Article in Press IJIMAI journal

RGBeat: A Recoloring Algorithm for Deutan and Protan Dichromats

M. Madalena G. Ribeiro[1], Abel J. P. Gomes[2,3,4] *

[1] Polytechnic Institute of Castelo Branco, CIPEC, Castelo Branco (Portugal)
[2] Universidade da Beira Interior, Covilhã (Portugal)
[3] INESC-ID, Lisboa (Portugal)
[4] Instituto de Telecomunicações, Lisboa (Portugal)

Received 8 January 2021 | Accepted 23 November 2021 | Early Access 20 January 2022

LA UNIVERSIDAD EN INTERNET

Abstract

Deutan and protan dichromats only see exactly two hues in the HSV color space, 240-blue (240°) and 60-yellow (60°). Consequently, they see both reds and greens as yellows; therefore, they cannot distinguish reds from greens very well. Thus, their color space is 2D and results from the intersection between the HSV color cone and the 60°-240° plane. The RGBeat recoloring algorithm's main contribution here is that it is the first recoloring algorithm that enhances the color perception of deutan and protan dichromats but without compromising the lifelong color perceptual learning. Also, as far as we know, this is the first HTML5-compliant web recoloring approach for dichromat people that considers both text and image recoloring in an integrated manner.

Keywords

Color Blindness, Contents Adaptation Dichromacy, Recoloring, Visual Accessibility.

DOI: 10.9781/ijimai.2022.01.003

I. Introduction

About 5% of the world population is affected by color vision deficiency (CVD), also called color blindness. This visual impairment hampers the color perception, ending up by limiting the overall perception of CVD people about the surrounding environment. A CVD individual may not distinguish between two different colors, which often originates confusion or a limited understanding of the reality, including web environments, whose web pages are plenty of media elements like text, still images, video, and sprites.

A. Color Vision

In the human eye, there are two types of cells in the retina: rods and cones. Rod cells only function in scotopic (dark) conditions so that they add up nothing to our perception of lightness and darkness in photopic (bright) conditions. That is, rods are responsible for our vision in light-absent environments (i.e., night vision), while cones are responsible for our perception of color.

There are three types of cone cells: L-cones (also known as red cones), M-cones (or green cones), and the S-cones (or blue cones), depending on their sensitivity to the type of wavelengths of light: long (L) wavelengths, medium (M) wavelengths, and short (S) wavelengths, respectively. The tristimulus theory tells us that the perception of color results from the combination of the light stimulation of those three types of cones [1].

* Corresponding author.

E-mail addresses: mribeiro@ipcb.pt (M. M. G. Ribeiro), agomes@di.ubi.pt (A. J. P. Gomes).

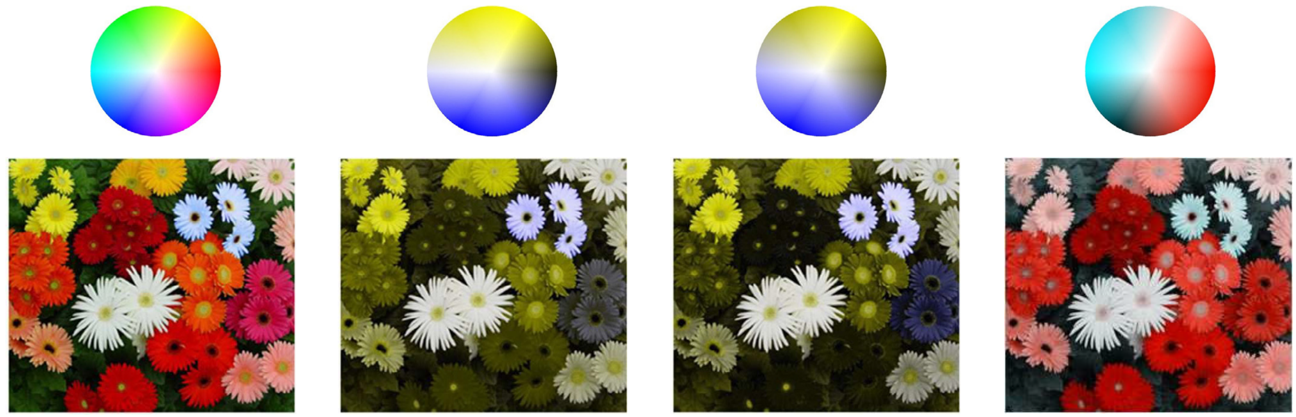
B. Color Vision Anomalies

Typically, human beings are trichromats, i.e., they see the entire visible light spectrum because their three types of cones are working correctly, as illustrated in Fig. 1(a). CVD, sometimes called color blindness, is the result of the misfunctioning of some cones. Accordingly, CVD fits in one of the following categories: anomalous trichromacy, dichromacy, and monochromacy [2].

Anomalous trichromacy is the less severe CVD type and occurs when (at least) a kind of cone cell does not work correctly, either because they are not distributed regularly on the retina or because their sensitivity is weak [3] and [4]. Consequently, there exists a displacement of the sensitivity curve of the corresponding color channel, changing the way one perceives the color as a whole, i.e., in a distorted fashion. Vision anomalies depend on the type of affected cone cells [5]. Protanomaly, also known as red-weak vision, denotes the existence of anomalous L-cones. Deuteranomaly, also known as green-weak vision, indicates the existence of anomalous M-cones. Tritanomaly, also called blue-weak vision, shows the existence of anomalous S-cones. In conformity with the MPEG-21 standard [6], the degree of CVD severity for anomalous trichromats continuously varies in the interval [0.1, 0.9]. For example, those with a severity degree of 0.1 have a minor color vision distortion, while those with a severity degree of 0.9 almost see colors as dichromat people do because dichromacy corresponds to a severity degree of 1.0.

Dichromacy occurs when cones of a given sort do not work, mainly because those cones do not exist on the retina. So, the color perception is found on the other two channels, significantly reducing the color spectrum perceived by dichromat individuals. Depending on the type of inexistent cone cells, the anomaly calls protanopy, deuteranopy, and tritanopy, which accounts for the absence of the L-, M- and S-cone cells, respectively. Thus, all colors visible for trichromat people appear

Please cite this article in press as:
M. M. G. Ribeiro, A. J. P. Gomes. RGBeat: A Recoloring Algorithm for Deutan and Protan Dichromats, International Journal of Interactive Multimedia and Artificial Intelligence, (2022), http://dx.doi.org/10.9781/ijimai.2022.01.003



(a) (b) (c) (d)

Fig. 1. Degrees of severity of color vision deficiency and its dichromat subtypes: (a) regular trichromat people; (b) deuteranope (or deutan) people; (c) protanope (or protan) people, and (d) tritanope (or tritan) people. Simulation of (b)-(c) using Brettel et al.'s algorithm [7] and (d) using Petrich's algorithm [8].

as two monochromatic hues for people with dichromacy: blues and yellows, both for people with deuteranopy and protanopy, and reds and bluish cyans for tritanope people [7], as illustrated in Fig. 1.

Monochromacy is the most severe CVD type due to the absence or non-functioning of two or three types of cone cells. This fact results in a rather severe reduction of the chromatic domain perceived by the individuals. There are two types of monochromacy: blue cone monochromacy, when only the S-cone cells are working [9], and rod monochromacy, when all types of cones are either missing or non-functioning for some reason. The blue-cone monochromacy leads to a gray-scale vision, yet some shades of blue may be noticeable [10]. Rod monochromacy, also known as achromatopsia, leads to a total lack of color experience and a low visual acuity, which is related to poor vision and high sensitivity to light [11] and [12].

Finally, let us mention that CVD has a prevalence of 5% in the Caucasian population on average, though its incidence is about 8% on men and 0.5% on women. Also, the prevalence of each CVD type decreases as the severity increases. Indeed, it is about 75% for anomalous trichromacy, 25% for dichromacy, and 0.00001% for monochromacy [13].

C. Contributions

RGBeat recoloring algorithm aims to help deutan and protan dichromat people. Like other recoloring algorithms, RGBeat aims at minimizing or even eliminating the likely confusion between reds and greens. Recall that deutan and protan dichromat people can distinguish some reds from greens, i.e., they can identify some reds because they have learned that such colors are reds. Nevertheless, dichromat people see reds as greenish colors. Indeed, lifelong color perceptual learning of each dichromat individual plays an important role to overcome part of ambiguity between reds and greens.

However, unlike other recoloring algorithms, RGBeat eliminates the color ambiguity as much as possible without compromising the lifelong color perceptual learning experienced by each dichromat individual. For this purpose, the following properties (or requirements) must be satisfied: color consistency, color naturalness, and color contrast. The challenge is how to increase the contrast between (confusing) colors and, at the same time, to maintain the consistency and naturalness of color.

The key contributions of the RGBeat recoloring algorithm are the following:

- It enhances the color perception of deutan and protan dichromats without undermining their lifelong color perceptual learning.
- It increases the contrast between confusing colors, though maintaining the color consistency and naturalness.
- It applies to HTML5-compliant web environments, including images, video, and text.
- It performs very fast because it only operates on the range of reds, making it feasible to recolor video in real-time.

The first contribution above concerns the research gap we have identified in the literature. Indeed, keeping the color perceptual learning of each dichromat person must be a priority for any recoloring algorithm.

D. Article Organization

The remainder of this article organizes itself as follows. Section II reviews prior recoloring algorithms against relevant requirements: color consistency, color naturalness, and color contrast. Section III details our recoloring algorithm, called RGBeat. Section IV approaches the text and background color adaptation, while Section V approaches color adaption for still images. Section VI presents the qualitative, quantitative, and performance results of RGBeat and competitor methods. Section VII describes usability testing and assessment of RGBeat and its competitor methods. Section VIII discusses the research work behind RGBeat. Section IX concludes the paper, pointing out some hints to future work in browser recoloring and adaptation, as needed for color-blind people.

II. Related Work

Dichromat people only see two distinct hues, although with different values of saturation and brightness. More specifically, deutan and protan dichromats see blues and yellows, respectively; in turn, tritan dichromats see reds and greenish blues. For example, as shown in Fig. 1, a deutan dichromat sees a weakly saturated yellow as a moss green. Besides, reducing the chromatic range to two hues may confuse what is seen in a given image (see Fig. 1).

As said above, the colorblind can distinguish some reds from greens because they have learned that some of such colors are reds. Indeed, the color perceptual learning of each dichromat individual is an essential tool to resolve the red-green ambiguity, even if it is partially. Consequently, in designing a new recoloring algorithm, it is of paramount importance to preserve the color perceptual learning of each dichromat individual. Thus, any contrast-based algorithm must apply minor contrast differences; otherwise, we end up undermining the color perceptual learning of each individual. Therefore, the challenge here lies in increasing the contrast between (confusing) colors and preserving the color consistency and naturalness. For more details, the reader is referred to Ribeiro and Gomes [14], a survey on recoloring methods based on these three concepts: color consistency, color naturalness, and color contrast.

Color consistency guarantees that if two colors are identical, the corresponding mapped colors will remain identical, independently of the set of colors subject to remapping. Note that the lack of color consistency creates bewilderment in the perception of the colorblind. Color consistency is an essential requirement that is gaining significance in recent recoloring methods [15]-[19], though others avoid approaching it [20] and [21]. Its importance stems from the fact that it prevents us from adding more color ambiguity to the typical ambiguity of reds and greens inherent to the colorblind. For example, let us consider that a pink hue maps to a magenta hue; one says that such color mapping is consistent when such pink always maps to the same magenta. Color consistency is vital for recoloring video; otherwise, it would be tough to maintain the temporal color consistency.

Color naturalness has to do with minimizing the perceptual difference between a color and its corresponding remapped color. This difference should be as low as possible so as not to break up the perceptual learning of the colorblind. Some works address this property [21]-[26]. However, others [27] and [28] do not show any concern about color naturalness.

Color contrast stems from increasing the perceptual difference of neighboring elements in an image to enhance the perception of the colorblind. In a way, color naturalness and contrast are contradictory requirements that make recoloring algorithms challenging to tune-up. For further details about color contrast in recoloring algorithms, the reader is referred to [23], [24] and [29]. However, this requirement has not been considered by other algorithms [21] and [22]. Interestingly, some algorithms create higher color contrast, although not referring to this goal explicitly [30].

Considering the three properties of color above, we developed a recoloring algorithm for dichromat people, RGBeat, which reduces the space for color ambiguity at the cost of a few colors that only slightly conflict with their perceptual learning. The reduction of color ambiguity between reds and greens occurs by increasing the color contrast between confusing colors. As will be seen ahead, we compare RGBeat to other two methods, which are due to Iaccarino et al. [24] and the Ching-Sabudin [30]. We selected these two methods among all those we may find in the literature because they satisfy the following requirements:

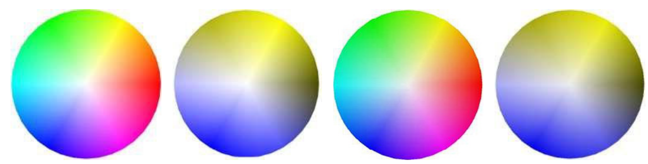
- They are color-consistent, a condition to prevent adding more confusion in the color perception.
- They preserve either color naturalness or increase color contrast.
- They apply to true-color images.

III. Recoloring Algorithm

RGBeat recoloring algorithm was designed for deuteranopy and protanopy simply because they are the most common types of dichromacy, and their color perception is quite similar.

A. Leading Idea

As shown in Fig. 2, deutan or protan dichromats only perceive two hues, yellow (60°) and blue (240°), yet with more or less luminance and saturation. We know that those people see greens as yellows, but they perceive them as unsaturated greens, i.e., they faintly perceive greens. Also, deutan or protan dichromats see reds as dark unsaturated yellows. Consequently, deutan and protan dichromats confuse reddish and greenish colors, though they can distinguish some reds from greens, which stems from their lifelong color perceptual learning.



(a) (b) (c) (d)

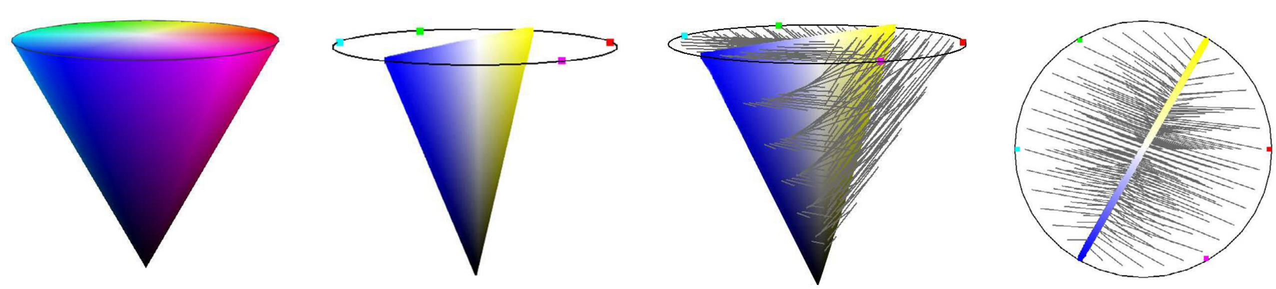
Fig. 2. HSV cone sections: (a) a section with value = 100%, as seen by trichromat people; (b) a section with value = 100%, as seen by deuteranope people; (c) a section with value = 75%, as seen by trichromat people; and (d) a section with value = 75%, as seen by deuteranope people. Deuteranope simulation based on Vienot et al.'s algorithm [31].

Thus, the leading idea of our algorithm is to reduce the confusion between reds and greens further so that only reds will be subject to a recoloring procedure. For that purpose, as mentioned in the previous section, it is crucial to preserve the color perceptual consistency and slightly increase the color contrast for reds to preserve the color naturalness as much as possible.

B. HSV Color Domain of Deuteranopy An Protanopy

In comparison to the color range seen by trichromat people, the color range seen by deutan or protan dichromats is quite limited. This turns up more evident when we consider HSV colors, as illustrated in Fig. 3. The HSV color space is a cone such that $H \in [0°,360°[$ stands for the hues (or color wheel), $S \in [0, 100]$ denotes the saturation range, which increases from the cone apex to base and perpendicularly to cone axis, and $V \in [0, 255]$ the brightness value, which increases from the apex to base of the cone [32]. In Fig. 3(a), we see the entire cone of colors seen by trichromat people, while the colors seen by deutan and protan dichromats map onto colors in the 60°/240° plane, which cuts the cone into two parts (cf. Fig. 3(b)).

As noted above, the deutan or protan dichromats only see yellows and blues. However, contrary to the general idea that such blues and yellows include multiple hues, protan and deutan people only see the yellow hue of 60° and the blue hue of 240°. In truth, they only see these two hues with more or less saturation and brightness. Our experiments confirmed this by using the simulation algorithm due to Brettel et al. [7], converting then the color to the HVS color space



(a) (b) (c) (d)

Fig. 3. The HSV color space when seen by: (a) trichromat people; (b) deuteranope people (deuteranope half planes); (c) and (d) deuteranope people, with the color projection lines, joining colors seen by trichromat and deuteranope people, being (c) a lateral view and (d) the top view. Deuteranope simulation based on Vienot et al.'s algorithm [12].

[33]. We constructed the deuteranope color gamut in the HSV color space by varying R, G, and B in the range [0, 255], converting RGB to RGB_{deutan} (i.e., using the method proposed by Vienot et al. [31]), and RGB_{deutan} to HSV afterward. This deuteranope color gamut reduces to two coplanar triangles, resulting from the intersection between a plane and the HSV cone (see Fig. 3). We can obtain a similar planar color gamut in the LMS color space [7] and CIE XYZ color space [34] for deuteranope people.

As shown in Fig. 3(c), the visual system of a deutan dichromat transforms the conical HVS color space (Fig. 3(a)) into a triangular color space (Fig. 3(b)). In other words, each hue of the HSV cone projects onto a triangle belonging to the plane defined by the apex, 60°-hue point and 240°-hue point. As illustrated in Fig. 3, such color projection entails a change of saturation and brightness (usually a loss). It is clear that colors projected onto the yellow part of the triangle]150°, 330°[noticeably lose value (brightness), while colors projected onto the blue part tend to keep value (brightness) unchanged. Regarding saturation, no significant changes occur (see Fig. 3(d)). When there is a change, the saturation may increase or decrease (although slightly). The behavior of the protan dichromat's projection is similar, though shades are slightly different.

C. RGBeat Recoloring Procedure

A glance at Fig. 2 shows us that deutan or protan dichromats tend to see reds as dark unsaturated greens, so that a pure red is seen as dark green, not to say black. As shown in Fig. 3, greens and reds are seen similarly by deutan or protan dichromats; hence, their well-known red-green confusion, also known as colorblindness. With this problem is mind, we decided not to change the saturation $S \in [0, 100]$ neither the brightness (value) $V \in [0, 255]$ in the HSV model; we only changed hues as follows:

- Hues in the range]0°, 60°[(range of reds and oranges) squeezed into the range]30°, 60°[.
- Hues in the range]300°, 360°] (range of reds, pinks, and magentas) squeezed into the range]300°, 330°].

The remaining hues in the range [60°, 300°] remain unchanged. This way, those deutan or protan dichromats end up having fewer dark hues (yellows and blues) in the range of reds (for trichromats). So, we ensure the fulfillment of the requirements of color consistency and naturalness. However, despite the soundness of this recoloring approach, we can ask ourselves about its actual help for colorblind. Indeed, it is convenient here to recall that:

- Reducing the hue range seems to us a good decision because we are just eliminating the subrange of confusing hues, i.e., the reds in this case. For example, in Figs. 4 and 5, we see that a deutan cannot distinguish a green flower from a red flower, but a deutan can easily distinguish them with our recoloring technique. In short, the question is not reducing the hue range but cutting off the subrange of reds after mapping reds to close hues as much as possible. The purpose is thus to be able to discriminate confusing hues.
- We must carry out the mapping of hues reducing at the same time the impact on the perceptual learning of the deutans as much as possible, i.e., without affecting the color naturalness that much. So, it makes sense to remap hues according to our technique, which keeps the color consistency while increases the contrast.

Before proceeding any further, let us recall that the hue compression of]0°, 60°[corresponds to the following non-linear interpolation formula:

$$H' = H + H.\left(\frac{60 - H}{60}\right) \tag{1}$$

while the hue compression of]300°, 360°[is given by

$$H' = H + (300 - H).\left(\frac{360 - H}{60}\right) \tag{2}$$

1. Mapping hues from]0°, 60°[: Let us consider the color (R, G, B), with $R, G, B \in [0, 255]$, being the corresponding normalized color (r, g, b) given by

$$r = R/255 \qquad g = G/255 \qquad b = B/255 \tag{3}$$

Let us also assume that the values of S and V remain unchanged. We know that by only changing the value of H in the range]0°, 60°[, we only change the value of G in the RGB color space. Indeed, considering $H \in]0°, 60°[$, the HSV-RGB conversion formula due to Smith [33] sets that

$$R = V \qquad G = V(1 - S(1 - 6H)) \qquad B = V(1 - S) \tag{4}$$

Since we stated that S and V remain unchanged in the HSV model, we conclude that G is the only RGB parameter that changes because of changing the parameter H in the HSV color space.

In these circumstances, we have $R = \max(R, G, B)$, $B = \min(R, G, B)$, and $G \in [B, R]$, being these equalities also valid for the (normalized) rgb colors. In other words, the values of R and B (resp., r and b) remain unchanged for $H \in]0°, 60°[$.

Now, recalling the RGB-HSV conversion formula due to Smith [33], and considering]0°, 60°[the domain of H, we get

$$H = 60.\left(\frac{g - b}{r - b}\right) \tag{5}$$

But we know that varying H in]0°, 60°[only provokes changes in the value of g. So, replacing the value of H given by Eq. (5) into Eq. (1), we have

$$60.\left(\frac{g - b'}{r - g}\right) = 60\left(\frac{g - b}{r - g}\right) + 60\left(\frac{g - b}{r - g}\right)\frac{60 - 60\left(\frac{g - b}{r - g}\right)}{60} \tag{6}$$

or, equivalently,

$$g' = g + (g - b)\left(\frac{r - g}{r - b}\right) \tag{7}$$

The novelty about the hue mapping of]0°, 60°[translates itself into a color mapping in the RGB color space given by Eq. (7). That is, there is no need to convert from RGB into HSV and *vice versa*. In short, we have only to remap the rgb reddish colors in conformity with Eq. (7), since $r' = r$ and $b' = b$. Note that in the range]0°, 60°[any hue H has more red than green ($r > g$); cf. line 1 of Algorithm 1.

2. Mapping hues from]300°, 60°]: Let us also assume that the values of S and V remain unchanged. By only changing the value of $H \in]300°, 360°]$, we end up only changing the value of B in the RGB color space. Accordingly, we have $R = \max(R, G, B)$, $G = \min(R, G, B)$, and $B \in [G, R]$, and the same applies to (normalized) RGB colors. Therefore, the values of R and G (resp., r and g) remain unchanged for $H \in [300°, 360°]$.

Now, taking into the account the RGB-HSV conversion formula due to Smith [33], with $H \in [0°, 360°]$, we get

$$H = 60.\left(\frac{g - b}{r - g}\right) + 360 \tag{8}$$

But we know that varying $H \in]300°, 360°]$ only provokes changes in the value of B. So, replacing the value of H given by Eq. (8) into Eq. (2), we obtain

$$b' = g - (g - b)\left(2 + \frac{g - b}{r - g}\right) \tag{9}$$

Note that in the range]300°, 360°[any hue H has more red than blue ($r > b$); cf. line 1 of Algorithm 1. In short, the recoloring procedure that builds upon Eqs. (7) and (9) translates itself into a color remapping in the RGB color space, as shown in Algorithm 1, not being necessary to make the RGB-HSV conversion, and *vice versa*, explicitly. This simplification constitutes a significant gain in processing time.

3. *Changes in perceived chroma and luminance*: The algorithm relies on —though it does not explicitly use— the HSV colour space. It maintains each color's saturation S and value V during recoloring. However, this does not mean that perceived chroma and perceived luminance hold. Indeed, as explained below, maintaining S and/or V in HSV space during recoloring does not maintain the perceived chroma nor perceived luminance of the color.

Regarding perceived chroma, its change is a result of changing the hues to close hues according to Eqs. (1) and (2); for example, an orange is mapped to a yellowish orange. Recall that we tried to reduce the color mapping to a minimum in order not to provoke significant perceived changes in the perceptual learning of deutan and protan dichromats.

As regards to changing the perceived luminance, it is not so obvious because the values of S and V remain unchanged. According to Poynton [35], the perceived luminance is given by

$$L = 0.299R + 0.587G + 0.114B \tag{10}$$

so that, taking also into consideration Eq. (4), we conclude that changes in G provokes changes in L; the values of R and B remain unchanged because the values of S and V do not change in the recoloring procedure. Thus, increasing the value of G results in an increase in the value of L; consequently, the contrast also increases, eliminating the confusion between reds and greens.

Algorithm 1: **RGBeat**
Input: r, g, b
Output: r, g', b'

```
1 if (r > g) ∧ (r > b) then // reddish hues
2   if (g > b) then          // reddish hues with g > b
3     g' ← g + (g − b) (r − g) / (r − b))                (7)
4   end
5   else                     // reddish hues with b > g
6     b' ← g − (g − b)(2 + (g − b) / (r − g))            (9)
7   end
8 end
```

Algorithm 2: **TextRecoloring**
Input: HTMLDocument

```
1  css[ ] ← style sheets of HTMLDocument
2  n ← number of style sheets in css[ ]
3  for i ← 1 to n do
4   css[i] ← i-th style sheet
5     m ← number of CSS rules of css[i]
6     for j ← 1 to m do
7        cssrule[j] ← j-th CSS rule
8        if cssrule[j].color then
9             [R, G, B] ← cssrule[j].color
10            cssrule[j].color ← RGBeat([R, G, B])
11        end
12        if cssrule[j].backgroundcolor then
13            [R, G, B] ← cssrule[j].backgroundcolor
14            cssrule[j].backgroundcolor ← RGBeat([R, G, B])
15        end
15     end
16 end
```

IV. Text Recoloring For HTML Documents

Algorithm 2 was designed for recoloring text in HTML documents using RGBeat. It involves three main steps, namely:

1. Accessing to all cascading style sheets (CSS) associated with such web page and to all CSS rules associated with each style sheet.
2. Recoloring each text block by changing its corresponding CSS rules whenever necessary. This task performs by changing the `color` and `background-color` properties associated with each CSS rule.
3. Rendering the HTML web page with the modified CSS rules, which is an automatic process provided by any web browser.

Alg. 1 (RGBeat) is used in Alg. 2 to change both text and background. To dynamically access and update the content, structure, and style of an HTML document, we use the HTML Document Object Model (DOM) as a programming interface for Javascript. Indeed, tasks like accessing each style sheet, each rule defined in a style sheet, each value of the rule properties, as well as determining the number of style sheets associated with an HTML document, and the number of rules defined in each style sheet, are all done using DOM object methods.

Thus, recoloring text blocks of a web page is done by changing the CSS rule objects associated to text blocks of an HTML document. This recoloring procedure operates on the CSS rules instead of being on the text blocks themselves. The recoloring procedure of all text blocks of an HTML document corresponds to Alg. 2. Recall that an HTML document usually is tied to a set of CSSs, so that we need to retrieve this set of CSS using the Javascript statement `var css = document.styleSheets;` (cf. line 1 in Alg. 2).

V. Image Recoloring For HTML Documents

Recoloring a single $M \times N$ image is described in Alg. 3. This algorithm calls the RGBeat algorithm (cf. Algorithm 1) for every single pixel of the image. Alg. 3 applies to all images associated with a given web page, as described in Alg. 4.

Algorithm 3: **ImageRecoloring**
Input: *Image*, *width*, *height*

```
1  for i ← 0 to width-1 do
2    for j ← 0 to height-1 do
3       R ← Image[i][j].R
4       G ← Image[i][j].G
5       B ← Image[i][j].B
6       [R, G, B] ← RGBeat([R, G, B])
7       Image[i][j].R ← R
8       Image[i][j].G ← G
9       Image[i][j].B ← B
10   end
11 end
```

Algorithm 4: **HTMLDocumentImagesRecoloring**
Input: HTMLDocument

```
1 Images[] ← set of HTMLDocument's images
2 n ← number of images in Images[ ]
3 for i ← 0 to n − 1 do
4  width ← Images[i ].width
5  height ← Images[i ].height
6    ImageRecoloring(Images[i ], width,height)
7 end
```

Recoloring starts with retrieving images from the HTML document (cf. line 1 in Alg. 4). The recoloring occurs in line 6, where one calls the procedure **ImageRecoloring** (i.e., Alg. 3), which in turn calls the procedure **RGBeat** (i.e., Alg. 1) to adapt the color of each pixel. As seen above, **RGBeat** also applies to recoloring of text and backgrounds from the CSS style sheet rules. Recall that the HTML5 specification provides a 2D context (or even a 3D context) to a canvas to get a pixelized image.

VI. Qualitative, Quantitative, and Time Results

As argued above, we designed the RGBeat recoloring algorithm for deutan and protan dichromat people because of the following: first, they are the most common dichromat people; second, deutan and protan people perceive colors in a very similar manner. As shown above, the RGBeat algorithm applies to text, still images, and video, no matter whether they are on web pages or not.

A. Setup

Before proceeding any further, let us say that we obtained all experimental results using a laptop equipped with a 32-bit Microsoft Windows operating system running on an Intel Pentium Dual CPU T2330 1.60GHz, with 3G RAM. Besides, the algorithms described in this paper were coded in Javascript programming language for HTML5 web browsers, in particular for Chrome.

B. Methodology

For a fair comparison with the RGBeat, we selected the recoloring algorithms due to Iaccarino et a [24] and Ching and Sabudin [30] because they share several features, namely:

- They apply to both deuteranopy and protanopy.
- They use a phenomenal color space. Recall that a phenomenal color space uses hue, saturation, and brightness as classifying descriptors [32], [36] and [37].
- They likely are some of the fastest color mapping methods based on phenomenal color spaces.
- Iaccarino et al.'s method [24] tends to preserve color naturalness at the cost of not reinforcing too much contrast. On the other hand, Ching and Sabudin [30] reinforces the contrast but does not preserve color naturalness.

We also implemented the algorithms proposed by Vienot et al. [31]. These algorithms simulate how deutan and protan people see the colors (see Fig. 4(b) to (d)). Also, we have carried out two sorts of evaluation of the methods: qualitative and quantitative. The qualitative evaluation is visual and subjective, in the sense that we attempt to grasp which is the best method in recoloring process. The quantitative evaluation is objective because it is based on mathematical metrics or formulas and works here as a way of confirming our subjective, visual evaluation.

C. Qualitative Evaluation

As known, deutan and protan people only see some yellows and some blues, although with varying saturation and brightness. Thus, yellows and blues must remain unchanged after the recoloring a given image. Interestingly, greens look unsaturated greens, but indeed they are little saturated yellows. As shown in Fig. 4, the three algorithms leave the yellows unchanged somehow; the same applies to blues (Fig. 5). Note that the original image in Fig. 5 exhibits the primary colors: red, green, and blue.

The differences between those three algorithms become noticeable when recoloring adjacent image elements that people with dichromacy perceive as similar. Recall that deutan and protan people mistake reddish colors (including pinks and oranges) with greenish colors. A glance at Figs. 4-5 shows the following:

Iaccarino et al.'s: Iaccarino et al.'s recoloring technique [24] does not significantly improve the original images when seen by deutan or protan people, though the yellows seem less vivid.

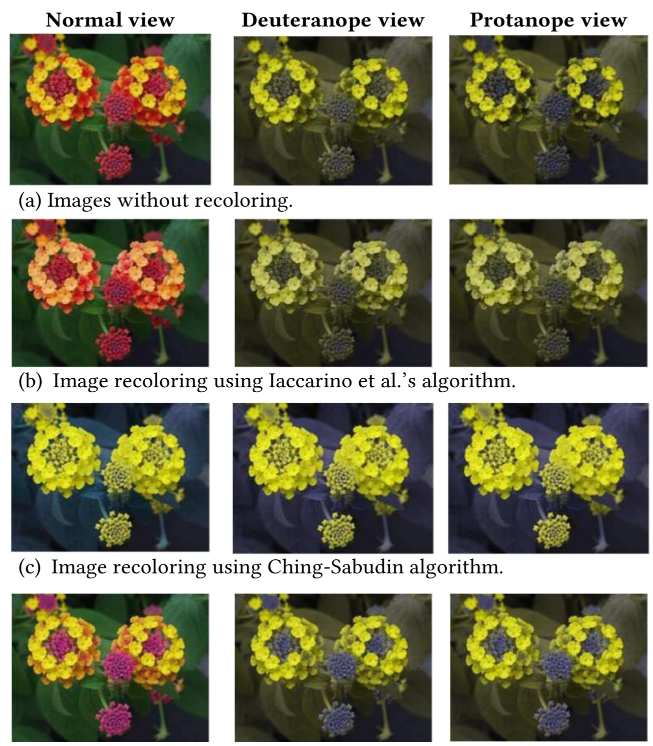
Ching and Sabudin's: On the other hand, Ching and Sabudin's technique [30] maps reds into yellows, which results in a loss of contrast between reds and yellows, i.e., between a primary color and a secondary color. Even worse it is the fact that greens map onto weak blues, so that deutan and protan people can no longer see greens (yet in the form of little saturated yellows).

RGBeat: Our recoloring technique preserves the colors seen by people with deuteranopy and protanopy, i.e., yellows and blues. Reds concerning hues (via RGB-HSV conversion) greater than zero (i.e., reds closer to oranges and yellows) map onto darkish yellows, while reds concerning hues less than 360 (i.e., reds close to pinks and magentas) are mapped to greyish blues.

D. Quantitative Evaluation

As mentioned in section I-B, RGBeat aims at eliminating the red-green ambiguity as much as possible. However, unlike other recoloring algorithms, RGBeat eliminates such color ambiguity without compromising each dichromat individual's lifelong color perceptual learning. Consequently, according to Ribeiro and Gomes [14], RGBeat must preserve the following properties: *consistency*, *naturalness*, and *contrast*.

1) Consistency-based Evaluation: The three benchmarking algorithms are all consistent in terms of recoloring. This means that the equally colored pixels of an image will exhibit the same color after applying the same recoloring procedure.



(a) Images without recoloring.

(b) Image recoloring using Iaccarino et al.'s algorithm.

(c) Image recoloring using Ching-Sabudin algorithm.

(d) Image recoloring using our RGBeat algorithm.

Fig. 4. (a) Images without recoloring as seen by trichromat people (left), deuteranope people (middle), and protanope people (right); (b) images recolored by Iaccarino et al.'s algorithm as seen by trichromat people (left), deuteranope people (middle), and protanope people (right); (c) images recolored by Ching-Sabudin algorithm as seen by trichromat people (left), deuteranope people (middle), and protanope people (right); (d) images recolored by the RGBeat algorithm as seen by trichromat people (left), deuteranope people (middle), and protanope people (right).

2) Naturalness-based Evaluation: As seen before in Section III, the color naturalness ensures that a mapped color will be close to the original color, as perceived by deutan and protan dichromats.

According to Flatla et al. [21], the naturalness of an image has the following formulation:

$$\nu = \frac{1}{n}\sum_{i=1}^{n} \Delta(P_i, P_i^*) \tag{11}$$

where $n = W \times H$ denotes the image resolution, P_i the color of the i-th pixel, and P_i^* the color of the i-th pixel after the recoloring, while $\Delta(P_i, P_i^*)$ denotes the color difference between P_i and P_i^* in conformity with the CIE76 color-difference formula expressed in CIE Lab space coordinates given by

$$\Delta = \sqrt{\left(L_i^* - L_i\right)^2 + (a_i^* - a_i)^2 + (b_i^* - b_i)^2} \tag{12}$$

where (L_i, a_i, b_i) and (L_i^*, a_i^*, b_i^*) represent the Lab colors of P_i and P_i^*, respectively. The smaller the value of ν, the more natural is the recoloring procedure of each image.

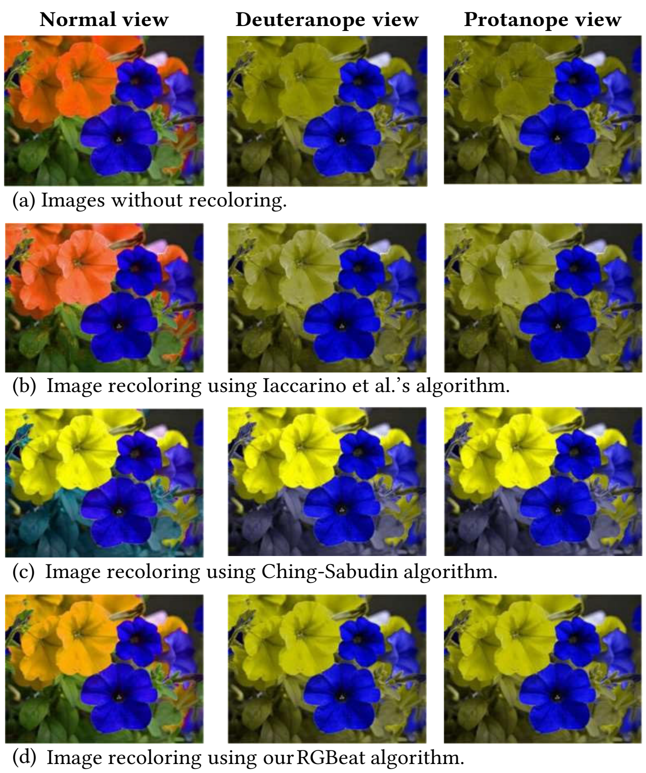


Fig. 5. (a) Images without recoloring as seen by trichromat people (left), deuteranope people (middle), and protanope people (right); (b) images recolored by Iaccarino et al.'s algorithm as seen by trichromat people (left), deuteranope people (middle), and protanope people (right); (c) images recolored by Ching-Sabudin's algorithm as seen by trichromat people (left), deuteranope people (middle), and protanope people (right); (d) images recolored by our algorithm as seen by trichromat people (left), deuteranope people (middle), and protanope people (right).

Eq. (11) applies to trichromats. However, it also applies to deutan and protan dichromats since we consider that P_i and P_i^* are the colors seen by them before and after the recoloring procedure, respectively. The naturalness benchmarking of the three algorithms was carried out regarding a dataset of 100 still images (Fig. 6 shows 15 of them) possessing reddish colors (i.e., confusing colors for deutan and protan dichromats):

Iaccarino et al.'s: Regarding naturalness, Iaccarino *et al.*'s recoloring technique [24] ranks second, with a mean score of $\bar{\nu} = 8.6$ for the entire image dataset. We can explain this relatively high score as follows. First, even though Iaccarino *et al.*'s algorihm changes almost all colors, only a few of them change noticeably. Second, the hue rotation resulting from recoloring does not exceed 45° (albeit the cumulative adjustments in saturation and lightness). At the same time, the remaining colors suffer a less pronounced change (about 10% in saturation and lightness).

Ching and Sabudin's: The algorithm proposed in [30] ranks third in terms of naturalness, with a mean score of $\bar{\nu} = 20.76$ for the entire image dataset. The reasons behind this high score are twofold. First, this happens because 2/3 of colors are subject to recoloring. Second, the reddish hues in the range [-60°, 60°] suffer a rotation that may attain 120°, and the same applies to greenish colors.

RGBeat: Our technique ranks first regarding naturalness, with a mean score of $\bar{\nu} = 3.8$ for the entire image dataset. To explain this fact, recall that 2/3 of colors remain unchanged, mainly because only those satisfying the condition R > G, B end up being changed. Furthermore, the remapped colors are subject to a rotation with a maximum amplitude of 30°.

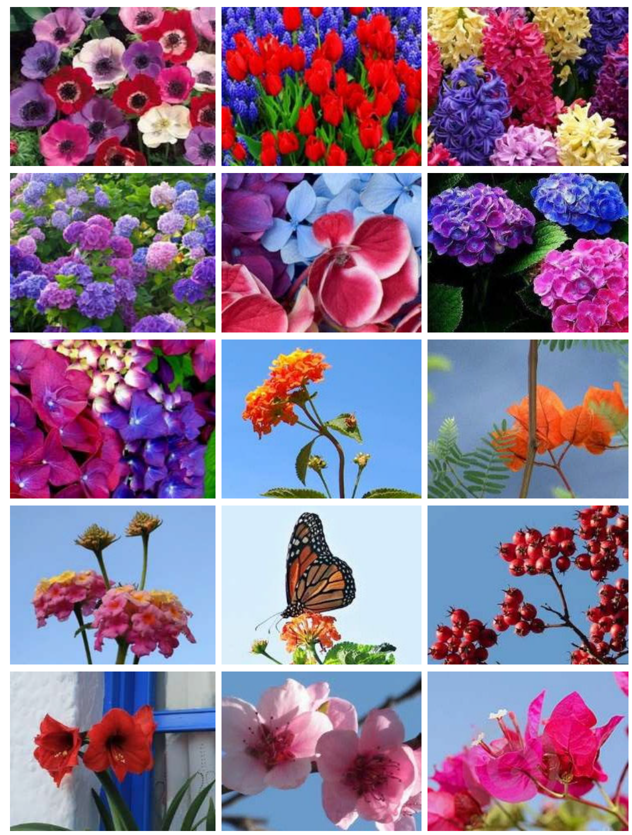


Fig. 6. Still images of a dataset with 100 images (350´270 resolution) that we used to study and benchmark algorithms in respect to the following properties: naturalness, contrast, and performance. All images possess reddish colors (i.e., confusing colors for deuteranope e protanope people), whose hues are in the range [-60°, +60°].

3) Contrast-based Evaluation: The contrast benchmarking of the three techniques was accomplished using the squared Laplacian (cf. [38]) as follows:

$$C = \frac{1}{W \times H}\sum_{x=1}^{W}\sum_{y=1}^{H} G(x,y)^2 \tag{13}$$

where $W \times H$ denotes the image resolution, while $G(x,y)$ is given by:

$$G(x,y) = \sum_{i=x-1}^{x+1} |I(x,y) - I(i,y)| + \sum_{j=y-1}^{y+1} |I(x,y) - I(x,j)| \tag{14}$$

where $I(x, y)$ is the intensity of the pixel (x, y), which in turn is given by (cf. [35]):

$$I(x, y) = 0.299\frac{R}{255} + 0.587\frac{G}{255} + 0.114\frac{B}{255} \tag{15}$$

The computation of contrast C through Eq. (13) applies to any color space. Using Eq. (13), we measured the contrast of the entire image dataset in the deutan (resp., protan) color space. We used the simulation algorithm due to Vienot et al. [31] to generate the entire image dataset as seen by deutan people. Therefore, our quantitative evaluation of contrast took place in the deutan color space. More specifically, in the deutan color space, we obtained a mean contrast value of C=0.0418 for the entire deutan image dataset before applying any recoloring procedure.

The contrast-based evaluation of the benchmarking algorithms output the following results:

Iaccarino et al.'s: Based on our testing, the algorithm due to Iaccarino et al. [24] does not show any contrast improvement because the mean contrast (in the deutan color space) after recoloring all dataset images is 0.0417, i.e., slightly lower than the mean contrast before recoloring. We explain this fact by the small changes in hue, saturation, and brightness inherent to the recoloring procedure of the Iaccarino et al. algorithm.

Ching and Sabudin's: Regarding Ching-Sabudin's technique [30], we noted its ability to enhance the contrast since the entire dataset of images scored 0.047 in mean contrast (in the deutan color space), featuring an increase of 12.4% relative to the mean contrast before recoloring. However, this contrast increase arises at the cost of some loss of naturalness. Indeed, the recoloring procedure remaps 2/3 of colors; but, more importantly, it is the fact that reddish hues in the range [-60°,60°] are all mapped to yellows, when it would be more natural to remap hues in the subrange [-60°,0°[to blues and hues in the subrange [0°,60°[to yellows.

RGBeat: Our technique also improves the contrast, but not so much as Ching-Sabudin's technique; it scored 0.045 in mean contrast (in the deutan color space), featuring an increase of 7.7% relative to the dataset images before recoloring. Recall that our recoloring technique only operates on the hue range [-60°,60°] (i.e., confusing hue range), so that hues in the subrange [-60°,0°[are mapped to blues, while hues in the subrange [0°,60°[are mapped to yellows.

Summing up, considering the color consistency, naturalness, and contrast requirements to maintain each dichromat individual's lifelong color perceptual learning, RGBeat performs better than Iaccarino *et al.*'s and Ching-Sabudin's algorithms. Indeed, they are all color-consistent, but RGBeat is the only one that is capable of enhancing the contrast with negligible loss of color naturalness.

E. Time Performance Evaluation

We encoded the three benchmarking algorithms in JavaScript. To assess their time performance, we used ten offline web pages containing a total of 160 images. Each page incorporates 16 images with identical resolution $n \times n$, but the resolution increases 100 pixels wide and 100 pixels high from page to page, i.e., we have images with resolutions of $n \times n$, with $n = 100, 200, ..., 1000$. Fig. 7 shows how the algorithms behave over images with increasingly higher resolutions. More specifically, Fig. 7(a) shows how much the average time spent by those algorithms depends on the resolution of the images, while Fig. 7(b) features the average time per pixel for each collection of images with identical resolution.

As expected, considering those three algorithms, the average time to recoloring images increases with the resolution (Fig. 7(a)). However, the average time per pixel decreases with the resolution, converging to a minimum that keeps constant when $n \to \infty$ (Fig. 7(b)). Therefore, the time complexity of the three algorithms is linear. To explain this fact, remind that not all the pixels are subject to recoloring. RGBeat is faster than Iaccarino *et al.*'s and Ching-Sabudin's algorithms because its time spent per pixel is shorter than for the other two algorithms. Indeed, the average time per pixel is about 1.4ms, 0.8ms, and 0.06675ms for the algorithms of Iaccarino *et al.*, Ching-Sabudin, and RGBeat, respectively, when $n \to \infty$.

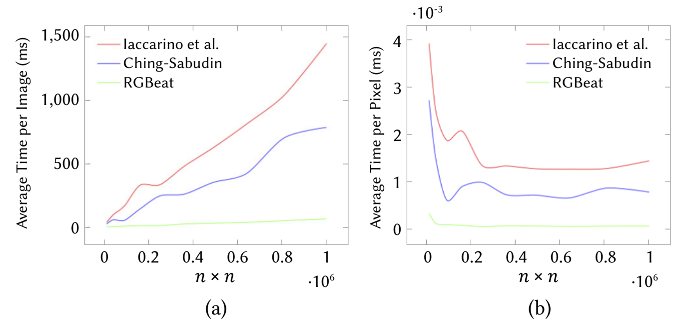


Fig. 7. Recoloring time performance: (a) average time per image against image resolution; (b) average time per pixel against image resolution.

VII. Usability Assessment

In section VI, we compared RGBeat with the other two methods from the algorithmic point of view. To make sure about the quality of the results produced by those algorithms, we proceeded to usability testing, i.e., testing from the user's point of view.

A. The Universe of CVD People

Testing involved a universe of thirteen CVD male volunteers, with ages between 17 and 69 years old. These individuals previously did the D-15 Color Arrangement Test [39]. The results of this test revealed the following distribution:

- 2 people with strong protanomaly (ages 32 and 49);
- 1 person with moderate protanomaly (age 27);
- 5 people with strong deuteranomaly (ages from 49 to 69);
- 4 people with moderate deuteranomaly (ages from 17 to 46);
- 1 person with deuteranopy (age 35).

We extended the usability testing to deutan and protan trichromat people because those with moderate or strong anomalies may have as poor color discrimination as dichromat people [5].

B. The Questionnaire

Although some authors have adopted the Law of Comparative Judgment (LCJ) of L.L.Thurstone for statistical studies [25] [26], we do not follow that pathway because LCJ does not allow the comparison of four alternatives simultaneously. Instead, we use descriptive statistics techniques to compare more than two methods simultaneously [40] and [41]. More specifically, we have used questionnaires as one of such descriptive statistics techniques.

In the makeup of the web questionnaire (see http://rgbeat.ipcb.pt), we considered five categories of images: visualization of information (InfoVis), indoor scenes (Indoor), outdoor scenes (Outdoor), visualization of scientific information (SciVis), and signage (Signage). We elected six images for each category, making up 30, precisely those depicted in Appendix. We selected these images regarding the importance of using a representative set of images (see Shaffer and Zhang [41]) to reduce the sampling error and, consequently, get a significant statistical confidence interval.

The questionnaire was designed for web browsers (via Google

	InfoVis				Indoor				Outdoor				SciVis				Signage				Overall			
Score	MWA	IACC	CHING	RGBeat	MWA	IACC	CHING	RGBeat	MWA	IACC	CHING	RGBeat	MWA	IACC	CHING	RGBeat	MWA	IACC	CHING	RGBeat	MWA	IACC	CHING	RGBeat
1	21	10	31	16	6	33	38	1	5	15	56	2	6	32	30	10	29	7	24	18	67	97	179	47
2	11	24	13	30	17	21	18	22	20	33	5	20	18	14	18	28	25	26	0	27	91	118	54	127
3	17	29	5	27	23	13	7	35	23	21	0	34	16	19	12	31	9	38	1	30	88	120	25	157
4	29	15	29	5	32	11	15	20	30	9	17	22	38	13	18	9	15	7	53	3	144	55	132	59
	(a)				(b)				(c)				(d)				(e)				(f)			

MWA: method without adaptation; IACC: Iaccarino et al.; CHING: Ching-Sabudin.

Fig. 8. Distribution of the preferences per image category and per recoloring method: a) *InfoVis*; b) *Indoor*; c) *Outdoor*; d) *SciVis*; e) *Signage*; and (f) *Overall*.

Forms) so that each category of images corresponds to a separate web page of the questionnaire. Each of these five pages displays 6x4 images, i.e., six rows of 4 optional images organized randomly in a horizontal manner. Each row includes the original image and more three recolored images produced by the above recoloring algorithms (Iaccarino et al., Ching-Sabudin, and RGBeat); these four images concerning the same scene appear randomly in each row. The questionnaire asks the volunteer for his/her preference order (i.e., from 1 to 4) among four images of each row, considering the criteria of naturalness and contrast. Note that this ranking scale is adequate to situations where the ranking involves a maximum of five alternatives [42]. Then, the image ranked first is assigned the score 4, the second the score 3, the third the score 2, and the fourth the score 1 (see [43] for further details about the design of questionnaires). Four specialists on visual representation and color vision deficiency researchers did validate the questionnaire.

C. Data Collecting

Fig. 8 shows the raw quantitative results of the questionnaire, where the CVD people's preferences are expressed relative to five categories of images mentioned in Section VIIB (see Figs. A1-A5 in Appendix A). Considering that we have a universe of 13 respondents and six images per category, the data sample size for each category is 78 responses (= 6´13). For example, for the InfoVis category in Fig. A1, the data sample of the RGBeat is 78, as a result of summing up 16 responses with score 1, 30 responses with score 2, 27 responses with score 3, and 5 responses with score 4. That is, we used scoring in the range [1,4], which has to do with the number of recoloring methods under benchmarking, those three above and the method without any adaptation (original images). Note that the overall data show up in Fig. 8(f).

D. Data Analysis

We carried out data analysis based on descriptive statistics. Specifically, our descriptive statistics-based analysis builds upon data collected from the questionnaire. For that purpose, we used two descriptive analysis tools: (i) box-and-whisker diagrams; (ii) coefficient of variation. The box-and-whisker diagram is a type of data visualization tool that allows us to display the distribution (and, inherently, the concentration) of preferences of the CVD people, while the coefficient of variation is a metric that quantifies such dispersion/ concentration of preferences.

The box-and-whisker diagram is a data visualization tool to examine datasets graphically in a quick manner. Its central box at least features 50% of the preferences of the respondents relative to each method. This box consists of the second and third quartiles, separated by the median of the data sample (78 responses). A horizontal straight-line segment represents the median; a cross represents the arithmetic mean.

A glance at the diagrams depicted in Fig. 9, which represent the data listed in Fig. 8, shows us the following regarding each category of images:

- *Infovis*: The method without adaptation (MWA, for brevity) (i.e., original images without adaptation) and Iaccarino *et al.*'s method gathered more than 56% of preferences with the top scores 4 or 3 (see Fig. 8(a) and Fig. 9(a)). Looking at box-and-whisker diagrams of these methods, we observe that their averages are similar (cf. Table I). However, Iaccarino *et al.*'s method preferences are much less dispersed, as its box is smaller than the others. Indeed, Iaccarino *et al.*'s standard deviation is less than the MWA's (cf. Table I), and the same applies to the coefficient of variation. Thus, for InfoVis-type images, the best solution is to use Iaccarino *et al.*'s method.
- *Indoor*: In this case, either MWA or RGBeat reunites 70% of the preferences with scores 4 and 3. Besides, their arithmetic averages are similar (see Fig. 8(b) and Fig. 9(b)). Consequently, even looking at their box-and-whisker diagrams, it is difficult to say which is the top-ranked method of those two methods for Indoor-type images because they have similar visual dispersion (i.e., boxes of the same size). However, we see in Table I that RGBeat's standard deviation is less than the MWA's. Additionally, RGBeat' coefficient of variation is also less than the one of the methods without recoloring. Thus, we conclude that RGBeat ranks first for Indoor-type images.
- *Outdoor*: The results are similar to those obtained for the Indoor category. Indeed, MWA and RGBeat were scored with 4s and 3s in more than 68% of the preferences (see Fig. 8(c) and Fig. 9(c)). Note that their arithmetic averages and dispersion boxes are visually indistinguishable in their box-and-whisker diagrams, so we cannot draw any conclusion about the top-ranked method of those two for Outdoor-type images. However, from Table I, we observe that the RGBeat's coefficient of variation (and standard deviation) is less than the MWA's. Thus, RGBeat ranks first in this category.
- *SciVis*: MWA got the higher scored preferences, with approximately 50% of preferences, and scored 4 (see Fig. 8(d) and Fig. 9(d)). Besides, its arithmetic mean is much higher than for the other methods, which aligns with the fact that its coefficient of variation is smaller than for any other method (cf. Table I). Thus, in SciVis-type images, the best solution is to leave them as they stand, i.e., without color adaptation.
- *Signage*: Ching-Sabudin's method reached 68% of responses scored as 4. Therefore, its arithmetic mean is higher than other methods' one (see Fig. 8(e) and Fig. 9(e)), but its dispersion is significant. On the other hand, Iaccarino et al.'s method ranks second in terms of mean, but its coefficient of variation is smaller than any other method's one. Thus, in Signage-type images, Iaccarino et al.'s method ranks first.

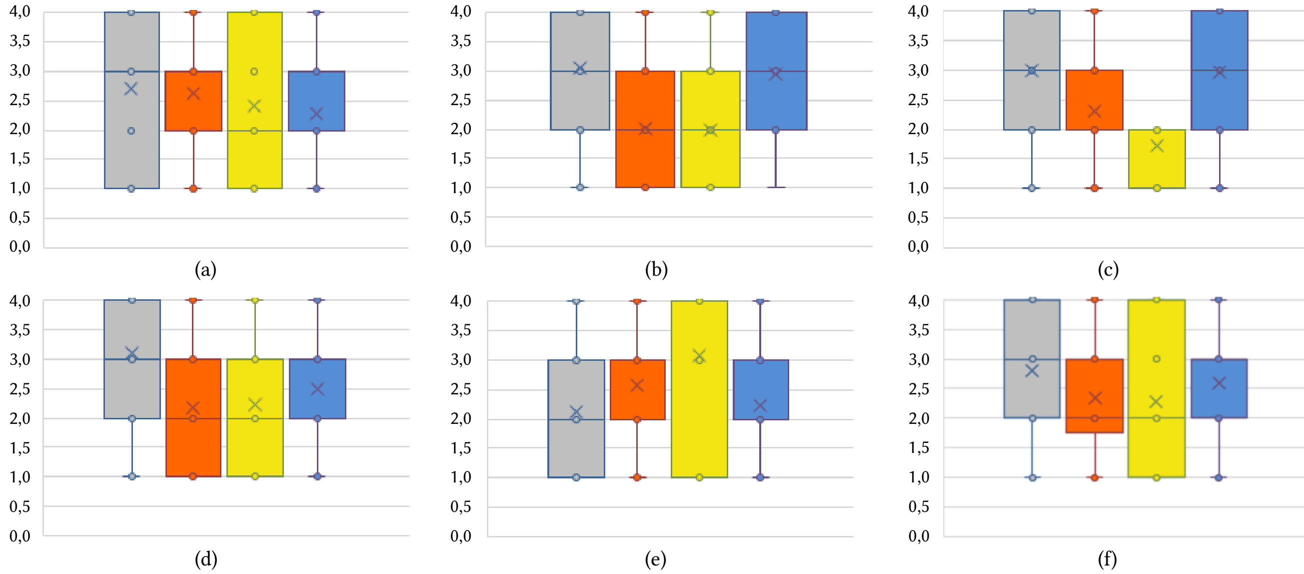


Fig. 9. Box-and-whisker diagrams of the distribution of the preferences per image category and per recoloring method: a) *InfoVis*; b) *Indoor*; c) *Outdoor*; d) *SciVis*; e) *Signage*; and (f) *Overall*. The mean is represented through a cross and the median by the horizontal line closer to the mean mark.

TABLE I. Statistical Results

Category	*Metric*	*MWA*	*Iaccarino et al.*	*Ching-Sabudin*	*RGBeat*
InfoVis	$\bar{x}$	2.69	2.63	2.41	2.27
	σ	1.231	0.941	1.343	0.863
	υ	46%	36%	56%	38%
Indoor	$\bar{x}$	3.04	2.03	1.99	2.95
	σ	0.973	1.081	1.168	0.771
	υ	32%	53%	59%	26%
Outdoor	$\bar{x}$	3.00	2.31	1.72	2.97
	σ	0.953	0.916	1.237	0.805
	υ	32%	40%	72%	27%
SciVis	$\bar{x}$	3.10	2.17	2.23	2.50
	σ	1.014	1.144	1.194	0.864
	υ	33%	53%	54%	35%
Signage	$\bar{x}$	2.13	2.58	3.06	2.23
	σ	1.121	0.782	1.390	0.852
	υ	53%	30%	45%	38%

Statistical metrics: $\bar{x}$: arithmetic mean; σ: standard deviation; υ: coefficient of variation.

In short, the RGBeat method ranks first in two categories, Indoor and Outdoor. Hence it preserves the naturalness more than any other method (see Section VI-D). On the other hand, Iaccarino et al.'s method gets on top in two other categories, InfoVis and signage, although it ranks second in terms of naturalness. However, its contrast varies only -0.24% compared to the contrast of the original images, while RGBeat's contrast is +7.7% (see Section VI-D).

Interestingly, the MWA ranks first in the SciVis category, i.e., there is no variation in naturalness and contrast for apparent reasons. These results show us that the recoloring process must not noticeably change the colors for SciVis-type images to preserve the individual's perceptual learning as much as possible. Recall that RGBeat only changes the red hues to close hues, whereas Iaccarino et al.'s method changes all hues to close hues. In contrast, the Ching-Sabudin method provokes significant color changes, i.e., the distance between an original hue and the mapped hue is greater than for the other two adaptation methods.

Overall, RGBeat ranks first because it ranks first in two categories (Indoor and Outdoor) and second in three categories (InfoVis, SciVis, and Signage), which explains why its coefficient of variation (34%) is lower than in any other method (see Table I). Moreover, it is the only method that outperforms the MWA, i.e., RGBeat images are perceptually better than original images.

VIII. Discussion

Now, we are in a position of highlighting important points of the RGBeat algorithm and its discussion, namely:

- *Color perceptual enhancement.* Adaptation methods are worthy of being investigated because they may enhance the perception of CVD people. Recall that RGBeat makes a noticeable enhancement relative to the original images (MWA). We have also learned that we cannot change the colors too much if we strike on preserving each individual's perceptual learning; otherwise, the naturalness and contrast may change significantly. We have demonstrated that it is possible to increase the color contrast without compromising the image naturalness and perceptual learning of CVD people, resulting in an augmented perception of CVD people. As shown in Table I, RGBeat is the only method that performs better than MWA because its coefficient of variation (34%) is less than the MWA's (40%).
- *Mathematical formulation.* RGBeat's mathematical formulation builds upon RGB and HSV color models, from which we have derived recoloring formulas that exclusively operate on the RGB color model (cf. Eqs. (7) and (10)).
- *Deuteranope and protanope's color space.* By using Brettel et al.'s simulation [7], we show that the deutan and protan color space is 2D, i.e., it consists of two coplanar half-planes (see Fig. 3), because deutan and protan individuals only see two different hues: 60° (yellow) and 240° (blue). A similar result was achieved by Brettel et al. for LMS color space and Meyer and Greenberg [34] for CIE XYZ color space.
- *Generality.* We have shown that RGBeat also applies to images and text in HTML documents. Supposedly, it also applies to video because a video is a sequence of frames. Considering RGBeat spends 0.06675ms per pixel (see Section VI-E) on average, we conclude that recoloring video in real-time is feasible for images with 623,220 pixels; for example, RGBeat can recolor youtube videos in the format 16:9 with resolutions 854×480 at most in real-time.

- *Time performance*. RGBeat attains real-time performance and thus outperforms the other two adaptation methods, primarily because it avoids the explicit conversion between the RGB and HSV color spaces.

Summing up, our method guarantees a balanced trade-off of four requirements, color consistency, naturalness maintenance, contrast improvement, and speed. At the same time, it is capable of augmenting the perception of CVD people.

IX. Conclusions

We have introduced a recoloring method, called RGBeat, that applies to HTML documents, including their images, videos, and text. The main novelty of this method is that it is the only one that produces images that are perceptually richer than the original images. RGBeat was capable of this accomplishment by stressing naturalness maintenance, which imposes limits to the increasing of contrast. Furthermore, RGBeat has revealed quite fast because it only operates on the range of reds, making it feasible to recolor video in real-time.

We have also developed an extension for the Chrome browser that automatically allows for online adaptation of web pages and their contents (e.g., text, still images, and video). Shortly, we intend to use some multi-threading or parallel processing tools (e.g., Web Workers API) to further speed up color-adaptive browsers in real-time.

Appendix A

As mentioned above, we used six images of each of the five datasets (*InfoVis*, *Indoor*, *Outdoor*, *SciVis*, and *Signage*) in the usability testing and assessment. Figs. A1-A5 show such images, as well as their corresponding images recolored by the three benchmarking algorithms.

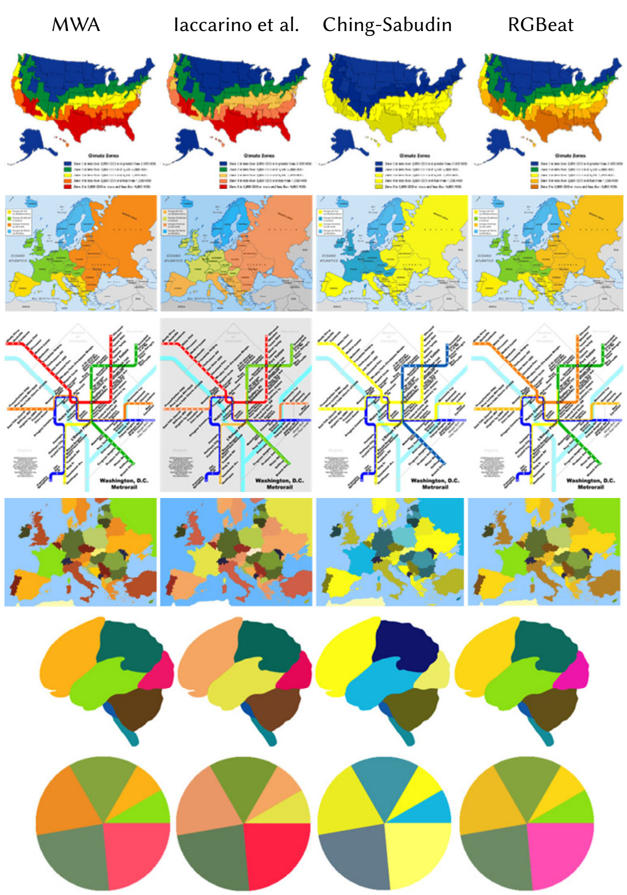


Fig. A1. Six images of the **InfoVis** dataset and recoloring algorithms.

Fig. A2. Six images of the **Indoor** dataset and recoloring algorithms.

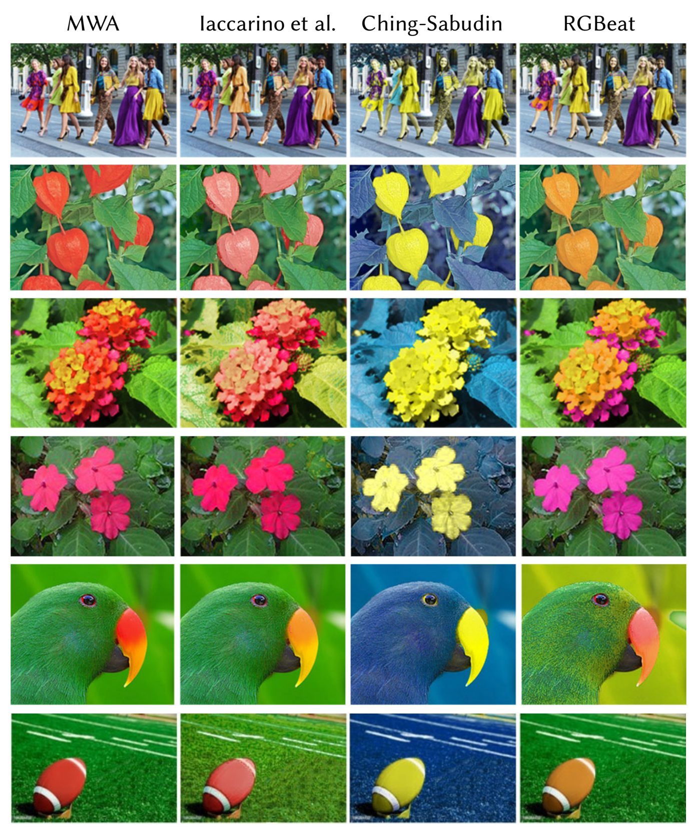


Fig. A3. Six images of the **Outdoor** dataset and recoloring algorithms.

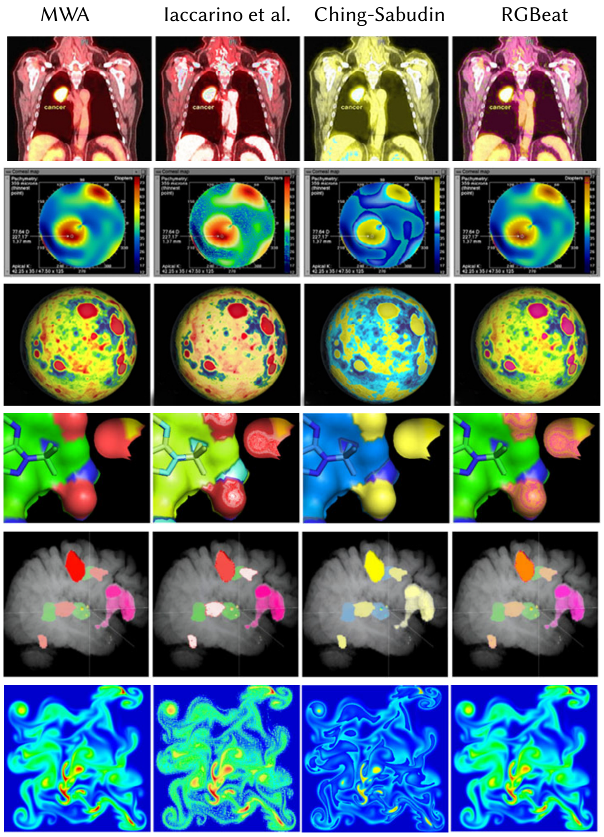


Fig. A4. Six images of the **SciVis** dataset and recoloring algorithms.

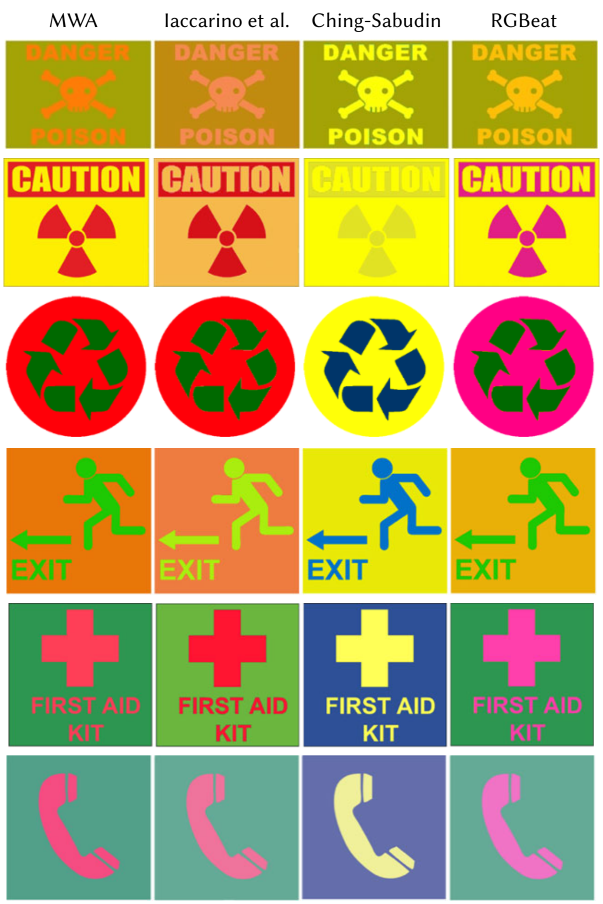


Fig. A5. Six images of the **Signage** dataset and recoloring algorithms.

Acknowledgment

The authors would like to thank Paulo Silveira and Carla S. Pedro for their support in the statistical analysis of the usability questionnaire, Marco Bernardo and Vasco Almeida for their criticism relative to color adaption techniques, as well as CVD participants for their help and time to answer the usability questionnaire.

This work has been partially funded by FCT/MCTES through national funds and when applicable co-funded EU funds under the project UIDB/50008/2020.

References

[1] E. Marieb and K. Hoehn, *Anatomy & Physiology*, Pearson, 2019.

[2] J. Birch, *Diagnosis of Defective Colour Vision*, Elsevier Science, 2001.

[3] J. Pokorny, V. C. Smith, and I. Katz, "Derivation of the photopigment absorption spectra in anomalous trichromats," *Journal of the Optical Society of America*, vol. 63, no. 2, pp. 232–237, 1973.

[4] D. McIntyre, *Colour Blindness: Causes and Effects*. Dalton Publishing, 2002.

[5] L. Sharpe, A. Stockman, H. Jagle, and J. Nathans, "Opsin genes, cone photopigments, color vision and color blindness," in *Color Vision*, K. Gegenfurtner and L. Sharpe (Eds.), Cambridge University Press, 1999.

[6] S. Yang, Y. M. Ro, J. Nam, J. Hong, S. Y. Choi, and J.-H. Lee, "Improving visual accessibility for color vision deficiency based on MPEG-21," *Electronics and Telecommunications Research Institute Journal*, vol. 26, no. 3, pp. 195–202, 2004.

[7] H. Brettel, F. Vienot, and J. D. Mollon, "Computerized simulation of color appearance for dichromats," *Journal of the Optical Society of America.–* A: Optics Image Science and Vision, vol. 14, no. 10, pp. 2647–2655, 1997.

[8] L. Petrich, "Color-blindness Simulators," https://cutt.ly/nboQhuP, accessed on 2021-04-27, 2021.

[9] J. C. Gardner, M. Michaelides, G. E. Holder, N. Kanuga, T. R. Webb, J. D. Mollon, A. T. Moore, and A. J. Hardcastle, "Blue cone monochromacy: causative mutations and associated phenotypes," *Molecular Vision*, vol. 15, pp. 876–884, 2009.

[10] A. Reitner, L. T. Sharpe, and E. Zrenner, "Is colour vision possible with only rods and blue-sensitive cones?," *Nature*, vol. 352, no. 6338, pp. 798–800, 1991.

[11] Y. Miyake, "Rod monochromacy," in *Electrodiagnosis of Retinal Dis-eases*. Springer Tokyo, 2006, pp. 136–137.

[12] OMIN (Online Mendelian Inheritance in Man), "An online catalog of human genes and genetic disorders," Johns Hopkins University, https://www.omim.org/ accessed on 2021-04-27, 2021.

[13] H. K. Kolb, E. F. Fernandez, and R. N. Nelson, "WebVision: The Organization of the Retina and Visual System," University of Utah Health Sciences Center, https://webvision.med.utah.edu/, accessed on 2021-04-27, 2021.

[14] M. Ribeiro and A. Gomes, "Recoloring Algorithms for Colorblind People: A Survey," *ACM Computing Sureys*, vol. 52, no. 4, Art. 71, pp.1-37, 2019.

[15] Y.-C. Chen and T.-S. Liao, "Hardware digital color enhancement for color vision deficiencies," *Electronics and Telecommunications Research Institute Journal*, vol. 33, no. 1, pp. 71–77, 2011.

[16] B.Liu, M.Wang, Y.Linjun, W.Xiuquing, and H.Xian-Sheng, "Efficient image and video re-coloring for colorblindness," in *Proc. IEEE Int. Conf. Multimedia and Expo* (ICME'09), 2009, pp. 906–909.

[17] G. M. Machado and M. M. Oliveira, "Real-time temporal-coherent color contrast enhancement for dichromats," *Computer Graphics Forum*, vol. 29, no. 3, pp. 933–942, 2010.

[18] C.-R. Huang, K.-C. Chiu, and C.-S. Chen, "Temporal color consistency-based video reproduction for dichromats," *IEEE Transactions on Multimedia*, vol. 13, no. 5, pp. 950–960, 2011.

[19] J.-Y. Jeong, H.-J. Kim, T.-S. Wang, Y.-J. Yoon, and S.-J. Ko, "An efficient re-coloring method with information preserving for the color- blind," *IEEE Transactions on Consumer Electronics*, vol. 57, no. 4, pp. 1953–1960, 2011.

[20] J.-B. Huang, C.-S. Chen, T.-C. Jen, and S.-J. Wang, "Image recol- orization for the colorblind," in *Proc. IEEE Inter. Conf. Acoustics, Speech, and Signal Processing* (ICASSP'09), Vols 1- 8. IEEE Press, 2009, pp. 1161–1164.

[21] D. R. Flatla, K. Reinecke, C. Gutwin, and K. Z. Gajos, "SPRWeb: preserving subjective responses to website colour schemes through automatic recolouring," in *Proc. Conf. Human Factors in Computing Systems* (SIGCHI'13). ACM, 2013, pp. 2069–2078.

[22] 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," in *Proc. Genetic and Evolutionary Computation* (GECCO'03). Lecture Notes in Computer Science, vol 2724. Springer, Berlin, Heidelberg, 2003, pp. 2134–2146.

[23] K. Wakita and K. Shimamura, "Smartcolor: Disambiguation framework for the colorblind," in *Proc. 7th Int. ACM SIGACCESS Conference on Computers and Accessibility* (ASSETS'05). ACM, 2005, pp.158–165.

[24] G. Iaccarino, D. Malandrino, M. Del Percio, and V. Scarano, "Efficient edge-services for colorblind users," in *Proc. 15th Int. Conf. World Wide Web* (WWW '06). ACM Press, 2006, pp.919–920.

[25] J.-B. Huang, Y.-C. Tseng, S.-I. Wu, and S.-J. Wang, "Information preserving color transformation for protanopia and deuteranopia," *IEEE Signal Processing Letters*, vol. 14, no. 10, pp. 711–714, 2007.

[26] G. Kuhn, M. Oliveira, and L. Fernandes, "An efficient naturalness-preserving image-recoloring method for dichromats," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 6, pp. 1747–1754, 2008.

[27] S. Oshima, R. Mochizuki, R. Lenz, and J. Chao, "Color-weakness compensation using Riemann normal coordinates," in *Proc. 2012 IEEE Int. Symp. Multimedia* (ISM'12). IEEE Press, 2012, pp. 175–178.

[28] T. Kojima, R. Mochizuki, R. Lenz, and J. Chao, "Riemann geometric color-weak compensation for individual observers," in *Proc. Int. Conf. Universal Access in Human-Computer Interaction* (UAHCI'14). Lecture Notes in Computer Science, vol 8514. Springer International Publishing, 2014, vol. 8514, pp. 121–131.

[29] C.Birtolo, P.Pagano, and L.Troiano,"Evolving colors in user interfaces by interactive genetic algorithm," in *Proc. World Congress on Nature & Biologically Inspired Computing* (NaBIC'09). IEEE Press, 2009, pp. 349–355.

[30] S.-L. Ching and M. Sabudin, "Website image colour transformation for the colour blind," in *Proc. 2nd Int. Conf. Computer Technology and Development* (ICCTD'10). IEEE Press, 2010, pp. 255–259.

[31] F. Vienot, H. Brettel, and J. D. Mollon, "Digital video colourmaps for checking the legibility of displays by dichromats," *Color Research and Application*, vol. 24, no. 4, pp. 243–252, 1999.

[32] A. Ford and A. Roberts, *Colour Space Conversions*. Westminster University, London, United Kingdom1998.

[33] A. R. Smith, "Color gamut transform pairs," *SIGGRAPH Computer Graphics*, vol. 12, no. 3, pp. 12-19, 1978.

[34] G. Meyer and D. Greenberg, "Color-defective vision and computer graphics displays," *IEEE Computer Graphics and Applications*, vol. 8, no. 5, pp. 28-40, 1988.

[35] C. Poynton, *Digital Video and HDTV: Algorithms and Interfaces*, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2003.

[36] S. D. Cotton, "Colour, colour spaces and the human visual system," University of Birmingham, United Kingdom, 1995.

[37] M. Tkalcic and J. F. Tasic, "Colour spaces: perceptual, historical and applicational background," in *Proc. IEEE Region 8 EUROCON 2003: Computer as a Tool*, vol. A. IEEE Press, 2003, pp. 304–308.

[38] X. Xu, Y. Wang, J. Tang, X. Zhang, and X. Liu, "Robust automatic focus algorithm for low contrast images using a new contrast measure," *Sensors*, vol. 11, no. 9, pp. 8281–8294, 2011.

[39] A. J. Vingrys and P. E. King-Smith, "A quantitative scoring technique for panel tests of color vision," *Investigative Ophthalmology and Visual Science*, vol. 29, no. 1, pp. 50–63, January 1988.

[40] J. W. Tukey, *Exploratory Data Analysis*. Addison-Wesley, 1977.

[41] D. S. Shafer and Z. Zhang, *Beginning Statistics*. Saylor Foundation, 2012.

[42] S.Abeyasekera,J.Lawson-Macdowell,andI.Wilson,"Converting ranks to scores for an ad hoc assessment of methods of communication available to farmers," DFID-funded work under the Farming Systems Integrated Pest Management Project, Malawi and DFID NRSP project R7033, Methodological Framework for Combining Qualitative and Quantitative Survey Methods., Tech. Rep., 2000.

[43] W. E. Saris and I. N. Gallhofer, *Design, Evaluation, and Analysis of Questionnaires for Survey Research*. John Wiley & Sons, 2007.

M. Madalena G. Ribeiro

M. Madalena G. Ribeiro Adjunct Professor in Web Design, Interfaces Design and Usability and Programming at Polytechnic Institute of Castelo Branco, Castelo Branco, Portugal. PhD in Computer Science (from the University of Beira Interior, Portugal), the research topics includes human computer interfaces, design of interfaces, color, color accessibility, color adaptation and image processing. Her publications include articles in international journals, as well as chapters in books and papers at conference's proceeding. Among others, the scientific work includes articles reviewing. She is a researcher member of the Centro de Investigação em Património, Educação e Cultura.

Abel J. P. Gomes

Abel J. P. Gomes is an Associate Professor in Computer Graphics at the University of Beira Interior, Portugal. He obtained a PhD degree in geometric modeling at Brunel University, England, in 2000. He has over 100 publications, including journal and conference articles, and 1 book published by Springer-Verlag. He was Head of the Department of Computer Science and Engineering, University of Beira Interior, Portugal, and the leader of a research unit of Instituto de Telecomunicações, which is one of the biggest research centers in Portugal. He is also a licensed Professional Engineer and member of the IEEE, ACM, and Eurographics. His current research interests include color accessibility, computer graphics algorithms, molecular graphics, geometric computing, and implicit curves and surfaces.