

# Adapting Palettes to Color Vision Deficiencies by Genetic Algorithm

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## ABSTRACT

In choosing a color palette, it is necessary to take into account the needs of color vision impaired users, in order to make information and services accessible to a broader audience. This means researching a space of color palettes aimed at finding a color combination which represents a good trade-off between aesthetics and accessibility requirements. In this paper, we present a solution based on genetic algorithms. Experimental results highlight this approach to be an efficient and at the same time effective way to assist user interface designers by suggesting appropriate variations of color palettes.

## Categories and Subject Descriptors

D.2.2 [Software Engineering]: Design Tools and Techniques—*user interfaces*; H.5.2 [Information Interfaces and Presentation]: User Interfaces; I.2.8 [Artificial Intelligence]: Problem Solving, Control Methods, and Search—*heuristic methods*

## General Terms

Algorithms, Design, Human Factors

## Keywords

Accessibility, Vision Impaired, Search Based Software Engineering

## 1. INTRODUCTION

In the Information Society, making information and services accessible to the widest audience possible represents an important social conquest. This requires that new issues be addressed in the designing of user interfaces. Among these there is the need of balancing aesthetics and functionality in choosing interface colors. Indeed, although attractive user interfaces are highly desirable (attractiveness is one of the

attributes defining usability in the ISO/IEC 9126-1 quality model), they should be made accessible to the largest audience possible in order to realize barrier-free services and applications. In this spirit, W3C has established guidelines [1] for designing accessible user interfaces. Among these, great relevance has been given to the selection of colors.

Color blindness, or Color Vision Deficiency (CVD), is known to be a significant barrier to effective computer use. A recent usability study conducted by the UK Disability Rights Commission [3] reported color accessibility to be the second most recurrent accessibility barrier to the Web for disabled users. Therefore a need exists to model CVD, simulate its effects and correct for them. This need is challenging because there are different types of CVD and the degree of CVD can vary from person to person.

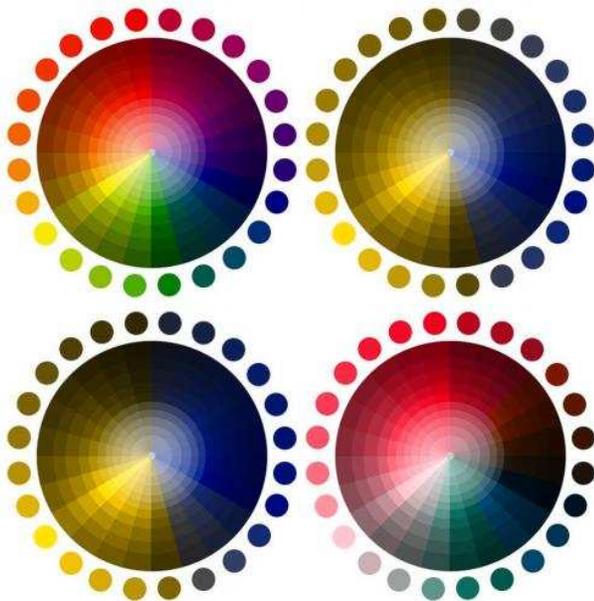
Color vision impaired users perceive colors differently from normal users. This means that although original colors could meet the required luminance contrast ratios for a normal user, the same colors, as perceived by visually impaired users, might not meet all those requirements: perceived colors can show up with a lower contrast ratio, making it difficult for some audiences to access information and services. This requires the adoption of color palettes that do not cause significant discomfort to users with color vision deficiencies.

This does not mean renouncing the original chromatic idea and making interfaces that are unattractive or boring. It is possible to look for a trade-off between chromatic choices and accessibility for impaired users. This requires finding among the possible color combinations, the palette which provides a high luminance contrast ratio, while still preserving the original chromatic choice.

Until now, this problem has been addressed mainly by providing recommendations for content creators or designers, and tools for simulating how people with CVD perceive colors. However, the choice of color palettes is left solely to the ability of interface designers. In this paper, we test the application of genetic algorithms in order to explore the palette space, and in order to automatically identify alternatives to the initial palettes that can be suggested to the designer. The advantage of this approach is two-fold: (i) the designer's attention is kept focused on the creative thought, leaving the algorithm to explore suitable alternatives, and (ii) alternative palettes can be automatically identified and used by a system in order to render a user interface, even though that particular user interface was not originally optimized for CVD users. The solution foreseen in this paper, can also serve to optimize a color palette for normal users,

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**Figure 1: Color vision deficiencies: normal (top-left), deuteranopia (top-right), protanopia (bottom-left), and tritanopia (bottom-right) .**

when color usability aspects are not taken into account at the very beginning of color selection, or when it is necessary to optimize the interface for different uses.

The remainder of this paper is organized as follows: Section 2 provides a brief overview of color deficiencies and how these have been addressed, together with preliminary information on color models; Section 3 describes how the problem has been modeled in our research; Section 4 presents the experimental results of this study; in Section 5 conclusions are drawn and future direction outlined.

## 2. PALETTES AND COLOR DEFICIENCIES

### 2.1 Color Vision

Color vision is normally trichromatic, as it is obtained by the absorption of photons in three classes of cones, whose peak sensitivity lie in the long-wavelength (L), middle-wavelength (M), and short-wavelength (S) regions of the visible spectrum. Reduced forms of color vision arise from the effective absence of one of the retinal photopigments, of type L, type M, and type S. The specific absence of one or more types of photopigments leads to the classification of different color vision deficiencies.

The three main types of abnormal color vision system are called *anomalous trichromatism*, *dichromatism* and *monochromatism*. Anomalous trichromatism results when one of the fundamental cones has had its peak sensitivity shifted. The types are classified as protanomaly and deuteranomaly depending on whether the L or M cones have been affected. Anomalous trichromats' perception of color ranges from almost normal to dichromatic depending on the extent to which the defective cone has had its peak sensitivity shifted. Dichromatism is a severe form of CVD that results when one of the fundamental cones is missing. Dichromats are classified as protanopes, deuteranopes or tritanopes, depending

on whether the L,M or S cones are missing. Monochromatism is the most severe form of CVD and is characterized by a total inability to distinguish colors. Monochromats typically have a complete lack of cone receptors in the retina.

An example of how colors are perceived by CVD users is provided by Fig.1.

Visual color deficiency can become an impairment in accessing information and services. Indeed, legibility is related to the spatial visual capabilities of observers. If a sufficient font dimension is assured, luminance contrast between foreground and background colors is a fundamental factor, and it is generally recognized that high luminance contrast enhances legibility [10]. According to recent studies on legibility and contrast [16] [6], legibility of a Web page text presented on a CRT display is significantly affected by color combinations. Color difference plays a more important role in legibility when luminance contrast is low.

In a recent work, Gradisa et al. [6], a lighter text on a darker background resulted in a lower mean score than a darker text on lighter backgrounds. Furthermore, results showed that the mean score of combinations with black text color was higher than the mean score of combinations with white text color. The main problem arises when a CVD user has to distinguish text or has to use an interface built by a developer who did not take color accessibility into account. Chromatic contrast has an unclear effect. Equiluminant colors of high chromatic contrast can also generate legible text, but no advantages of color contrast have been found for low-vision reading [11].

According to these studies, we can conclude that focusing only on color contrast is not a good strategy in designing visual displays because of the limiting effect this has on people affected by Color Vision Deficiencies. It is, however, possible to compute color confusions and to simulate dichromatic color vision, in this way respecting Chromatic contrast and luminance contrast at the same time, and enabling the designer to guarantee information accessibility.

### 2.2 Methods for simulating CVD

Color blindness, or color vision deficiency (CVD), is known to be a significant barrier to effective computer use. A recent usability study conducted by the UK Disability Rights Commission [3] reported color accessibility to be the second most recurrent accessibility barrier to the Web for disabled users. Therefore a need exists to model CVD, simulate its effects and correct for them. This need is challenging because there are different types of CVD and the degree of CVD can vary from person to person.

Methods for simulating CVD date back to the beginning of the 19th century, when Goethe produced a water-color landscape painting in colors intended to demonstrate the view as seen by a blue-blind CVD observer. More recently, it is possible to map colors in digital images to permit a normal color viewer to experience color as seen by a CVD viewer.

Brettel [2] presents a computerized method that allows color-normal observers to appreciate the range of colors experienced by dichromats. The algorithm is expressed in the LMS color space as three piecewise projections, one for each type of dichromacy. The algorithm has three parts:

- compute the LMS tristimulus values from RGB data
- apply the projection

- compute the RGB color values from the resulting LMS coordinates.

Vienot [4] proposes replacement color-maps that allow a designer to check which colors are effectively seen by protanopes and deuteranopes. He constructs colormaps for replacing a standard palette of 256 colours, including 216 colours that are common to many graphics applications of MS Windows and Macintosh computing environments, and shows how a colour image would look for protanopes and for deuteranopes.

In his work Vienot adopted a seven-step method to simulate the color-map seen by visually impaired people such as protanopes and deuteranopes. The method is based on the LMS system, which specifies colors in terms of the relative excitations of the longwave sensitive ( $L$ ), the middlewave sensitive ( $M$ ), and the shortwave sensitive ( $S$ ) cones. As dichromats lack one class of cone photopigment, they confuse colours that differ only in the excitation of the missing class of photopigment. Therefore from the original RGB values given by 8 bit DAC values for each of the RGB video channels, Vienot et al. construct a computational procedure in order to simulate dichromatic vision. The result is a reduced colourmap with real sighted colors.

Recently, a number of automatic adaptation algorithms have been proposed to modify content for CVD viewers. Yang et al.[12] propose methods to adaptively change colors in images for people with CVD. The proposed adaptation allows for the adapting of color anytime and anywhere according to the type and severity of CVD. To solve the problem of discrimination between two often confused colors, the authors propose the adaption of saturation of these confused colors. The saturation of color is reduced to give discrimination between the hue-adapted colors and the original colors with the same hue. This aims to decrease the chromatic component of the colors. So the adaptation for dichromat is as follows:

$$H' = H + \Delta H, S' = S + \Delta S, I' = I \quad (1)$$

where  $H$ ,  $S$  and  $I$  are the hue, saturation and intensity of a color and  $H'$ ,  $S'$  and  $I'$  are those of the adapted color, and  $\Delta H$  and  $\Delta S$  are the variations of the hue and saturation. In the proposed adaptation, they use magenta, cyan and yellow ratio of color. The magenta, cyan and yellow ratio represents the amount that of a color contains of magenta, cyan and yellow, respectively. Regarding the CVD, they fix the  $\Delta H$  and  $\Delta S$  value.

Jefferson [8, 9] formulates the problem of adapting the colors of images for CVD viewers as one of optimization. The goal is to modulate colors in the image so that when they are viewed by a CVD person, the perceived difference between any pair of colors is of the same magnitude as that perceived by a normal color viewer. This algorithm uses the World Web Consortium (W3C) accessibility evaluation criteria to re-color images for dichromatic viewers. The algorithm has four parts:

1. select a subset of key colors from the problem image
2. compute the target differences using color and brightness differences between key colors
3. develop an optimization to find an adaptation of the colors for the dichromatic CVD viewer

4. interpolate the resulting colors across the remaining colors in the image using inverse-distance weighted interpolation

In the work of Karl Rasche, Robert Geist, and James Westall [13] the optimization is constrained by restricting the mapping to be a composition of two transforms containing twelve parameters, which reduces the search space. Although this method has considerable computational advantages, it has not been extended to handle common practical problems such as the desire to force certain colors to have particular mappings.

The problem of finding the right palette for the user interface is a common problem for a designer. Although transformation techniques exist in literature, finding an appropriate color palette is an optimational and combinatorial problem. It is necessary to provide a set of colors which respects some requirements which are:

- Luminance contrast among correlated colors (e.g. foreground and background) to improve legibility
- Preservation of chromatic choices and requirements as planned by interface designers (e.g. to preserve the meaning of colors)
- Guarantee color accessibility to a broader audience (e.g. color vision impaired users).

These requirements can often be conflicting.

Such considerations suggest that genetic algorithms are able to solve the problem. This approach has been tested by Ichikawa [7] who describes manipulation of Web page color for color-deficient viewers and designs a fitness function to preserve detail and minimize the distance between an input color and its corresponding remapped color. He first decomposes the page into a hierarchy of colored regions. These spatial relations determine important pairs of colors to be modified.

For our research we start with an initial palette used in a Graphical User Interface and with a model which describes the relationship among the colors, e.g. a color could be related with two colors. In other words, we optimize a given color palette which can be composed of several different colors and correlated according to a simple or more complex schema. Ichikawa's objective function is:

$$Fitness = \alpha \cdot f_c + (1 - \alpha) \cdot f_b \quad (2)$$

where  $f_c$  evaluate color  $C_1$  represented by an individual,  $f_b$  evaluate the brightness of the color properly to control it depending on the brightness of color  $C_2$  and the brightness difference between  $C_1$  and  $C_2$ , whilst  $\alpha$  is a weighting coefficient.

The function (2) is minimized by Ichikawa using a GAsRM with proportional selection [7]. According to the research of Ichikawa et al., we choose a function to maintain distances between colors. This attempts to preserve both the original naturalness of the colors and the detail in the remapped color image.

### 3. PROBLEM DEFINITION

Color palettes are arrays of colors. Several color models exist, each aimed at describing colors as tuples of numbers (typically three or four values), called color components.

RGB and CMYK are well known color models. In RGB, a color is described by three primary components  $R$ =red,  $G$ =green,  $B$ =blue. A color is obtained by additively combining intensities of the primary components. Vice versa in CMYK, primary components are  $C$ =cyan,  $M$ =magenta,  $Y$ =yellow,  $B$ =black, and colors are obtained by a subtractive aggregation of components. Both RGB and CMYK models are good for describing how to produce or print colors through devices. But besides them, there are also other models that refer to how colors are perceived. For this purpose, the CIE (International Commission on Illumination) introduced the XYZ model in 1931. Despite its age, it is still widely used in practice, especially as a reference for converting colors from one model into another. Similarly to RGB, XYZ adopts a system of additive primary components, namely  $X$ ,  $Y$ , and  $Z$ . Each of these components represents the power perceived when RGB primaries are emitted. However, XYZ does not represent the response of cones at short, middle and long wavelengths. To better address the human perception of colors, in 1976 the CIE introduced the the CIELab model. In this model, color components are  $L^*$  that is a measure of color luminance,  $a^*$  being its position of red/magenta and green, and  $b^*$  its position between yellow and blue. When  $L^* = 0$ , color is equivalent to black, whilst  $L^* = 100$  describes white. Uniform changes of components in the CIELab model aim at corresponding to uniform changes in the perceived color. Therefore, this color model is suitable for measuring the perceptual distance between colors by means of the Euclidian distance  $\Delta E$  between points in  $L^* \times a^* \times b^*$ , that is

$$\Delta E = \sqrt{(L^*_1 - L^*_2)^2 + (a^*_1 - a^*_2)^2 + (b^*_1 - b^*_2)^2} \quad (3)$$

The maximum distance  $\Delta E^*$  is between green and blue values.

Distance  $\Delta E$  provides a measure of both hue and density changes. According to recent studies, an average observers are able to notice differences above  $\Delta E = 5$  or 6, whilst a trained eye can notice differences from  $\Delta E = 3$  or 4. The human eye, however, is much more sensitive to changes in gray levels and mid-tones; in that case differences of 0.5 delta-E may be noticed. The advantage of the CIELab model resides also in it being device-independent, thus resulting in more objective measures of colors. The same combination of  $L^*$ ,  $a^*$  and  $b^*$  will always describe exactly the same color. Color spaces are generally homeomorphic. Thus, there are formulas for transforming a color representation in one model, into an equivalent representation in another model.

The other key metrics we consider is the color contrast between contiguous colors. The W3C's WCAG [1] defines the *contrast ratio* as

$$C = \frac{\max(L_1, L_2) + 0.05}{\min(L_1, L_2) + 0.05} \quad (4)$$

where  $L$  is the *relative luminance*<sup>1</sup> computed as

$$L = 0.2126 \cdot r + 0.7152 \cdot g + 0.0722 \cdot b \quad (5)$$

<sup>1</sup>Relative luminance is defined as the relative perceived brightness of any point, normalized to 0 for black and 1 for maximum white. We notice that relative luminance  $L$  as defined by W3C's WCAG differs from luminance  $L^*$  defined in CIELab.

and

$$r, g, b = \begin{cases} R, G, B/12.92 & R, G, B \leq 0.03928 \\ ((R, G, B + 0.055)/1.055)^{2.4} & otherwise \end{cases} \quad (6)$$

Contrast ratios can range from 1 to 21 (commonly written 1:1 to 21:1). According to W3C to reach level AAA of accessibility: "text (and images of text) must have a contrast ratio of at least 7:1, except if the text is pure decoration. Larger-scale text or images of text can have a contrast ratio of 5:1". This means that solution utility passing the contrast ratio threshold  $T_c$  is  $C_u = 1$ , decreasing below  $T_c$ . In our problem we assumed the utility function described in Fig.2

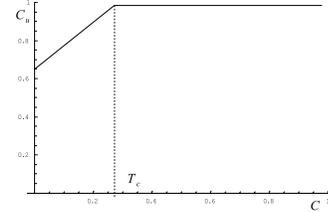


Figure 2: Contrast ratio utility function.

Contiguity of colors depends on the position of elements on the interface, as depicted in Fig.3. For this, a contiguity

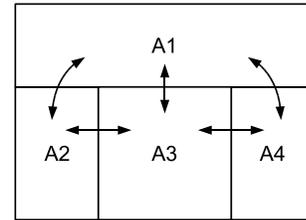


Figure 3: UI Color Model, an example.

matrix holding 1 for contiguous colors, 0 vice versa, is built as part of the problem definition.

In summary, we adopted:

- RGB, for describing the palette colors
- CIELab, for measuring the distance between colors
- CIEXYZ, as the means for transforming RGB into CIELab

The model for representing colors having been chosen, the palette chromosome coding is straightforward, as depicted in Fig.4. In particular, the chromosome is a bit string, reserv-

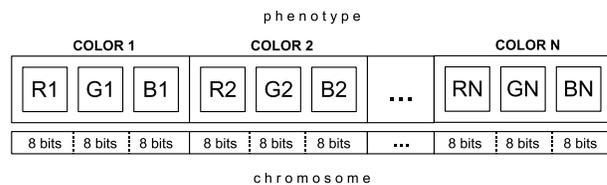


Figure 4: Chromosome structure and phenotype mapping.

ing 24 bits (8 bits per component) to represent each color in the RGB space.

Our aim is to find a palette that improves the luminance contrast between contiguous colors, while still preserving the original chromatic setting. This is done considering a fitness function depending on color distances and contrast ratios. The fitness function we adopted is

$$f = \left( \prod_{i=1}^n (1 - d_i) \prod_{j=1}^k c_j \right)^{\frac{1}{n+k}} \quad (7)$$

where  $d_i$  is the distance of resulting color  $i$  from the original one, and  $c_j$  the contrast ratio of the  $k$  pairs of contiguous colors. In particular,

$$d_i = \frac{\Delta E_i}{\Delta E^*} \quad (8)$$

$$c_j = \frac{20 + \min(C_j - T_j, 0)}{20} \quad (9)$$

where  $C_j$  is the contrast ratio as defined in Eq.4 and  $T_j$  is the contrast threshold (i.e. 7 or 5) as recommended by W3C's guidelines. It results that  $f, d_i, c_j \in [0, 1]$ . The maximum fitness value is  $f = 1$ , but this value is ideal as it is only reachable when  $c_j = 1$  and  $d_i = 0$  for all  $i, j$ , leading to the conclusion that the original palette is already optimal, thus not requiring any variation. In general, this value is below 1 because there is a need to vary colors ( $d_i > 0$  for some  $i$ ), or because some contrasts are below the threshold ( $c_j < 1$  for some  $j$ ).

### 3.1 Vision Deficiency Model

In the case of color vision deficiencies, distance  $d_i$  is still computed between the palette color and the original one, as we are interested in preserving the original palette chromaticity. Instead, the contrast ratio is computed between contiguous colors as they are perceived by the user. For this purpose we adopted the model proposed by Vienot et al. [4].

Given  $(R, G, B)$  as the 8-bit DAC values for each of the  $(R, G, B)$  video channels, Vienot computes the relative photometric quantities  $R_1, G_1, B_1$ . Then, in order to produce reduced colors that are included in the color gamut of the monitor, the author slightly reduces the color domain of the initial palette. This is achieved through the appropriate scaling of the relative photometric quantities, obtaining  $R_2, G_2, B_2$ . According to what is described in Smith et al.[14], following the transformation technique proposed by Vienot [4], we get:

$$\begin{aligned} \begin{pmatrix} L \\ M \\ S \end{pmatrix} &= (RGB\_to\_LMS) \begin{pmatrix} R_2 \\ G_2 \\ B_2 \end{pmatrix} = \\ &= \begin{pmatrix} 17.8824 & 43.5161 & 4.11935 \\ 3.45565 & 27.1554 & 3.86714 \\ 0.0299566 & 0.184309 & 1.46709 \end{pmatrix} \begin{pmatrix} R_2 \\ G_2 \\ B_2 \end{pmatrix} \end{aligned} \quad (10)$$

Vienot considers the following linear transformations in the LMS color space for reducing the normal color domain to the dichromat color domain, in particular for protanopes:

$$\begin{pmatrix} L_p \\ M_p \\ S_p \end{pmatrix} = \begin{pmatrix} 0 & 2.02344 & -2.52581 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} L \\ M \\ S \end{pmatrix} \quad (11)$$

Whilst for deuteranopes:

$$\begin{pmatrix} L_d \\ M_d \\ S_d \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0.494207 & 0 & 1.24827 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} L \\ M \\ S \end{pmatrix} \quad (12)$$

Transformation of  $L_d, M_d, S_d$  or  $L_p, M_p, S_p$  to RGB is obtained using the inverse matrix of matrix :

$$\begin{pmatrix} R_d \\ G_d \\ B_d \end{pmatrix} = (RGB\_to\_LMS)^{-1} \begin{pmatrix} L_d \\ M_d \\ S_d \end{pmatrix} \quad (13)$$

The components  $R_d, G_d$  and  $B_d$  have been obtained, we can compute an appropriate contrast ratio, following the scheme outlined previously.

## 4. EXPERIMENTAL RESULTS

In our experimentation we implemented a Simple GA as described in Goldberg [5], and depicted in Fig.5.

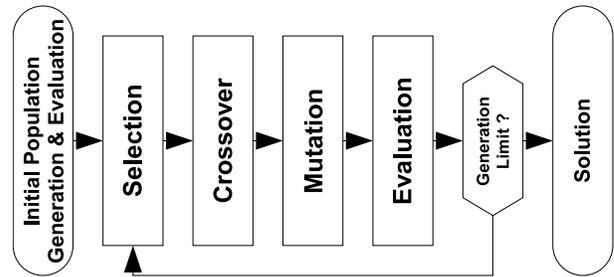


Figure 5: Algorithm structure.

Genetic operators are the single point crossover and bit switch mutation. Selection is a 2-way tournament, in order to make the algorithm less sensitive to the distribution of fitness values; elitism is 5. Parameters are summarized in Tab.1.

Parameter	Value
Crossover rate	0.8
Mutation rate	0.2
Selection tourn.	1
Elitism	5

Table 1: Algorithm parameters.

These parameters have been chosen by a preliminary qualitative analysis, proving to be a good trade-off between exploration and exploitation behavior. In particular, a higher rate of mutation helped to keep the genetic diversity high, keeping the target focused on the optimization goal by a higher elitism.

The algorithm was tested against two palettes, respectively made of 6 colors (132 bits) and 16 colors (372 bits). Indeed, palettes of 4-6 colors are common in user interface design. The 16-color palette serves to study the robustness of

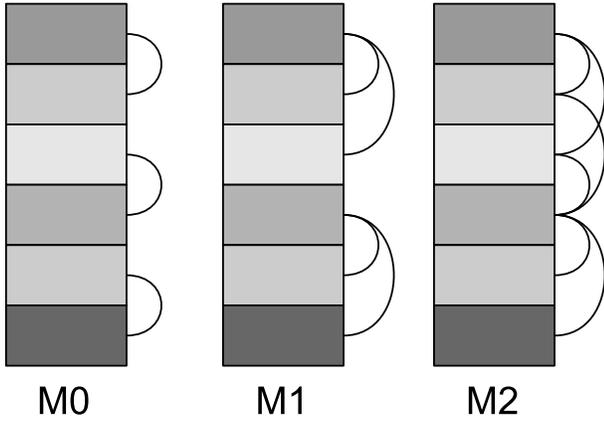


Figure 6: Color contiguity models.

the algorithm when the number of colors increases. For color relationships, we considered 3 models: *simple* ( $M0$ ), *intermediate* ( $M1$ ), and *complex* ( $M2$ ), as described in Fig.6.

In the simple model ( $M0$ ), each pair of colors is put in the relationship of contiguity. In  $M1$ , triples of colors are made contiguous.  $M3$  is aimed at stressing the algorithm in more complex cases. We repeated 10 runs for different problem configurations. The average behavior of the algorithm is depicted in Fig.7. We note that generally the population size does not play a relevant role in the algorithm convergence, and also with small populations it is possible to obtain good results. This is also confirmed by the fitness behavior when deuteranopia and protanopia are simulated, as shown in Fig.8 and Fig.9.

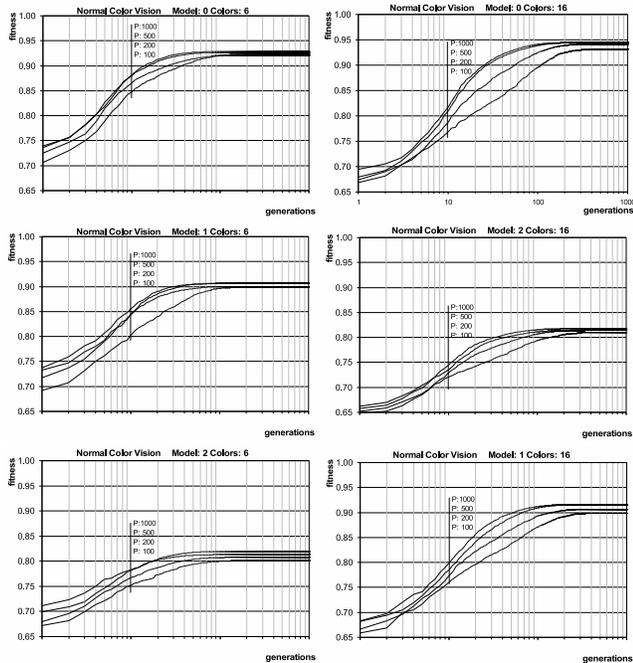


Figure 7: Average fitness behavior for normal vision.

Algorithm convergence is also confirmed by a comparison with random search, summarized in Fig.10, where average

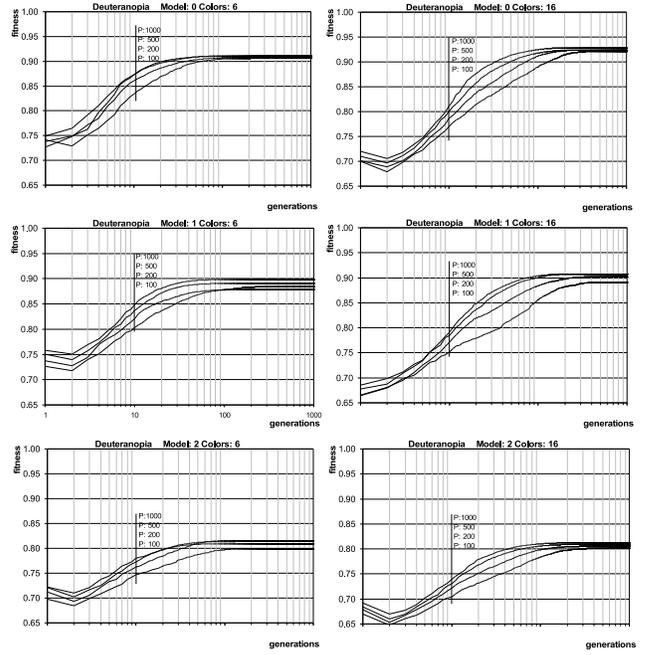


Figure 8: Average fitness behavior for deuteranopia.

with standard deviation of fitness is plotted in the case of genetic algorithm and random search.

As an example of application we can consider an initial palette of  $N$  colors  $c_n$  and the proposed algorithm provides a final accessible palette as a solution. As shown in Fig.11, starting with a set of 6 colors, related according to model  $M1$ , we observe how  $(c_1, c_2, c_3)$ , whose contrast ratio is 2.3 : 1 and 1.3 : 1 with  $c_3$ , evolves into  $(g_1, g_2, g_3)$  with contrast ratio of 9.8 : 1 and 7.1 : 1. Furthermore  $c_4$ , which has a contrast ratio of 1:1 with  $c_5$  and 2.7:1 with  $c_6$  evolves into  $g_4, g_5$  and  $g_6$  with a contrast ratio of 5.2 : 1 and 6.5 : 1 respectively.

$$\begin{aligned}
 c_1 &= (255, 128, 128) \\
 c_2 &= (255, 255, 0) \\
 c_3 &= (51, 220, 0) \\
 c_4 &= (204, 0, 0) \\
 c_5 &= (204, 0, 0) \\
 c_6 &= (0, 204, 0)
 \end{aligned} \tag{14}$$

where color  $c_i$  (with  $i = 1 \dots N$ ) is represented by the RGB components.

$$\begin{aligned}
 g_1 &= (127, 15, 31) \\
 g_2 &= (255, 255, 0) \\
 g_3 &= (79, 243, 48) \\
 g_4 &= (99, 0, 0) \\
 g_5 &= (255, 119, 55) \\
 g_6 &= (15, 208, 11)
 \end{aligned} \tag{15}$$

The original palette and solution ( $f = 0.94601$ ) are shown in Fig.11. In Fig.12 and in Fig.13 we present the optimization results for deuteranopes and for protanopes. Starting

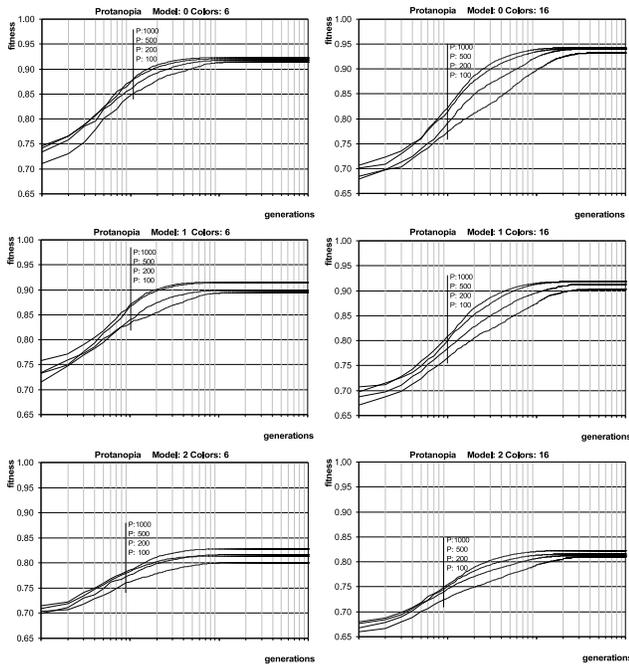


Figure 9: Average fitness for protanopia.

with the same palette (Eq.14) we adapt the colors in order to satisfy contrast luminance requirements for deuteranopes while preserving chromatic choices and requirements as planned by interface designers. We show in Eq.16 the values of the fitness for the two optimization problems.

$$\begin{aligned} fitness_{deuteranopes} &= 0.953255 \\ fitness_{protanopes} &= 0.961878 \end{aligned} \quad (16)$$

Although the initial palette is unreadable for most of the users, thanks to the proposed algorithm the palette satisfies accessibility requirements. For instance, the first two colors ( $c_1, c_2$ ) have at the beginning a low contrast ratio for a normal viewer ( $r_{1,2} = 2.3$ ), for deuteranopes ( $s_{1,2} = 2$ ) and for protanopes ( $p_{1,2} = 2.8$ ), whilst after the proposed algorithm the two colors increase their contrast ratio ( $r'_{1,2}=7.3, s'_{1,2}=6.1, p'_{1,2}=6$ ).

## 5. CONCLUSIONS AND FUTURE WORK

Addressing color vision deficiencies is a key point in providing accessible information and services. Designing accessible interfaces does not necessarily mean making them boring, and abandoning an original color scheme. In this paper we presented an approach that explores the color palette space, searching for a solution that represents a good compromise between aesthetics and accessibility requirements. This search is performed by using a genetic algorithm. Experimental results prove that this approach is feasible, leading automatically towards solutions that otherwise would be time consuming for the interface designers. Future work will address questions that have here been left unanswered. The reference color palettes are assumed to be fully defined before the optimization begins. However, we know that chromatic choices can change when alternatives are proposed to users. Thus, it would be worthwhile to introduce the

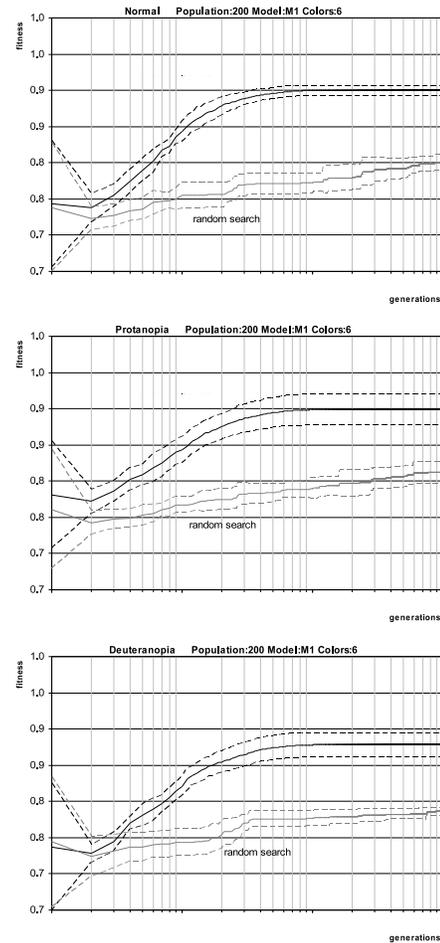


Figure 10: Comparison to random search.

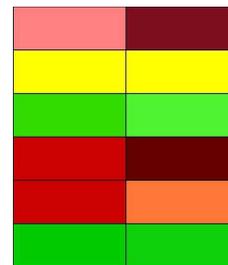
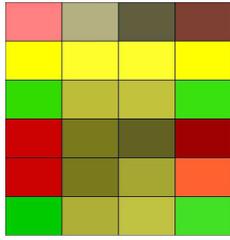
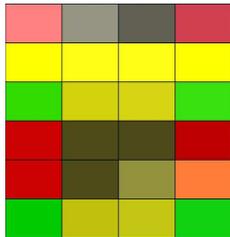


Figure 11: Optimization of the original palette for normal color viewers.



**Figure 12: Optimization of the original palette for deuteranopes.** The 1<sup>st</sup> column is the original palette, the 2<sup>nd</sup> column is the perceived palette for deuteranopes, the 3<sup>rd</sup> and 4<sup>th</sup> columns are the optimized result seen by deuteranopes and by normal color viewers respectively.



**Figure 13: Optimization of the original palette for protanopes.**

user into the development process, as described by Takagi in Interactive Evolutionary Computation [15], leading to the application of interactive genetic algorithms. On the other hand, simulation proved to be expensive, especially for larger populations and color palettes. This requires a reduction of the search space, so that smaller populations can effectively lead to an optimal solution. This result can be achieved by reducing the color space, as small variations are not perceived by the user in any case.

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