. 6: (a) The colors in the visible spectrum from blue (shortest wavelength) to red(longest wavelength) – C_S. (b) The image as perceived by a deuteranope – C_P. (c) After overlaying the line-based patterns based on the distance from the deuteranope's color plane – C_T. Completely vertical lines show the maximum tendency towards green and as the lines rotate in a clockwise direction the tendency towards red increases. Note how these lines disturb the perception of the blues and yellows though the deuteranope can perceive these colors correctly. (d) After the pattern contrast is modified based on the distance of the original color from the deuteronope's color plane – C_F. Note that now the blues and yellows are devoid of patterns to provide a secondary cue to the deuteranope on the fidelity of his color perception. However note that the small slanted line segments are not continuous and hence interpreting the direction is still hard. (e) After shifting the overlaid patterns to achieve continuity of the lines. Note that the use of continuous lines makes it easier to observe the orientation. (f) This is (e) as perceived by a deuteranope. (g) The visible spectrum as perceived by a Tritanope. (h) This is the pattern overlaid image generated by our method for the tritanope. (i) This is (h) as perceived by a tritanope.

the perception of the underlying color by the dichromat and a normal trichromat; and (c) shifting the patterns to achieve continuous lines for accurate pattern interpretation. We describe these steps in the rest of this section in details and also illustrate them with examples in Figures 6 and 7.

3.1 Overlay the Patterns in a Perceptually Uniform Manner

In this step we first replace each pixel with color C by a set of $m \times m$ pixels of the same color on which the pattern will be overlaid. We call this small patch that is colored with C as C_S. Note that a dichromat perceives C as a color which is close to the projection of C on P, denoted by C_p. This is ambiguous since all the colors along $C + dN$, where d is a real number, will be mapped to the same color. Our goal is to resolve this ambiguity in the direction of N by overlaying patterns. Thus, the overlaid pattern provides a third dimension (along N) and allows a unique representation for each color perceivable by a normal trichromat.

We desire to assign patterns in a perceptually uniform manner so that the set of distinct patterns sample d uniformly. Hence, we map perceptually equal lengths of d to equal changes of the pattern. In order to achieve this, we find the distance d_p of C from C_p in the perceptually uniform CIE Lab color space. We set the sign of d_p to be the same as d to detect the side of the plane P (left or right) on which C lies.

There are several patterns that can possibly be used to convey the color information along N. Any cue that can represent a real value in a small spatial scale can be used for our purpose. Further, more than one pattern attributes (e.g. shape, size, orientation) can be candidates for encoding d_p. We use a vertical white line to show the most negative value of d_p. This line is rotated in a clockwise manner as d_p becomes less negative. The line becomes close to horizontal when d_p is zero and then becomes of the opposite orientation as d_p becomes positive. However, note that mapping the most positive d_p to 180 degrees rotation would result in vertical lines for both most positive and negative d_p. Hence, we set the maximum rotation to be less than 180 degrees (around 170 degrees) to prevent any ambiguity. We denote the patch after overlaying the patterns by C_T (Figures 6(c) and 7(c)).

3.2 Modify the Pattern Contrast for Secondary Cue

Patterns are used in our method to encode the distance d of C from P. $d = 0$ denotes colors that are perceived correctly by the dichromats. Hence, it is desirable to eliminate the patterns for colors that lie on P to indicate the high fidelity of the perceived color. In fact, the visibility of the patterns can act as a secondary cue to the dichromat to decide the fidelity of her color perception. Hence, we reduce the contrast of the patterns based on the absolute value of d_p to convey this information. Let us assume the absolute maximum value of d_p is d_{max}. We use a weighted average of C_S and C_T using $\alpha = \frac{|d_p|}{d_{max}}$ as the weighting coefficient to create the final patch C_F as follows:

$$C_F = \alpha C_T + (1 - \alpha) C_S. \tag{2}$$

This controls the visibility of patterns depending on the absolute value of $|d_p|$ (Figures 6(d) and 7(d)). Please note that performing such a linear interpolation does not guarantee a perceptually uniform interpolation between C_T and C_S since a straight line in the RGB space does not match to a straight line in the CIE Lab color space. However, the subjects can still use the primary cue of the line direction to interpret the perceptual difference. Further, performing the linear interpolation in the CIE Lab space can result in colors which are outside the color plane of a dichromat.

3.3 Shift the Patterns for Continuity

In a line-based pattern it is desirable to use continuous lines in regions with uniform colors for greater visibility. However, the above approach provides small discontinued line segments even for contiguous patches with uniform color (Figures 6(d) and 7(d)). In order to maintain the continuity of the lines, we designed a simple algorithm to shift the small line segments based on their location in the image. For this, for each line orientation, we first compute the amount of horizontal and vertical shift, $0 \leq (s_x, s_y) \leq m$, needed to keep the line continuous while passing through the adjacent patches. This depends on the slope L of the line

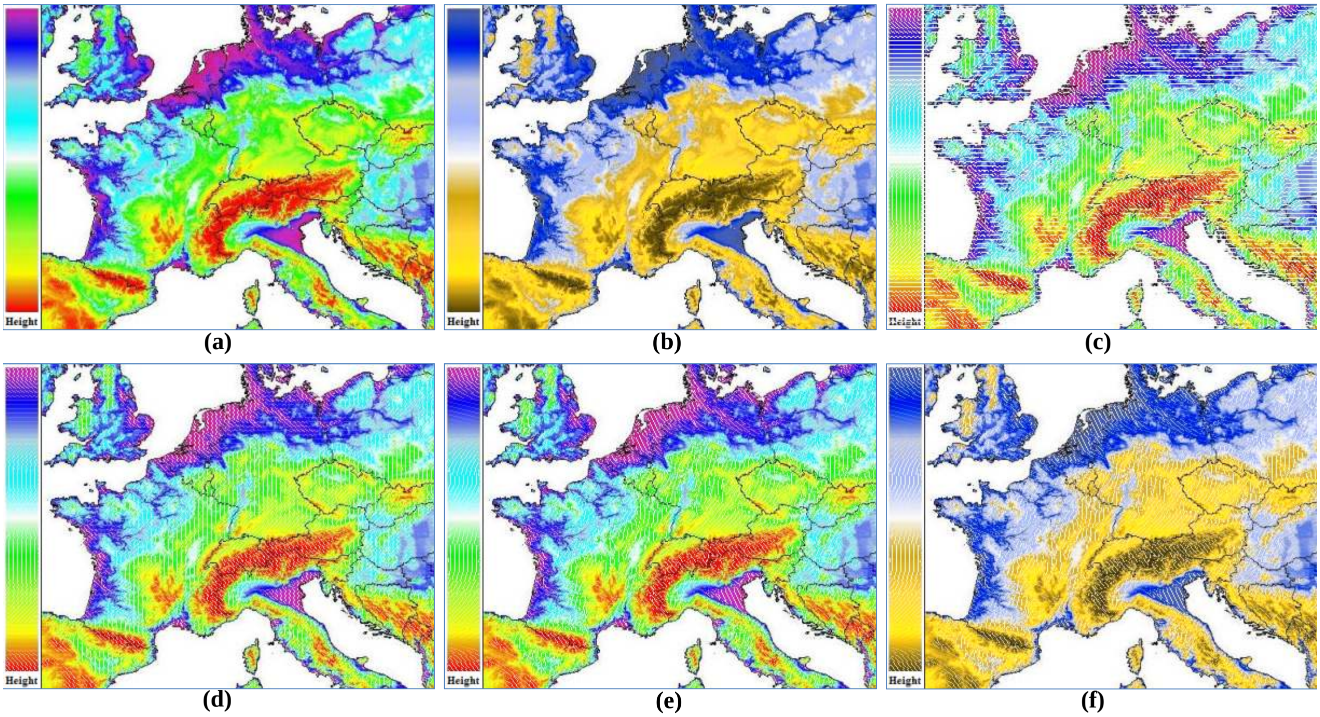

Fig. 7: (a) Original image as perceived by a normal trichromat. (b) Original image as perceived by a deuteronope. (c-e) The image going through the pipeline of our method – (c) after overlaying the patterns, (d) after adjusting the contrast to convey the fidelity of the dichromat's color perception, and (e) after making the line segments continuous. (f) The image in (e) as perceived by a deuteronope.

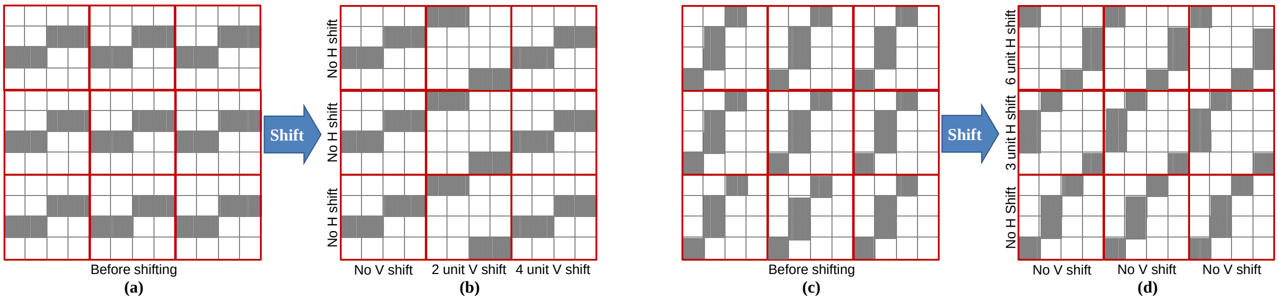

Fig. 8: Here we show a 4×4 pattern being used to overlay the color at each pixel for two different directions before shifting (a,c) and after shifting (b,d). Note that the shifts occur in only one direction and result in longer continuous line segments.

– specifically $s_x = \lfloor \frac{m}{L} \rfloor$ and $s_y = \lfloor m \times L \rfloor$ pixels respectively. Figure 8 shows these shifts for lines of a few orientations, assuming $m = 4$. Note that since any line segment spans either all the m rows or m columns of pixels in the $m \times m$ region of pixels, always either s_x or s_y is equal to m; therefore, the shifting effectively happens only in one direction. If the absolute value of the slope of the line is more than 1 then the shift is effective only in the horizontal direction and otherwise only in the vertical direction.

When applying the line pattern at a pixel location (x, y), we apply a shift of $((y \bmod m)s_x \bmod m, (x \bmod m)s_y \bmod m)$. This shifting mechanism guarantees that the line segments form continuous lines within uniform patches of color (Figures 6(e) and 7(e)). Further, this is achieved without examining the spatial neighborhood of a pixel making it conducive to real-time implementation.

3.4 Interpret the Pattern Overlaid Image

The plane P is very similar for protanopes and deuteranopes since they both suffer from red-green ambiguity. However, P for the much more rare case of tritanopes is significantly different and they suffer from blue-yellow ambiguity. Hence, though our method will generate pattern overlaid image for both the cases, the interpretation of the patterns will be slightly different when dealing with red-green ambiguity than when dealing with blue-yellow ambiguity.

Since red-green ambiguous CVDs correspond to over 99.9% of all cases of CVD, we first discuss this case. Further, almost all our results are shown for this case and the user study is also conducted on such dichromats due to the much higher availability of these subjects. As mentioned before, the visibility of the patterns in the final patch C_T, indicates the fidelity of the dichromat's color perception. Since these kinds of dichromats suffer from red-green ambiguity, only blue, yellow, and gray shades of the original image can map to colors devoid of any patterns, indicating an accurately perceived color. When the patterns are visible, their contrast will indicate their proximity to the plane P. Hence, for colors for which the

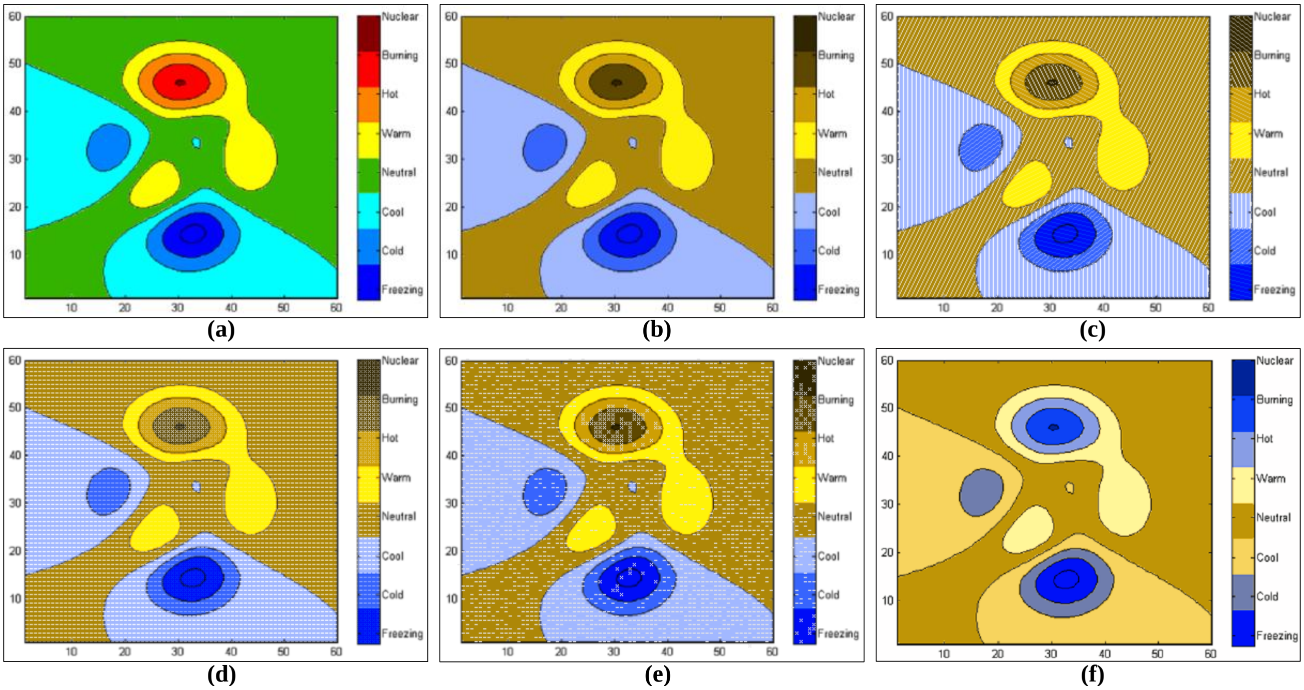

Fig. 9: (a) An elevation map with various colors. (b) Simulated view of a deuteranope. (c-f) the image in (a) as perceived by a deuteranope after various patterns are overlaid it: (c) using the line-based pattern used in our algorithm in Section 3(c); (d) using two different shapes, x for red (positive d_p) and – for green (negative d_p) and varying their contrast to indicate the magnitude of d_p; (e) using the same two patterns but vary their density to indicate the magnitude of d_p. (f) recolored image using [21] for deuteranopes. Please zoom in to see the patterns.

dichromats error in perception is high, the overlaid pattern will have a high contrast. Finally, the orientation of the patterns provides cues to interpret the proportion of red and green colors. Lines with slopes from 0 to 85 degrees would indicate colors from green to yellow through cyan, close to horizontal lines would indicate yellow, and lines with slopes from 85 to 170 would indicate colors from yellow to red through orange. Thus, when trained appropriately, the dichromat can estimate the ratio of red, green, and blue using the patterns and the underlying color he perceives. For example, for a protanope though all shades of red and green will be mapped to shades of yellow, he can use the patterns to interpret the contribution of red and green in this yellow shade and find an approximation of the ratio of the colors in the content.

The interpretation of the patterns is slightly different for tritanopes who suffer from blue-yellow ambiguity. The orientation of the patterns will provide cues to resolve the blue-yellow ambiguity for a proper interpretation. Red and cyan colors will be devoid of patterns in the pattern overlaid image indicating high fidelity in the dichromat's perception. Finally, though all shades of blue and yellow will be mapped to shades of cyan, he can use the patterns to interpret the contribution of blue and yellow in this cyan shade.

3.5 Implementation

For our pattern-based content augmentation method (Section 3) we use $m = 4$ in our implementation. Each pixel is replaced by a 4×4 pattern and we use 16 different orientations for the line patterns.

Real-Time Implementation: Our method lends itself to an easy realtime implementation via GPUs. The method includes projection of the colors onto a plane, followed by the selection of patterns based on a simple deterministic function. Finally the selected pattern for each pixel can be found using a simple lookup table and applied on the projected colors. Blending can be used to modify the contrast of the overlaid patterns as per Equation 2. We have implemented this for realtime pattern augmentation of images. In this implementation, we allow the user to zoom-in anywhere in the content while only the image is being scaled but not the patterns. Therefore there will be more line segments assigned to the same area of the original image that is particularly useful for high-frequency contents. Further, the users can change the contrast of the patterns as they wish to get better cues (Demonstration in the accompanying video).

4 Alternate Possibilities for Patterns

Though we used a line-based pattern in the previous section, our technique is general and does not limit the patterns that can be used. Further, though we use the orientation and contrast of the line-based pattern to encode d_p, other properties of a patten such as size and shape can be equally good candidates to encode d_p. In fact, one can anticipate situations and applications where a kind of pattern and a particular attribute thereof would work better than others. Though analyzing this relationship between patterns, their attributes and suitability for disambiguating the color information in different applications demand a separate in-depth analysis, we have made some initial explorations with a few other patterns and their attributes to illustrate some of the possible options.

For example, we can use two different shapes, $\times$ and $-$ to encode the positive and negative values of d_p respectively. The magnitude of d_p can be encoded by the contrast or density of the patterns (Figure 9(d,e)). However, when using density to encode the magnitude of d_p, we found that this only works well for contiguous patches of color that are large enough to show visible differences in the density. Hence, this is more suited for applications such as color chart visualization where the color is uniform within a large contiguous region. Further, to implement this, one approach is to separate such contiguous segments in the image and then fill the patch with the proper shape and density based on the value of d_p. However, such an approach does not easily lend itself to a real-time implementation. Therefore we can alternatively use a probabilistic pattern that automatically produces similar results as long as the patch sizes are relatively large. In this case, at each location in the image, we overlay a pattern with probability $\frac{|d_p|}{d_{max}}$ and the type of the pattern is decided based on the sign of d_p (Figure 9(e)). The advantage of this pattern is that it does not require subjective contrast evaluation for interpretation of d_p and therefore is independent of the brightness of the underlying content. Thus, for such applications, it makes it easier for the user to interpret the absolute value of d_p. The disadvantage, however, is that it can be misleading if the patch is not large enough due to the probabilistic nature of the pattern. However, for both the cases of density and contrast, we cannot use a secondary cue as with the line-based pattern. All these observations motivated us to choose orientation as our primary cue and contrast as a secondary cue as described in Section 3.

5 User Studies for Evaluation

Color is important for many visualization tasks and colormaps (*e.g.*, elevation maps, heat maps) are one of the most common ways to encode information in visualization applications. Color is also critical for visualizing categories (*e.g.*, different types of vegetation, landmarks, charts). To validate our technique, we choose the two visualization tasks of *colormap interpretation* and *categorization* (See Figure 10 for example images).

While conceptually these two tasks share many similarities, the analysis of their results pose significantly different challenges in evaluating the performance. The answers of normal trichromats for *categorization* tasks tend to be very consistent and can easily provide us with a good reference to compare the answers of individuals with CVD. On the contrary, in *colormap interpretation*, one observes that normal trichromats' answers vary within a range in the continuous color scale, making it difficult to establish a ground truth. Thus, it becomes very difficult to design a simple performance metric that identifies the answer of the individual with CVD as correct or wrong.

Considering this, we designed and carried on two user studies to assess the benefits of using patterns to improve

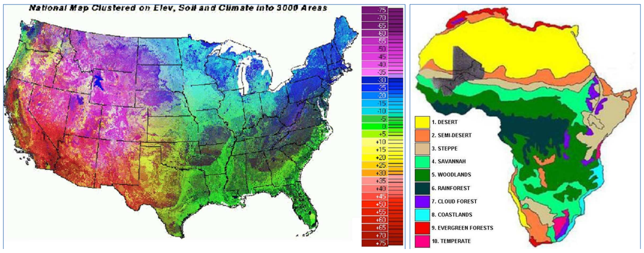

Fig. 10: Left: A sample test image for the colormap interpretation test. Right: A sample image for the categorization test.

the performance of individuals with CVD for visualization tasks, which are described in details in the following subsections. One involves categorization tasks and allows us to evaluate the performance using simple metrics (Section 5.1). Another involves both categorization and colormap interpretation tasks and is evaluated using a more complex dual scaling method. Dual scaling allows us to evaluate the performance based on the consistency of the answers provided by a group of individuals (Section 5.2). Both studies included individuals with (red-green) CVD as well as normal trichromats. The specific test images and other relevant details of the user studies can be found in the supplementary materials.

5.1 Study based on Categorization Tasks

For this study, we started with 215 images available on the Internet. From those, we pre-selected 100 images that are expected to be ambiguous for both protanopes and deuteranopes, according to the simulation model in [22]. We then asked one protanomalous subject (P) and one deuteranomalous subject (D) to separately examine all these images. For each image, they were asked to indicate regions that appear to have the same colors (according to their perception). Whenever these selected regions of similar colors had dissimilar colors in reality, we asked them to rate how difficult it is for them to notice any difference between these colors, using a scale from 1 to 5, 5 being the most difficult. Such data was saved through an interface that stored the pixel coordinates of the pairs of ambiguous colors, as well as the informed level of difficulty. In this step, D and P rated 18 and 41 images respectively with a difficulty level of 5.

As expected, a large number of these images were tagged to be of difficulty level 5 by both D and P. From the set of image which either D or P had tagged to be of difficulty level 5, we chose 18 images. These contained all the images that both D and P had tagged to be of difficulty level 5 and the ones that were amongst the most difficult ones for either P or D.

Using the pixel locations of the points recorded as ambiguous by P and by D, we defined a set of points G_I where the subjects were not able to easily interpret the data. This provided us a total of 30 points over 18 images. The task constituted of determining the correct category or the correct value from the color map at these 30 locations.

For this, first we needed to find a reference correct answer for each point – the *ground truth*. We asked 19

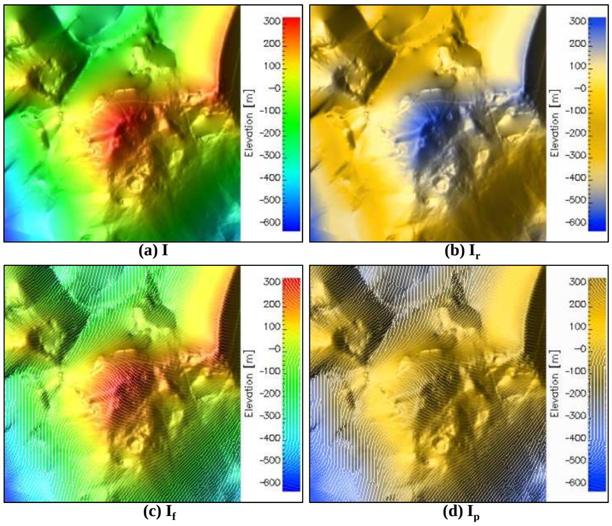

Fig. 11: Example of a group of images from the test set: (a) Original image (I); (b) Recolored version of (a) obtained with the technique described in [21] (I_r); (c) Original image with overlaid patterns (I_f); (d) The image with original colors projected on the color plane of the dichromat ($C \to C_p$) overlaid with patterns (I_p).

trichromats to perform the task at the 30 points. This group of normal trichromats consists of 17 male (ages 20 to 32) and 2 female (ages 22 to 24) subjects. Then we considered only the questions for which all 19 normal trichromat subjects consistently provided the same answers (zero variance), as these answers provide a reliable ground truth. This left us with 16 images in total, involving only categorization tasks: 24 questions for protans and 22 questions for deutans.

Next, we considered a group of subjects with CVD (*CVD group*). This excluded volunteers P and D and consisted of 11 male subjects. These 11 subjects consisted of 4 protanopes (ages 25 to 32) and 1 protanomalous (age 56), which constitute the *protan group*, and 4 deuteranopes (ages 21 to 47), and 2 deuteranomalous (ages 19 to 30), which comprise the *deutan group*. The classification of these subjects was done after the application of the Ishihara test [14]. Due to the low number of anomalous trichromat subjects and the differences in the severity of their conditions, we did not study them as separate categories but grouped them with dichromats with similar CVD.

To run the tests with the *CVD group*, we created new legends for each individual image I. The legends included the ambiguous as well as other colors found in the image. For each image I, we use prior work [21] to generate a recolored version I_r of I and use our algorithm in Section 3 to generate the corresponding pattern overlaid image, I_f. In addition to overlaying the patterns on the original image, we also created another variation, I_p, by projecting all the colors on the color plane of the dichromat, Π, and overlaying the patterns on it. We call this the *projection+pattern* technique. It provides a content-independent mapping of the colors visible to a normal trichromat to patterns and colors visible to a dichromat and results in a brighter image compared to I_f when viewed by the dichromat. Hence, for each image we create a set of four variants (*i.e.* I, I_r, I_f, and I_p, Figure 11). Note that the legends also change during the same process. We then interleaved the images from different groups using a pseudo-random order and also shuffled the order of the categorization legends for all images in a variant set to avoid the influence of memorization. We perform the experiments using 17-inch CRT flat screen monitors (model LG Flatron E701S, 1024 $\times$ 768 pixels, 32-bit color, at 85 Hertz). The monitors are calibrated with a ColorVision Spyder 3 colorimeter using Gamma 2.2 and a 6500K white point. Both calibration and tests were performed in a room with dimmed lights.

TABLE 1: Improvement in correct answers and confidence levels achieved by subjects with CVD when using patterns. Improvements computed with respect to their performances on the original images.

Factor	Org. + Pat.	Proj. + Pat.	Machado
Imp. of Correct Answers (P)	17.58%	10.99%	9.89%
Imp. of Correct Answers (D)	34.82%	42.70%	35.95%
Imp. of Confidence Level (P)	15.40%	13.37%	6.62%
Imp. of Confidence Level (D)	31.76%	41.07%	15.62%

The subjects in the *protan group* (*deutan group*) were then asked to perform the categorization tasks for the set of ambiguous points (questions) selected by subject P (D). The questions were asked for the four variants of the image I. In addition, the CVD subjects were also asked to inform their level of confidence on each of their answers on a scale of 1 to 10. Collecting this information was suggested by subject P, who told us that a major benefit of our technique is to increase the confidence with which an individual with CVD can make a color-related decision. We also measured the time (in seconds) required to perform each task.

Figures 12 (a) and (b) show the percentage of correct answers achieved by protans and deutans when using the various techniques. One can notice a significant improvement in the correct answers as patterns are added to both the original images, and the image with projected colors. While patterns are anticipated to improve dichromat's performance, existent recoloring techniques such as [21] (*Machado*) perform close to our method in the presence of a relatively small number of colors, which is the typical case involving categorization tasks. When considering the level of confidence with which the subjects answered the questions in Figures 12 (c) and (d), one observes that the use of our patterns on the original images or images with projected colors, outperforms the recoloring technique. We attribute this to the additional content-independent cues provided by our patterns. Table 1 summarizes the improvements in the percentage of correct answers and in the confidence levels experienced by subjects with CVD when using our patterns. The average time required to answer one question was approximately 10 seconds, with no significant variations among the techniques.

5.2 Study based on Both Tasks

Though our user study on categorization demonstrates that using patterns help in disambiguating colors, we evaluate the effect of our technique on other kinds of tasks, especially ones that involve a large number of colors (like

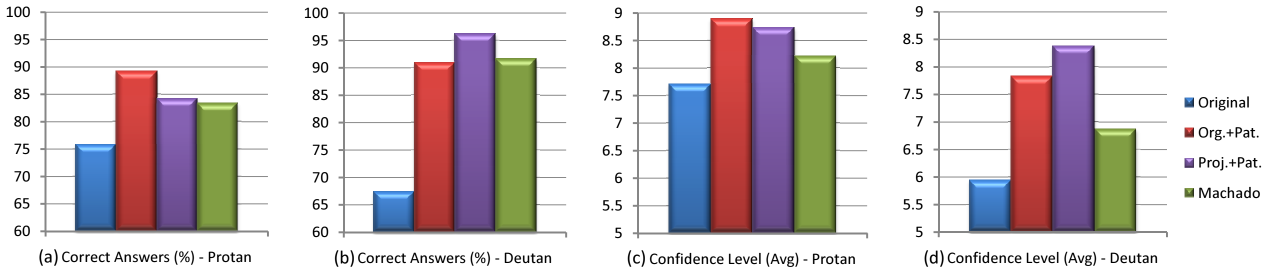

Fig. 12: Results of the user study for categorization task, considering the points for which all 19 normal trichromats agreed on the answers. Percentage of correct answers provided by subjects for different techniques for protans (a) and deutans(b). Average confidence level of the subjects (in a scale from 0 to 10) when answering the questions for protans (a) and deutans (b).

color map interpretation) where earlier recoloring techniques cannot resolve the ambiguities entirely (Figures 2 and 11). We chose six groups of images (four colormap interpretation, and two categorization examples) for this purpose, each group represented by a different color image I and consisting of its four variants (*i.e.*, I, I_r, I_f, and I_p as in Figure 11). For each image I, we simulate the dichromat's view using the model described in [22] and find a set of points, G_I, where the dichromat's condition is expected to result in ambiguous interpretation of the image. We chose four such points for each group of images. During the tests, the images are presented to the volunteers in a pseudo-random order, enforcing that images from the same group (*i.e.*, variants of the same image) are interleaved with images from the other groups, avoiding bias due to memorization. Further, the order of the set of points, G_I, vary for the different variations of the same image to further reduce the effect of memorization. The test was performed under similar conditions as the first experiment in terms of the calibration parameters of the monitors and the environment.

The group of subjects with CVD (*CVD group*) for this study consists of 16 male volunteers, distributed as 5 protanopes (ages 25-53), 4 protanomalous (ages 27 to 62), categorized as the protan group and 3 deuteranopes (ages 20 to 46), and 4 deuteranomalous (ages 19 to 30), categorized as the deutan group. As before, the classification of these subjects was done after the application of the Ishihara test [14]. The group of normal trichromats consists of 19 male (ages 19 to 27) and 3 female (ages 22 to 28) subjects.

We presented the four image variants to the subjects in the CVD group, and asked them to interpret the data values at G_I. We ask normal trichromats to perform the same task, but only for I and I_f. For the image variants including patterns (*i.e.*, I_f and I_p), we also ask all subjects to indicate whether they based their answers on *color only*, *pattern only*, or on a combination of *color and pattern*. For any class of image variants (*e.g.*, I or I_f), the CVD group provides a total of 384 answers (16 subjects $\times$ 6 images $\times$ 4 data points per image). The normal trichromat group provides a total of 528 answers (22 subjects $\times$ 6 images $\times$ 4 data points per image) for the classes of images in their test.

As explained earlier, while we expected to use the answers given by normal trichromats (for the original images) as references to evaluate the correctness of answers of individuals with CVD, we found a significant variation among the answers of trichromats for colormap interpretation tasks. The answers covered a range rather than a fixed value. Further, for two dissimilar but close answers, it is hard to find a numerical evaluation of the closeness of the answer. Because of these difficulties in the evaluation of the data collected in this user study, we used *dual scaling* [26] to analyze its results. Dual scaling is a statistical technique for analyzing qualitative data, which captures both linear and non-linear relationships among the variables. Figure 13 shows three plots obtained by projecting the collected data onto the two dimensions (solutions) that best describe the relations among data elements. Large relative distances among elements of the same class correspond to large variance in the provided answers.

Figure 13 shows the projection of the answers of the protan (top), deutan (middle), and normal trichromat (bottom) groups for the various techniques. Each point indicates a user and the shape of the point ('$\diamond$', '$\triangle$', '+' or 'x') indicates the variant of image – original, original+patterns, projection+patterns, and recoloring [21], respectively. We also indicate the mean of the answer of the trichromats for the original images with '$*$'. The amount of clustering of the values indicate the level of consistency amongst the answers provided by the users. Further, when the answers provided by the *CVD group* are centered around the mean of the answers of the trichromats, it means that the corresponding technique has helped the CVD subjects to perform closer to the trichromats.

The plot shows that the answers provided by protans in the context of the recoloring technique [21] in I_r present high variability, indicating that they were unable to eliminate the ambiguity for the set of test images. The combined use of patterns with the original images I_f (Org. + Pat.) and the images with projected colors I_p (Proj. + Pat.) help to reduce this variability. Similar observations can be made for the deutan group (Figure 13, middle).

In order to quantify the improvements, we also measured the average distance of the points for each variant of the image in the dual scaling graph from the mean of the answers of the normal trichromats. The results are summarized in Table 2 and show the advantage of using our pattern-based method compared to the use of the original image or the recoloring technique. More interestingly, Figure 13 (bottom) suggests that images enhanced with our patterns (Org. + Pat.) also seem to improve the performance of

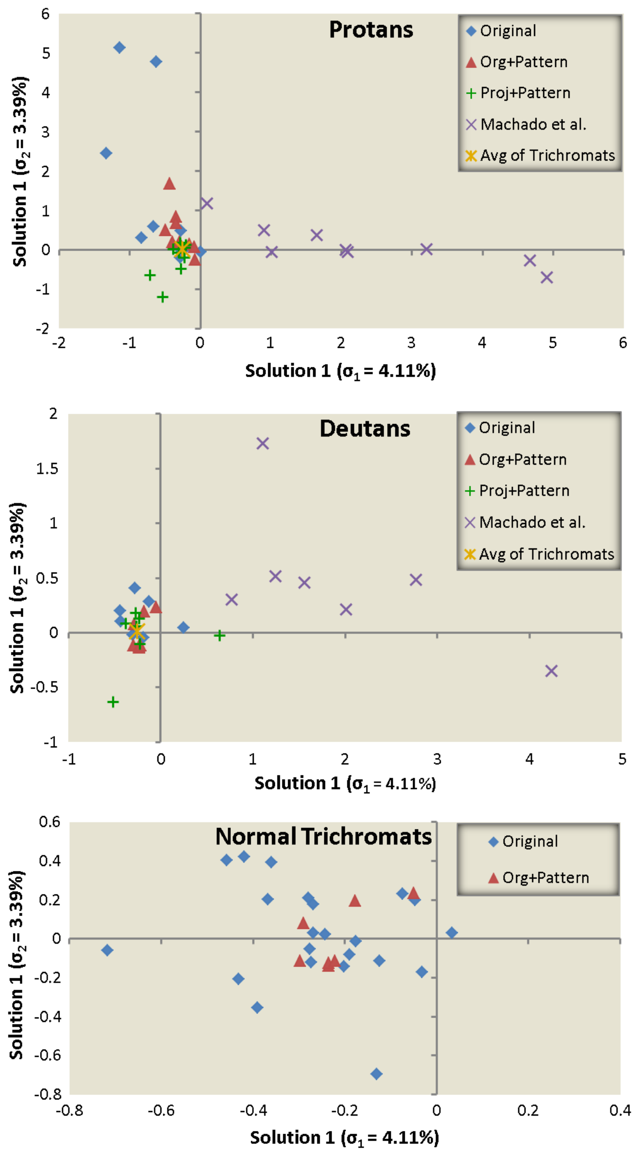

Fig. 13: Results of the user study based on both tasks and analyzed using dual scaling. Plot obtained after projecting the collected data onto the two dimensions (solutions) that best describe the relationships among the data. (Top) Results of the protan group for the various techniques, compared with the mean of the answers of the normal trichomats. (Middle) Results of the deutan group, also compared with the mean of the answers of the normal trichomats. (Bottom) Comparison of the answers of normal trichromats for the original images with and without enhancing with the patterns.

normal trichromats (reduce the variance in their answers). We quantified this by measuring the average distance of the clusters (formed by the trichromats when using the image with and without using patterns) from their centroids. We observed that the average distance reduced from 0.2 to 0.16 after adding patterns over the images. This shows that our patterns even help normal trichromats to refine their decisions when dealing with continuous color scales. It may also be that patterns provided additional cues in situations where the local contrast of surrounding colors can affect the perception of the center one. Finally, we also noticed that some subjects with CVD performed relatively well on some of the original images (possibly making use of shading cues

TABLE 2: Average distance of the answers provided by the CVD subjects from the mean of the answers of the trichromats.

Subjects	Original	Org. + Pat.	Proj. + Pat.	Machado
Protans (%) (P)	2.54	0.70	0.53	3.03
Deutans (%) (D)	0.30	0.17	0.44	2.59

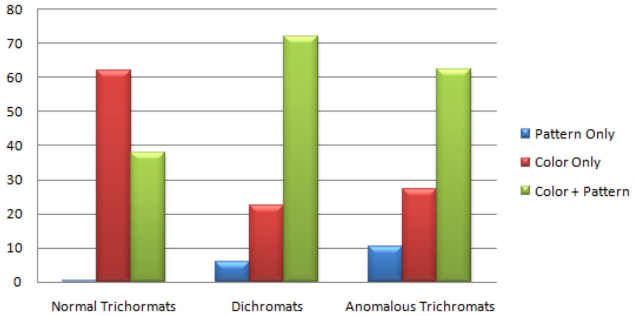

Fig. 14: Cues used by groups of subjects to answer the user-study questions. The numbers represent the percentage of their answers.

and the information of the surrounding regions).

Figure 14 shows the distributions of cues used by each group of subjects when answering the questions. Dichromats relied only on patterns for 5.7% of the questions, and anomalous trichromats reported using patterns as their primary cue in 10.4% of the questions. But, as expected, normal trichromats only used them in 0.1% of the questions. However, the combined use of color and pattern was used as the main hint by normal trichromats in 37.9% of the cases. For dichromats and anomalous trichromats, combination of color and pattern was used 71.9% and 62.5% of the time, respectively. These numbers confirm the importance of the use of patterns in the decisions made by subjects with CVD, while allowing the normal trichromats to refine their choices.

6 Discussions

In this section we discuss the behavior of our system with respect to several parameters.

6.1 Spatial Resolution

We overlay $m \times m$ patterns or textures for each pixel. Further, the size of the pattern (m) to be used for each pixel increases with number of distinct patterns used to disambiguate colors. Hence, if we want to display the pattern overlaid image in the same scale as the original image, this compromises the spatial resolution of the image by a factor of m in each direction. Therefore, part of the high-frequency color contents will be inevitably lost when using our pattern-based approach. Fortunately, the highest frequency of the chroma which dictates the patterns is often less than the highest frequency of the brightness of the colors, which alleviates the situation.

6.2 Scale Dependence

Another limitation is that the perception of the overlaid patterns is scale dependent and hence users have to view the pattern-embedded image in the appropriate scale to retrieve the color information faithfully. To alleviate this, we can

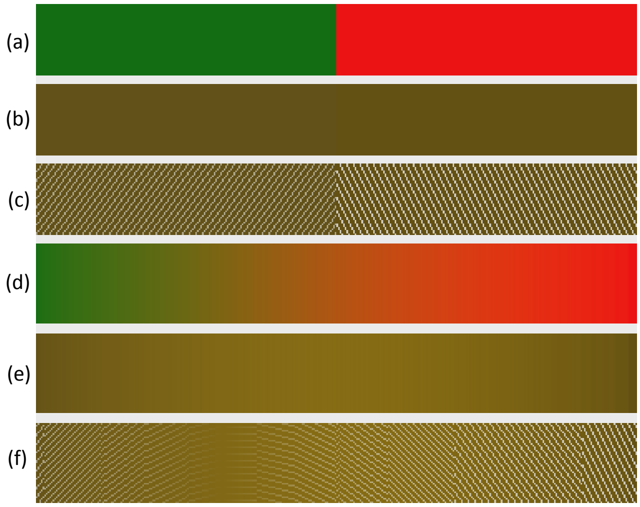

Fig. 15: (a) Two color patches that look identical to a deuteranope. (b) Color patches as perceived by a deuteranope. (c) Color patches as perceived by a deuteranope after overlaying the line-based patterns. (d) A smooth ramp between the two colors shown in (a). (e) The smooth ramp as perceived by a deuteranope. (f) The smooth ramp as perceived by a deuteranope after overlaying the line-based patterns.

provide viewing interfaces where the scale, contrast and even the resolution of the patterns can be controlled by the dichromat users. This should alleviate the scale factor issue significantly. We have provided such an interface in the GPU-based implementation of our method shown in action in the accompanying video. We hope that future explorations on suitable patterns for this purpose reveal scale-independent patterns to achieve the same goals.

6.3 Identical Colors

Due to the ambiguity in the color space of the dichromats, two colors that are completely different for a normal trichromat may look identical to a dichromat. Fortunately, out method can easily allow the dichromats to distinguish such colors. This is demonstrated in Figure 15(a-c). However, distinguishing the different becomes harder when there is a smooth ramp between the two colors that look identical to a dichromat. This situation is demonstrated in Figure 15(d-f). In this case, the ability of the dichromat to distinguish the change depends on the number of distinct values that can be represented using our pattern (16 for our line-based pattern) and also the perceptual difference of the two colors in the color space of a normal trichromat.

7 Conclusion and Future Work

We presented a general framework of using patterns to encode color information facilitating proper color information retrieval by dichromats. In contrast to content specific recoloring techniques, our method is content independent and provides a consistent way to faithfully resolve color ambiguities for dichromats. More importantly, it retains the underlying color information and hence does not hamper color perception for normal trichromats. Our method can be easily implemented on GPUs for real-time performance and thus can be used for interactive applications. We demonstrated the effectiveness of our proposed technique with two user studies. This confirmed that use of patterns improves the performance of dichromats in several color-interpretation tasks making their performance almost as good as of normal trichromats. More interestingly, our pattern-overlaid images increase the performance accuracy of normal trichromats by providing them with reinforcing cues.

Many components of our framework need more exploration and analysis. We would like to explore larger number of patterns and their attributes and evaluate their suitability in an absolute sense and also in comparison to our current line-based patterns. We would like to seek patterns that are scale independent and thus could be interpreted faster. We would like to explore automatic approaches to determine the suitability of a pattern for a target application based on the parameters of the pattern.

Finally, we hope to integrate our system with popular operating systems to help the dichromats in perceiving digital contents on their personal computers. We believe that the presented technique have the potential to motivate further research in designing tools that can aid dichromats in color information retrieval.

Acknowledgments

We deeply thank our volunteers. Aditi and Behzad would like to acknowledge funding agencies NSF IIS-0846144. Manuel and Rosália acknowledge CNPq-Brazil fellowships (grants 308936/2010-8 and 131311/2011-5).

References

[1] H. Brettel, F. Vienot, and J. D. Mollon. Computerized simulation of color appearance for dichromats. *Journal of Optical Society of America*, 14(10):2647–2655, 1997.
[2] Y. Chang, S. Saito, K. Uchikawa, and M. Nakajima. Example-based color stylization of images. *ACM Trans. Appl. Percept.*, 2:322–345, July 2005.
[3] D. DeBry, J. Gibbs, D. D. Petty, and N. Robins. Painting and rendering textures on unparameterized models. *Proceedings of SIGGRAPH*, 2002.
[4] B. Freudenberg, M. Masuch, , and T. Strothotte. Real-time halftoning: A primitive for non-photorealistic shading. *Proc. 13th Eurographics Rendering Workshop*, 2002.
[5] G. Gorla, V. Interrante, and G. Sapiro. Texture synthesis for 3d shape representation. *IEEE Transactions on Visualization and Computer Graphics*, 9(4):512–524, 2003.
[6] C. G. Healey and J. T. Enns. Large datasets at a glance: Combining textures and colors in scientific visualization. *IEEE Transactions on Visualization and Computer Graphics*, 5:145–167, 1999.
[7] C. G. Healey, L. Tateosian, J. T. Enns, and M. Remple. Perceptually-based brush strokes for nonphotorealistic visualization. *ACM Transactions on Graphics*, 23:64–96, 2004.
[8] A. Hertzmann. Fast paint texture. *Non-Photorealistic Animation and Rendering*, 2002.
[9] G. Iaccarino, D. Malandrino, M. D. Percio, and V. Scarano. Efficient edge-services for colorblind users. *Proceedings of WWW*, pages 919–920, 2006.
[10] M. Ichikawa, K. Tanaka, S. Kondo, K. Hiroshima, K. Ichikawa, S. Tanabe, and K. Fukami. Web-page color modification for barrier-free color vision with genetic algorithm. *Lecture Notes in Computer Science 2724*, page 21342146, 2003.

[11] M. Ichikawa, K. Tanaka, S. Kondo, K. Hiroshima, K. Ichikawa, S. Tanabe, and K. Fukami. Preliminary study on color modification for still images to realize barrier-free color vision. *IEEE SMC*, 1:36–41, 2004.

[12] V. Interrante, H. Fuchs, and S. Pizer. Conveying the 3d shape of smoothly curving transparent surfaces via texture. *IEEE Transactions on Visualization and Computer Graphics*, 3(2):98–117, 1997.

[13] V. Interrante and C. Grosch. Visualizing 3d flow. *IEEE Computer Graphics and Applications*, 18(4):49–53, 1998.

[14] S. Ishihara. *Tests for colour-blindness*. Kanehara Shuppan Co., 1979.

[15] L. Jefferson and R. Harvey. Accommodating color blind computer users. *Proc. of ASSETS*, pages 40–47, 2006.

[16] R. D. Kalnins, L. Markosian, B. J. Meier, M. A. Kowalski, J. C. Lee, P. L. Davidson, M. Webb, J. F. Hughes, and A. Finkelstein. Wysiwyg npr: Drawing strokes directly on 3d models. *Proceedings of SIGGRAPH*, 2002.

[17] S. Kim, H. Hagh-Shenas, and V. Interrante. Conveying shape with texture: experimental investigations of texture's effects on shape categorization judgments. *IEEE Transactions on Visualization and Computer Graphics*, 10(4):471–483, 2004.

[18] R. M. Kirby, H. Marmanis, and D. H. Laidlaw. Visualizing multivalued data from 2d incompressible flows using concepts from painting. *IEEE Visualization*, 1999.

[19] S. Kondo. *A computer simulation of anomalous color vision in Y. Ohta, editor, Color Vision Deficiencies*. Symp. Int. Res. G. on CVD, Kugler and Ghedini, 1990.

[20] G. R. Kuhn, M. M. Oliveira, and L. A. F. Fernandes. An efficient naturalness-preserving image-recoloring method for dichromats. *IEEE Transactions on Visualization and Computer Graphics*, 14:1747–1754, 2008.

[21] G. M. Machado and M. M. Oliveira. Real-time temporal-coherent color contrast enhancement for dichromats. *Computer Graphics Forum*, 29(3):933–942, June 2010. Proceedings of EuroVis.

[22] G. M. Machado, M. M. Oliveira, and L. A. F. Fernandes. A physiologically-based model for simulation of color vision deficiency. *IEEE Transactions on Visualization and Computer Graphics*, 15(6):1291–1298, November/December 2009.

[23] A. Majumder and M. Gopi. Real time charcoal rendering using contrast enhancement operators. *Proceedings of Symposium of Non Photorealistic Animation and Rendering*, 2002.

[24] B. J. Meier. Painterly rendering for animation. *Proceeding of Siggraph*, pages 477–484, 1996.

[25] G. W. Meyer and D. P. Greenberg. Color-defective vision and computer graphics displays. *IEEE Computer Graphics Applications*, 8(5):28–40, 1988.

[26] S. Nishisato. *Elements of Dual Scaling: An Introduction to Practical Data Analysis*. Psychology Press, 1993.

[27] V. Ostromoukhov and R. D. Hersch. Multi-color and artistic dithering. *Proceeding of Siggraph*, 1999.

[28] E. Praun, H. Hoppe, M. Webb, and A. Finkelstein. Real-time hatching. *Proceedings of Siggraph*, 2001.

[29] K. Rasche, R. Geist, and J. Westall. Detail preserving reproduction of color images for monochromats and dichromats. *IEEE Computer Graphics Applications*, 25(3):22–30, 2005.

[30] K. Rasche, R. Geist, and J. Westall. Re-coloring images for gamuts of lower dimension. *Computer Graphics Forum*, 24(3):423–432, 2005.

[31] M. Salisbury, C. R. Anderson, D. Lischinski, and D. Salesin. Scale-dependent reproduction of pen-and-ink illustrations. *Proceeding of Siggraph*, pages 461–468, 1996.

[32] M. Salisbury, S. E. Anderson, R. Barzel, and D. Salesin. Interactive pen-and-ink illustration. *Proceeding of Siggraph*, pages 101–108, 1994.

[33] M. Salisbury, M. Wong, J. F. Hughes, and D. Salesin. Orientable textures for image-based pen-and-ink illustration. *Proceeding of Siggraph*, 1997.

[34] A. Secord. Weighted voronoi stippling. *Non-Photorealistic Animation and Rendering*, 2002.

[35] H. J. Ted Sharpe, Andrew Stockman and J. Nathans. Color vision: From genes to perception. *chapter Opsin genes, cone photopigments, color vision, and color blindness, Cambridge University Press*, page 351, 1999.

[36] G. Turk and D. Banks. Image-guided streamline placement. *Proceeding of Siggraph*, pages 453–460, 1996.

[37] K. Wakita and K. Shimamura. Smartcolor: disambiguation framework for the colorblind. *Proc. of ASSETS*, pages 158–165, 2005.

[38] G. Winkenbach and D. Salesin. Computer-generated pen-and-ink illustration. *Proceeding of Siggraph*, pages 91–100, 1994.

[39] G. Winkenbach and D. Salesin. Rendering parametric surfaces in pen and ink. *Proceeding of Siggraph*, pages 469–476, 1996.

[40] S. Yang, Y. M. Ro, E. K. Wong, and J.-H. Lee. Quantification and standardized description of color vision deficiency caused by anomalous trichromats - part i: Simulation and measurement. *EURASIP Journal on Image and Video Processing*, 1, 2008.

Behzad Sajadi is a PhD student at the Department of Computer Science in University of California, Irvine since 2007. He received his Bachelor's degree from Sharif University of Technology in 2006. His main research area is Computer Graphics and Visualization with particular interest in multi-projector displays and computational projectors and cameras. He has published several works on geometric and photometric registration of multi-projector displays with the focus of practical designs for commodity large area displays. He has won the Best Paper award in Virtual Reality (VR) 2010 and the Second Best Paper award in Visualization 2009. Recently, he has been working on novel camera and projector designs that provide new degrees of freedom to the users. Along this line, he has published a work on multi-modal cameras which has appeared in Siggraph 2011.

Aditi Majumder is an associate professor at the Department of Computer Science in University of California, Irvine. She received her PhD from Department of Computer Science, University of North Carolina at Chapel Hill in 2003. Her research area is computer graphics and vision, image processing with primary focus on multi-projector displays. Her research aims to make multi-projector displays truly commodity products and easily accessible to the common man. She has won three best paper awards in 2009-2010 in premier venues of IEEE Visualization, IEEE VR and IEEE PROCAMS. She is the co-author of the book "Practical Multi-Projector Display Design". She was the program and general co-chair of the Projector-Camera Workshop (PROCAMS) 2005 and the program chair of PROCAMS 2009. She was also the conference co-chair for ACM Virtual Reality Software and Technology 2007. She has played a key role in developing the first curved screen multi-projector display being marketed by NEC/Alienware currently and is an advisor at Disney Imagineering for advances in their projection based theme park rides. She is the recipient of the NSF CAREER award in 2009 for Ubiquitous Displays Via a Distributed Framework.

Manuel Menezes de Oliveira Neto is a faculty member at the Federal University of Rio Grande do Sul (UFRGS), in Brazil. He received his PhD in Computer Science from the University of North Carolina at Chapel Hill, in 2000. Before joining UFRGS in 2002, he was an Assistant Professor of Computer Science at the State University of New York at Stony Brook from 2000 to 2002. During the Fall 2009 - Spring 2010, he was a Visiting Associate Professor at the MIT Media Lab. His research interests cover most aspects of computer graphics, but especially in the frontiers among graphics, vision (both human and machine), and image processing. This includes image-based and real-time rendering, physiologically-based models of the human visual system, measuring visual acuity, 3D photography, 3D scanning, representation and rendering of surface details, and surface reconstruction from point clouds.

Rosália G. Schneider received the BSc. degree in Computer Science from the Universidade Federal do Rio Grande do Sul in 2010. She is working toward the MSc. degree in the Computer Graphics group at the Universidade Federal do Rio Grande do Sul. Her main research interests lie in the area of computer graphics, where she tries to combine techniques from vision and graphics to generate new types of interaction with media.

Ramesh Raskar joined the Media Lab from Mitsubishi Electric Research Laboratories in 2008 as head of the Labs Camera Culture research group. His research interests span the fields of computational light transport, computational photography, inverse problems in imaging and human-computer interaction. Recent projects and inventions include transient imaging to look around a corner, a next generation CAT-Scan machine, imperceptible markers for motion capture (Prakash), long distance barcodes (Bokode), touch+hover 3D interaction displays (BiDi screen), low-cost eye care devices (Netra,Catra), new theoretical models to augment light fields (ALF) to represent wave phenomena and algebraic rank constraints for 3D displays(HR3D).

He is a recipient of TR100 award from Technology Review, 2004, Global Indus Technovator Award, top 20 Indian technology innovators worldwide, 2003, Alfred P. Sloan Research Fellowship award, 2009 and Darpa Young Faculty award, 2010. Other awards include Marr Prize honorable mention 2009, LAUNCH Health Innovation Award, presented by NASA, USAID, US State Dept and NIKE, 2010, Vodafone Wireless Innovation Award (first place), 2011. He holds over 40 US patents and has received four Mitsubishi Electric Invention Awards. He is currently co-authoring a book on Computational Photography.