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On the edge: A scalable daltonization method focusing chromatic edges and contrast

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Abstract

Color Vision Deficiency (CVD) leads to a reduced capability to identify chromatic edges and contrast and may cause significant problems in various color tasks like, for example, comparative color tasks. Many daltonization methods to improve color perception of color-deficient people, however, change naturalness of confusion colors, which might complicate other color tasks like, for example, connotative and denotative color tasks.

Thus, we present a daltonization method focusing on the enhancement of chromatic edges and contrast while preserving the naturalness of object colors as good as possible.

Our proposed method, Yoshi-II-edge, is based on a previously presented method, Yoshi-II, which projects and rotates the lost information by color-deficient observers along the direction of optimal visibility. Yoshi-II-edge limits this enhancement to chromatic edges and contrast by computing an edge map obtained from the gradient of the error image between the original and its simulation. Furthermore, we propose a threshold and dilation to influence the width of the daltonized edge. We show that the performance of this method depends on the juxtaposition of confusion colors in the image. More precisely, Yoshi-II-edge performs well in images with adjacent areas of confusion colors but performs poorly in images with non-adjacent areas of confusion colors.

Introduction

Luminance and chromatic edges and contrast play a major role in the processing of visual information of the human visual system (HVS) [2]. Neurons in the visual cortex are specialized in extracting contour information from achromatic and chromatic edges along the dimensions black–white, red–green and blue–yellow [3]. Especially, chromatic edges and contrast play a major role for pre-processing in the early stages of the human visual system (HVS) [3–5].

Color perception is initiated by, among others, the output of three photoreceptors in the retina, called cones, that are sensitive to light of long, medium and short wavelengths [6]. In observers with color vision deficiency (CVD), however, certain types of cones are missing, or their sensitivity is significantly altered as compared to the cones of an observer without CVD [7]. CVD is known to affect up to about 8% of the male population [7]. Color-deficient observers can be said to have a higher level of metamerism than normal-sighted observers. This leads them to see two colors as identical that are easily distinguished by a normal-sighted observer. The set of these colors is often referred to as confusion colors [8] [9][p.70]. Confusion colors can lead to harmless but notable restrictions in daily life connected to various color tasks like, for example, when reading information graphics or maps, judging the ripeness of fruits, cooking meat, detecting berries against foliage, etc. [8]. Color-deficient people might also have problems in differentiating the colors of sports jerseys or finding berries in the forest (cf. Figure 1). Cole [10] categorized color tasks that might be difficult for color-deficient people into comparative, connotative, denotative and aesthetic color tasks. Additionally, CVDs make it harder to detect chromatic edges and contrast, typically along the red–green axis [3].

Daltonization methods can help color-deficient people by adjusting confusion colors in a color image to improve color perception for color-deficient people [11]. Daltonization methods can be categorized according to their characteristics like processing area (if confusion colors are modified globally or spatially) or enhancement type (how confusion colors are modified) [12]. Enhancement types typically contain recoloring, texturing, labeling or modal augmentation. Global recoloring is the most common daltonization strategy, in which the hue and/or the lightness of confusion colors independent of spatial organization of objects and areas are shifted to increase the perceived contrast [11, 13–16].

However, downsides of global recoloring tools include unnatural colors, overall color contrast loss, and no specific edge enhancement. Firstly, recoloring can change the overall aesthetic impression of the image caused by the introduction of unpleasant and/or unnatural colors. A red tomato might be recolored blue, purple or orange, for example. Unnatural colors can impede color identification and make object identification more difficult [17]. Secondly, recoloring can cause a reduction of overall color contrast. While increasing the contrast between confusion colors, a confusion color might be adapted to resemble an existing non-confusion color. In other words, increasing the contrast between confusion colors might decrease contrast to non-confusion colors. Lastly, global strategies often do not focus on the enhancement of chromatic edges, which is the fundamental problem of CVD. In fact, a good daltonization method should especially enhance chromatic edges and contrast. Thus, we challenged global daltonization recoloring tools that do not sufficiently focus on the improvement of chromatic edges and contrast in a previous paper [18]. We presented a spatial daltonization method based on transformations in the gradient domain and scale-space improving chromatic edges and contrast at different scales of the image.

In this paper, we propose a more subtle strategy of daltonization by enhancing edges to highlight areas and objects colored in confusion colors rather than shifting the color of objects and areas altogether. We introduce a strong edge marker around areas of confusion colors to facilitate chromatic edge detection. This edge marker can serve as a visual guide for the extraction of relevant visual information from the image in, for example, comparative

(a) Wrestlers (b) Berries

Figure 1: The first row shows the original images, while the second row shows the deutan simulations. The images have been simulated using the Brettel simulation [1].

color tasks. The edge marker also preserves the original natural colour, which is important in connotative or denotative color tasks. In the present paper, we show how this kind of edge enhancement can be implemented and discuss its performance on various image types. Our proposed method is a spatial recoloring method that changes colors at each point with respect to its surrounding according to the categorization in [12]. The method aims at improving chromatic edges and contrast in natural images for comparative, connotative and denotative color tasks.

Introduction
Methodology

Our proposed method, Yoshi-II-edge, is a modification of a previously presented method called Yoshi-II [18]. In Yoshi-II-edge, we introduce an edge map that restricts daltonization only to chromatic edges and contrasts that are difficult to perceive by color-deficient people. We also propose an option for "artificial mach bands" to highlight said chromatic edges more clearly [6][pp.131].

Computations for both Yoshi-II-edge and Yoshi-II take place in the gradient domain, which is well suited to detect chromatic edges and contrast. In Yoshi-II, we create a modified gradient, $\mathbf{G}$, by projecting and rotating in color space the lost information between the original image and its simulation towards the direction of optimal visibility that is orthogonal to both the direction of lightness and the direction of maximum information loss:

$$\mathbf{G} = \nabla \mathbf{u_0} + (\nabla \mathbf{u_0} \cdot \mathbf{e}_d)(\chi \mathbf{e}_c) \tag{1}$$

In this formula, $\mathbf{e_d}$ and $\mathbf{e_c}$ are unit vectors representing the direction of maximum information loss and direction of optimal visibility respectively. $(\nabla \mathbf{u_0} \cdot \mathbf{e}_d)$ represents an approximation of the lost information. χ is an spatial scalar influencing how much a confusion color is changed at any given point. The red component of colors are changed for positive χ-values, whereas the green component of colors are changed for negative χ-values. The χ-values are computed automatically as described in [18]. Lastly, we can solve the Euler-Lagrange equation for $\mathbf{G}$ resulting in a Poisson equation that can be solved numerically by gradient descent.

In our proposed method, Yoshi-II-edge, we compute an edge mask, $\mathfrak{M}$, containing information about the location of chromatic edges and contrast that are difficult to discriminate for color-deficient people by using a threshold on the gradient of the difference between the original and its simulation, combined with dilation to adjust the strength of the edges. (i) An error image, $\mathbf{u_0}$, is obtained by subtracting a simulated version of the original, $\mathbf{s}(\mathbf{u_0})$, from the original image, $\mathbf{u_0}$: $\mathbf{d_0} = \mathbf{u_o} - \mathbf{s}(\mathbf{u_0})$. (ii) We blur $\mathbf{d_0}$ by applying a Gaussian filter to minimize noise. (iii) Then, we

(a) Wrestlers (b) Berries

Figure 2: The first row shows the magnitude of the gradient, M. The second row shows the edge map, $\mathfrak{M}$, with $\varepsilon = 0.15$ and one round of dilation.

compute the gradient of the error image, $\nabla\mathbf{d_0}$, and compute the magnitude of the gradient, M: $M = \|\nabla\mathbf{d_0}\|_2^2$. M is normalized to the range $[0.0, 1.0]$. (iv) From the magnitude, we filter only strong edges and contrast by applying a threshold, $\varepsilon \in [0.0, 1.0]$, as such: $\mathfrak{M}_0 = 0$ if $M(x) < \varepsilon$, and $\mathfrak{M}_0 = 1$ otherwise. ε can be chosen by the user of the daltonization method and influences whether the algorithm includes strong contrasts ($\varepsilon \approx 0.0$) or sharp edges (greater ε). (v) We dilate the initial mask, $\mathfrak{M}_0$, by a kernel with a square connectivity of one to increase the area around the edges intended to be influenced by daltonization to obtain the final edge mask, $\mathfrak{M}$ [19]. The user can influence the width of the resulting edges by the number of times dilation is applied to the initial mask. To sum up, we compute a binary edge mask, in which each point on the daltonized edge is denoted by 1, and 0 else. The user can adjust the thickness of the edge through the threshold value, ε, and the number of times that dilation is applied to the initial mask. By choosing a small ε value, for example, the edges will be thicker than for a high ε value. By choosing no dilation, the edges will be thinner than when dilation is applied several times.

Then, we use the original method Yoshi-II in combination with the edge mask $\mathfrak{M}$ as following: (i) Yoshi-II-edge only computes the modified gradient G for pixels defined by the edge mask $\mathfrak{M}$. (ii) Likewise, the gradient descent to obtain $\mathbf{u}$ is only applied to pixels within the edge mask $\mathfrak{M}$.

Finally, we propose an option to create “artificial mach bands” to emphasize edges. As discussed before, the χ-values in Equation (1) specify how much the gradient is changed at any given point in the image. Positive and negative χ-values influence, whether the red or green component of confusion colors are modified. This means in practice that positive and negative values modify confusion colors on opposite sides of and chromatic edge along complementary directions. By computing two version of the original image with positive and negative χ-values and combining both versions, we obtain an “artificial mach band”. More precisely, we compute the absolute value of the difference between daltonized version and the original image for each version. Then, we assign the color value of the daltonized version with the highest absolute difference to each point defined by the edge mask.

Implementations and Results

We implemented the proposed method in Python based on the implementation we introduced for Yoshi-II [18]. We tested the method on two images representing natural images with confusion colors that are adjacent to each other, e.g. images that contain strong chromatic edges in confusion colors (berries, cf. Figure 1(a)), and images with confusion colors that are not adjacent to each other, e.g. images that do not contain chromatic edges in confusion colors (wrestlers, cf. Figure 1(b)). We tested the proposed method (i) with a threshold value of $\varepsilon = 0.15$ but without the "artificial mach band" option, (ii) with different threshold values ε, (iii) with and without "artificial mach band" option.

Firstly, we show examples for Yoshi-III with the described parameters in Figure 3. There is almost no change in colors for images where confusion colors are not adjacent to each other (cf. Figure 3(a)). However, we observe noticeable edge enhancement in images where confusion colors are adjacent to each other (cf. Figure 3(b)).

Secondly, we chose the results for different threshold values ε in Figure 4 to give examples for how ε influences the width of the daltonized edge. For $\varepsilon = 0.01$, we observe daltonization results that cover virtually the whole object with confusion colors (cf. Figure 4(a)). The edge characteristics become more apparent for higher ε values: We observe, for example, daltonized edges for $\varepsilon = 0.20$ that have a width of a few pixels only (cf. Figure 4(c)). However, for higher threshold values – like, for example, $\varepsilon = 0.5$ – there is almost no daltonization present in the image anymore (cf. Figure 4(e)).

Thirdly, we show the results for the "artificial mach band" option in Figure 5. We can observe a subtle halo-like effect in the wrestlers and berries images.

Discussion

The presented examples show opportunities and shortcomings of an edge-focused daltonization method.

Firstly, edge daltonization is strongest where confusion colors are adjacent to each other (like, for instance, in the berries image), and weakest where confusion colors are located apart (like, for example, in the wrestlers image). Edge daltonization is strongest where there is an edge between confusion colors as we would expect.

Secondly, using the gradient of the error image to compute the edge map returns an optimal representation of edges that are hard to discriminate for color-deficient people (cf. Figures 2(a) and 2(b)). We offer an opportunity to adjust the width of the resulting daltonization edge through the threshold ε and dilation. However, the adjustment through the threshold ε is somewhat rough, and the results can be difficult to predict (cf. Figures 2(c) and 2(d)). For the berries image, for example, ε can change the width of the daltonized edge from a few pixels (cf. Figure 4(c)) to an edge that is almost covering the whole object dyed in the confusion color (cf. Figure 4(a)).

Thirdly, edge daltonization highlights the edges of an object without changing the overall color of the object. In the berries image, for example, edges become purple while the berries maintain their red hue (cf. Figure 4(c)). However, the perceived object color is influenced by the daltonized edge, especially when looking at the object from a distance. More precisely, the berries for $\varepsilon = 0.20$ might seem to be colored in almost the same colors as the berries for $\varepsilon = 0.01$ although a significantly smaller area of the object color has been changed. One reason for this might be the watercolor illusion that describes the coloring of an area from a relatively thin colored edge that surrounds the area [20]. The difference between perceived and physical color becomes more apparent when zooming into the area in question. However, we argue that this watercolor illusion might actually be a strength for edge daltonization because it allows a color-deficient observer to perceive a visually enhanced color that will help the discrimination of confusion colors in comparative colors tasks, at the same time as the original color is preserved to complete connotative and denotative color tasks successfully. Especially, anomalous trichromatic observers might benefit from this effect because anomalous trichromatic observers do not perceive the world in a two-dimensional color space that typically spans the axes black–white and blue–yellow only, but perceive the world in a three-dimensional color space spanning the axes black–white, blue–yellow and red–green that is significantly skewed or reduced as compared to normal-sighted observers.

Fourthly, the "artificial mach band" option only gives consistent daltonization results where areas of confusion colors are adjacent to each other and share a chromatic edge. The "artificial mach band" option in the current implementation is based on the assumption that confusion colors on opposite sites of an edge are changed to opposite directions in color space. For example, the red berries change color to a dark purple whereas the surrounding leaves change color to a light cyan. These color changes create an halo-like artificial mach band effect to highlight the berries more strongly. However, this approach fails in images without direct chromatic edges between areas of confusion colors. In the wrestlers image, for example, the red and green jersey colors, both confusion colors, are not adjacent. Thus, they cannot be mapped to the opposite perceptual color by the algorithm. This example shows that the "artificial mach band" option makes only sense in areas where confusion colors are directly adjacent to each other.

Lastly, we follow many of the guidelines for a good daltonization method discussed in [21]: (i) We preserve naturalness of confusion colors as good as possible by only changing the chromatic edges and not the object colors, which also maintains color identification and sustains color communicability. (ii) We allow customization for different degrees and severities of CVDs by making it possible to substitute the simulation in Equation (1) by personalized simulation methods. However, we only use dichromatic simulations in the current implementation. (iii) We define the visual goal of the recoloring method as improving chromatic edges and contrast that support comparative, connotative, and denotative color tasks. (iv) We define target images as natural photographic images. However, the presence of chromatic edges as requirement for successful daltonization results shows the limitations of the present method. (v) Lastly, we are missing the evaluation by real color-deficient observers and the assessment on different image types. We should compare and rank the present method against other state-of-the-art daltonization methods.

Conclusion

We present a daltonization method focusing on the improvement of chromatic edges and contrast while maintaining the overall object color of areas of confusion colors.

Firstly, we compute an edge map from the gradient of the difference between the original and its simulation. The user can modify the width of the edge by thresholding the absolute value of the gradient magnitude and dilation on the initial edge map. Secondly, we create a modified gradient in the points described by the edge map. For the modified gradient, we project and rotate the lost information of the original image along the direction of optimal visibility defined by the directions of lightness and maximum information loss. Thirdly, we obtain the daltonized image from the

(a) Wrestlers (b) Berries

Figure 3: The first row shows the daltonized images with $= 0.15$ and one round of dilation, while the second row shows the deutan simulations. The images have been simulated using the Brettel simulation [1].

modified image by solving the Euler-Lagrange equation, which returns a Poisson equation that can be solved numerically through a gradient descent. We also introduce an "artificial mach band" option that creates a halo-like effect around chromatic edges to emphasize said edges.

We show that Yoshi-II-edge performs well in images where areas of confusion colors share a direct chromatic edge but performs poorly for images in which areas of confusion colors are not directly adjacent to each other. Likewise, we show that the "artificial mach band" option works only in parts of the images with direct chromatic edges between areas of confusion colors.

In future work, we want to test different options to compute the edge map, for example, by using a Canny edge detector [22]. A Canny edge detector returns an edge map, in which edges have a width of 1 px. This 1 px edge map would allow the user to define the width of the daltonized image more precisely when we combine the original Canny edge map with multiple rounds of dilation. Furthermore, we want to combine Yoshi-II-edge with strategies like multiscaling to identify edges at different scales to enhance areas of confusion colors that are not directly adjacent to each other. Finally, we want to assess the present method by real color-deficient observers on various image types through behavioral and psychometric evaluation.

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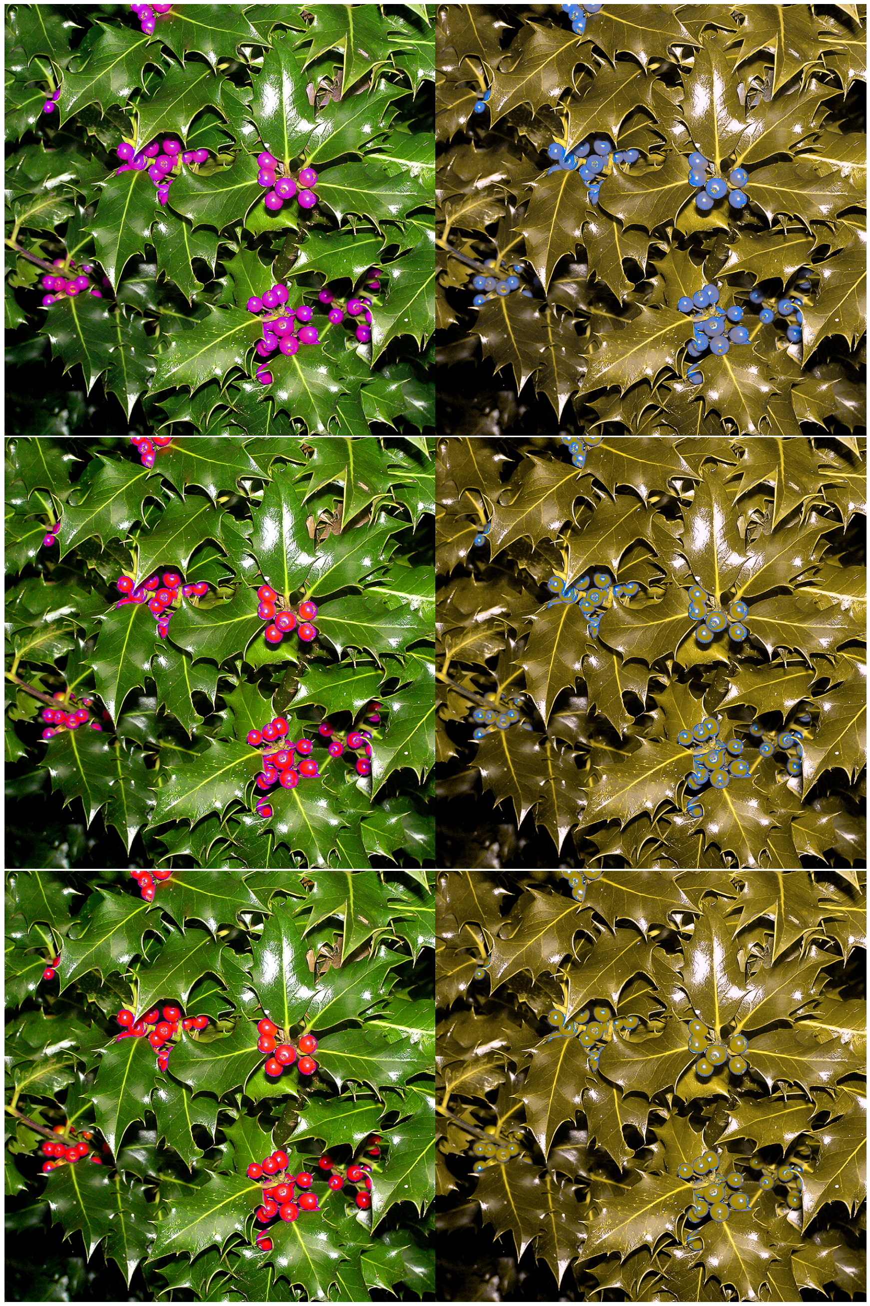

Figure 4: We used $\varepsilon = 0.01$ in the first row, $\varepsilon = 0.20$ in the second row, $\varepsilon = 0.50$ in the third row. The left column shows the daltonized versions, whereas the right columns represents the daltonized images simulated by the Brettel method for deuteranopes [1].

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(a) Wrestlers (b) Berries

Figure 5: The first row shows the daltonized images with "artificial mach bands", while the second row shows the deutan simulations. The images have been simulated using the Brettel simulation [1].

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