Spatial Intensity Channel Replacement Daltonization (SIChaRDa)

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ABSTRACT

Color-deficient observers are often confronted with problems in daily life due to the fact that some colors appear less differentiable than for normal sighted people. So-called daltonization methods have been proposed to increase color contrast for color-deficient people. We propose two methods for better daltonization solutions by Spatial Intensity Channel Replacement Daltonization (SIChaRDa). We propose replacing the intensity channel with a grayscale version of the image computed by using spatial color-to-gray methods that are either capable of translating color contrasts into lightness contrasts or that are capable of translating color edges into lightness edges, and/or integrating information from the red–green channel into the intensity channel. We tested two implementations on different types of images, and we could show that results depend on the one hand on the algorithm used for computing the grayscale image, and on the other hand on the content of the image. We show that the spatial methods work best on real-life images were confusing colors are directly adjacent to each other, respectively where they are in close proximity. On the contrary, using composed artificial images with borders of white space between colors – like for example in the Ishihara plates – leads only to unsatisfactory results.

Keywords: daltonization, color deficiency simulation, color deficiency, color image quality, image enhancement, spatial image processing

1. INTRODUCTION

Trichromatic vision in humans is made possible through photoreceptors containing pigments, so-called opsins, that filter light in the short, medium and long wavelength range of the electromagnetic spectrum called cones.[1,2] Ganglion cells in the latter parts of the human eye combine the signals from the cones into pathways that roughly correspond to different perceptual attributes: One pathway for intensity, one pathway for red–green opponency, and one pathway for blue–yellow opponency.[3] Color deficient observers can be divided into the groups of anomalous trichromats and dichromats, making up about 5.9% and about 2.1% respectively of the male population,[4] in which at least one type of the photopigments has a shifted color sensitivity as compared to normal sighted observers or is entirely missing respectively due to a genetic variation on the X-chromosome.[5] Consequently, the color contrast – most typically along the red–green axis – is significantly reduced and color edges become less visible, leading to difficulties when retrieving visual information.[6] Daltonization methods[7–10] improve image quality for color-deficient observers by increasing and/or reintroducing lost or decreased color contrast in order to regain lost information. Most methods use color deficiency simulation methods in order to determine which colors in the image are of difficulty for color-deficient observers.[7,8] In some other methods the colors of the image are replaced by simulating the image for color-deficient observers, clustering colors in RGB space, and increasing contrast for problematic colors for color-deficient observers.[9,10]

In our proposed method Spatial Intensity Channel Replacement Daltonization (SIChaRDa), we increase image contrast for color-deficient people by replacing the intensity channel with an improved-contrast image. In the next sections, we will present our methodology, and describe our current implementation. We will then discuss the results, and finally conclude the article.

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2. METHODOLOGY: SICHARDA AND SICHARDA:αβP

Our proposed methods increase correlation between channels for especially deuteranomalous, protanomalous, deuteranopes, and protanopes through *Spatial Intensity Channel Replacement Daltonization* (SIChaRDa). Firstly, the intensity channel of the image is replaced by an grayscale image containing contrast and edge information from the color channels. This will restore lost information since the information in the intensity channel is clearly visible by most color-deficient and normal sighted people. Secondly, we emphasize for our methods spatial color-to-gray methods. Color-to-gray methods are defined by methods that reduce an image from typically three (color) layers to only one (grayscale) layer. Spatial methods adapt pixel values in the image according to their local surrounding rather than globally for the whole image. Thus, spatial color-to-gray methods are known to focus on preserving color edges and color contrast in the image through spatial image processing.

2.1 SIChaRDa

Our basic method (SIChaRDa) consists of four major steps: (i) In the first step we translate the original RGB image into a perceptual pathway image i.e. an image that consists of three layers corresponding to the three perceptual pathways of the human visual system described in the introduction. The perceptual pathway image is typically abbreviated to IPT:[11] a lightness, a red–green, and a blue–yellow layer (cf. Sec. 1). (ii) In the second step we create a grayscale version, called G of the original RGB image using a method that focuses on preserving color edges and/or color contrast spatially, especially for red–green contrast and/or along red–green edges. (iii) In the third step we replace the lightness channel of the perceptual pathway image (IPT) with the newly computed grayscale image, i.e. $I_{new} = G$ resulting in $(I_{new})PT$, and (iv) convert the adapted perceptual pathway image into the final $(RGB)_{new}$ image.

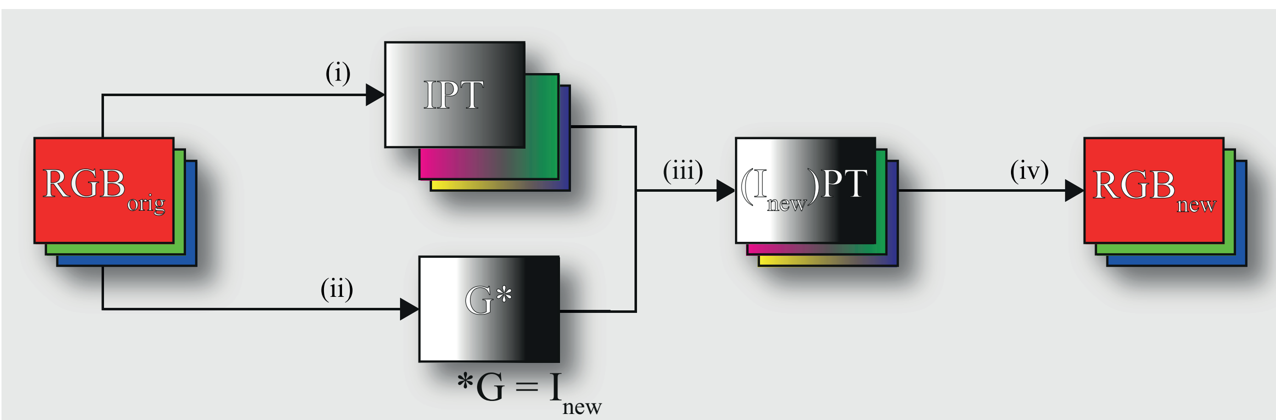

Figure 1: Basic SIChaRDa workflow: (i) Converting image from RGB to IPT, (ii) computing grayscale image $G = I_{new}$, (iii) replacing I with I_{new}, and (iv) converting back to RGB.

2.2 SIChaRDa:αβP

Our alternative method (SIChaRDa:αβP) differs from the first one by including additional information from the P-channel into the newly computed gray channel, both layers scaled by the factors αand β: (i) *As before for SIChaRDa in the first step.* (ii) *As before for SIChaRDa in the second step.* (iii) In the new third step we are combining the newly computed grayscale image with information from the P-channel, i.e. the red–green channel of the perceptual pathway image, as such: $I_{new} = \alpha \cdot G + \beta \cdot \frac{P+1}{2}$. Since the P-channel of the IPT space ranges from -1 to +1, we have to normalize it as written. (iv) In the fourth step we replace the intensity channel of the original perceptual pathway image IPT with the combination of grayscale image and P-channel, I_{new}, like in step three of the basic method resulting in $(I_{new})PT$, and (v) convert the adapted perceptual pathway image into the final$(RGB)_{new}$ like in step four of the basic method.

We suggest that these methods will improve color image quality by making color contrast and/or color edges more visible for color-deficient observers. Since information, represented by color contrast and/or color edges in

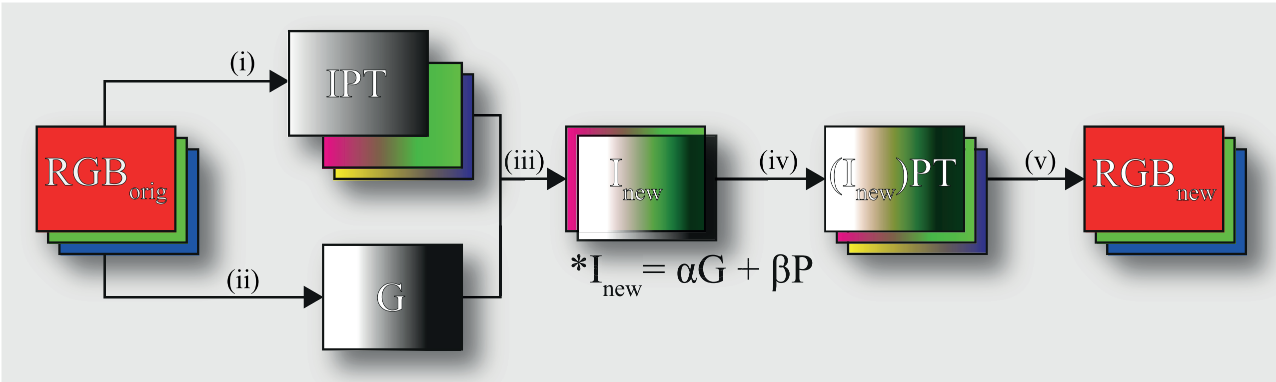

Figure 2: SIChaRDa:αβP workflow: (i) Converting image from RGB to IPT, (ii) computing grayscale image G, (iii) combining G and P to I_{new}, (iv) replacing I with I_{new}, and (v) converting back to RGB.

the red–green layer that is hardly visible or almost invisible for color-deficient observers, has been made available in the lightness channel that is visible with more ease for both color-deficient and normal sighted observers.

3. IMPLEMENTATION

When choosing color-to-gray algorithms for our proposed method, we focused on algorithms that would benefit local color contrast and/or edges. The best fit for this requirement were so-called spatial color-to-gray methods. First reason for that is the fact that color contrast varies locally in real life images, i.e. color contrast and/or color edges vary strongly depending on their location and environment in the image. Taking into account this aspect is one of the main characteristics of spatial algorithms. Secondly, edges and contrast are important attributes for the HVS in order to identify objects and thus retrieve information from an image. Thirdly, spatial methods can emulate perceptual phenomena like simultaneous color contrasts etc. Our implementations focus on two color-to-gray algorithms: (i) FastColour2Grey (FC2G) by Alsam *et al.*[12] that emphasizes color contrast implemented in Matlab, and (ii) STRESS by Kolås *et al.*[13] that emphasizes color edges implemented in C++. For the computation of the perceptual pathway image, we decided on using the IPT color space proposed by Ebner *et al.*,[11] a color space which is supposed to be close to uniform, and predict hue accurately. The IPT color space is supposed to be the perceptual most accurate color space up-to-date 2014. Also Ebner *et al.*[11] claim that the P-channel actually represents the information that protanopes are missing due to their color deficiency.

4. RESULTS

The two proposed methods have been tested on four different images: an Ishihara chart, a holly berry image, a wrestler image, a berry image, and a baseball caps image. The colors in the images have been chosen and adapted in a way that they are of minor difficulty for normal sighted observers, but of huge problems for color-deficient observers. More precisely, color-deficient observers will have difficulties extracting the correct number in the Ishihara image, seeing the difference between holly berries and background, discriminating color difference in the jersey of the wrestlers, and discriminating differences in color of the baseball caps. In order to understand perception of the color-deficient observers, we simulated perception of a deuteranope/protanope using the color deficiency simulation method proposed by Brettel *et al.*[14] The results for basic SIChaRDa can be seen in Figures 3 to 6. The results for the improved SIChaRDa:αβP have been divided into two groups: (i) β independent from α with beta values of {0.0, 0.33, 0.67}, and constant alpha value of {0.9} can be seen in Figures 7 and 8. (ii) β as function of α: $\beta = 1 - \alpha$ can be seen in Figures 9 and 10 with alpha values of {0.0, 0.33, 0.67}. In this case the image is redefined as convex linear combination such that the image values lay between the range of [0.0, 1.0].

5. DISCUSSION

An improvement in image quality can be measured according to how much easier it is to extract visually certain information for the three different images used as discussed above (cf. Sec. 4). Observers should be enabled to extract the correct number in the Ishihara image, identify berries more clearly from the background, and see a clear difference in color of the jerseys for the wrestler image. According to these criteria we obtained for the investigated images, and the presented implementations

To begin with, the number in the “Ishihara” image (cf. Figure 3) is not more visible after daltonization. Both the SIChaRDa:STRESS and the SIChaRDa:FC2G show increasing local contrast. However, information-carrying differences between the significant colored dots have not gotten bigger. The reason for this might have to do with the graphical nature: The “Ishihara” image consists of colored dots that are surrounded by white space, and none of the colored dots are actually touching. Thus, a spatial color-to-gray method that emphasizes color edges would only emphasize the edges around the dots and not the colors inside the dots, and a spatial color-to-gray method that emphasizes color contrast would only emphasize color contrast between dots and background and not between the colors of the dots. Thus, we can expect that a spatial method would not significantly improve image quality for images like the Ishihara plates. It would be interesting to test the method on the alternative Ishihara plates that have been proposed by Rizzi *et al.*[15] containing dots that actually overlap.

Secondly, the colors of the “holly” berries image (cf. Figure 4) become not significantly more distinguishable after daltonization. The SIChaRDa:FC2G implementation shows that the berries become slightly brighter than the background. The SIChaRDa:STRESS shows that the berries become slightly darker than the background. In contrast to the previous method, the problematic areas in the image, namely the berries, are directly surrounded by problematic colors in the background, namely the leaves. In theory, the methods should emphasize color edges and include color contrast where it is needed, and improve images more clearly than can be seen for our chosen image. However, when looking at grayscale images computed by the implemented methods, we did not observe a significant increased local color contrast either. This leads to the assumption that the color-to-gray methods just do not perform very convincingly on this particular image.

Thirdly, the colors of the wrestlers’ jerseys in the “Mijaín vs. Heiki” image (cf. Figure 5) did improve for the implementation using FC2G after daltonization. Especially the SIChaRDa:FC2G implementation shows that the wrestler to the right got a much darker jersey than the one on the right. Th SIChaRDa:STRESS implementation shows that the color of jersey of the wrestler to the right got darker than the jersey of the wrestler to the left, but much more subtle than for SIChaRDa:FC2G. In contrast to the Ishihara image, the colored areas actually touch, at the same time as there is no consistent background color. All areas in the image are surrounded by other elements in the image. However, the areas that lead to confusion for color-deficient observers, namely the jerseys of the wrestlers, are not adjacent to each other. Thus, the spatial daltonization algorithms change these colors according to its direct environment. Color contrast between the two jerseys is not altered by the algorithm leaving it a game of chance whether the method is actually working or not. In this image, the results are quite convincing, but other images with different backgrounds might lead to results that are poorly discriminable even after daltonization.

Finally, the colors of the “baseball caps” image (cf. Figure 6) did improve a lot. In the original simulation it can be seen that for example the three caps on the left have a similar hue, and that the contrast between cap four and five is visually not as prominent as in the original without simulation. Both SIChaRDa implementation gave remarkable results. Especially, the SIChaRDa:FC2G implementation changed the colors in a way that all five caps changed their colors in a way that they obtained five individual colors that differ both in hue and/or lightness. Similar results can be seen in the SIChaRDa:STRESS implementation, but the lightness difference is not as clear as for the SIChaRDa:FC2G implementation.

Integrating the P-channel into the daltonization can mean both some advantages, but also some additional problems. Choosing weights α and β independently from each other, for example by choosing both $\alpha = 0.9$ and $\beta = 0.67$, might result in out-of-gamut colors, namely that high contrast areas become over- or underexposed respectively (cf Figures 7 and 8). The reason for this is obviously that since both G and the normalized P-channel $\frac{P+1}{2}$ have values in the range of $[0, 1]$, we have to make sure that weights are chosen in order to keep the resulting combined layer in the range of $[0, 1]$ as well. Thus, we proposed reformulating the combination of the gray image and the P-channel as convex linear combination, i.e. by defining β as a function of α. More precisely, by defining $\beta = 1 - \alpha$, we can make sure that the combination of both layers does not result in out-of-gamut colors. We might, however, encounter low contrast and artificial colors (cf Figures 9 and 10), if α is chosen to small, like for example $\alpha = 0.33$, or no additional improvement if α is chosen to high, like for example $\alpha = 0.67$. If choosing a middle value for $\alpha = 0.5$ is really the best solution, is left open for discussion.

In future work we might (i) compute the grayscale image using STRESS or FC2Gs method directly from the IPT image instead of from the RGB image. Since the RGB image is not perceptually representative for our visual system, the contrast and/or edges in the resulting grayscale image do not necessarily result in perceptually pleasing results. Color spaces like the IPT color space that correspond more to the properties of the HVS might give better results when extracting color contrast and/or color edges. (ii) We might use different perceptual pathway images than IPT that mean better representations for our human visual system. We can for example use a color space based on one of the color deficiency simulations proposed by Brettel, Viénot and Mollon,[14,16] also another "complete" color space has been proposed by Kotera[17] (iii) We might choose other color-to-black-and-white conversions that are better suited for grayscale conversion than the proposed methods STRESS by Kolås *et al.* and FC2G by Alsam *et al.*. (iv) We might choose different possibilities of combining the black-and-white image with the P-channel. In other words, we might want to find the perfect pair of α and β for each individual image that might result in the optimal color image quality. (v) Finally, we might reformulate the spatial daltonization newly by defining a variational approach from three normal sighted color planes down to only two color-deficient color planes. Since both methods proposed by Kolås and Alsam are based on variational approaches, we are taking advantage of this indirectly now.

6. CONCLUSION

We proposed a Spatial Intensity Channel Replacement Daltonization (SIChaRDa) method for deutan and protan color-deficient observers that uses enhancement in the intensity channel by increasing correlation between the RGB channels. More precisely, we suggest replacing the intensity channel with an improved grayscale version of the image containing additional color contrast information. We introduced two implementations that focus on spatial color-to-gray algorithms, STRESS and FastColour2Grey, that emphasize color edges and/or color contrast. We showed that the performance of the method depends, (i) on the one hand, on how much the color-to-gray algorithm really increases color contrast and enhances color edges, and, (ii) on the other hand, on the content of the image, and that it works best for real life images in which problematic colors are directly adjacent to each other. The daltonization methods can be improved by integrating information from the red–green channel into the intensity channel. However, how the different layers should be weighted in this combination is left for further investigation.

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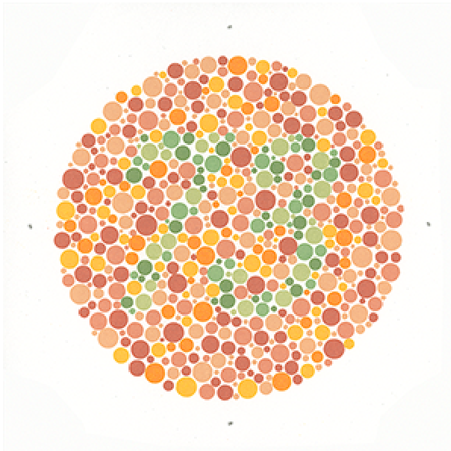
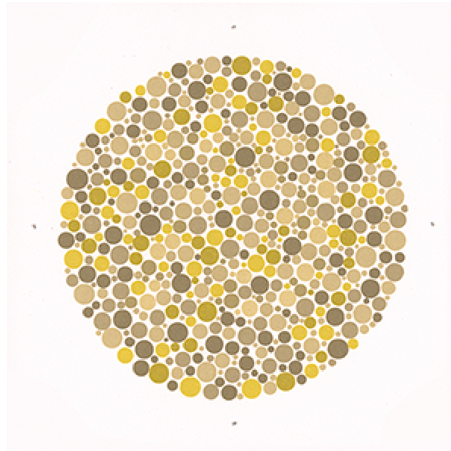
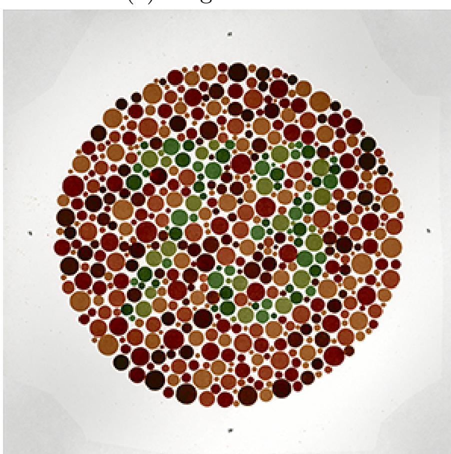


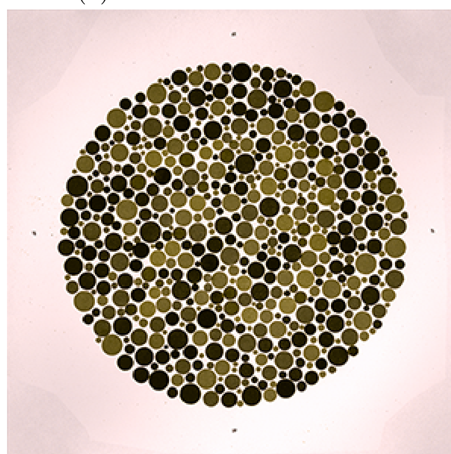
(a) Original version



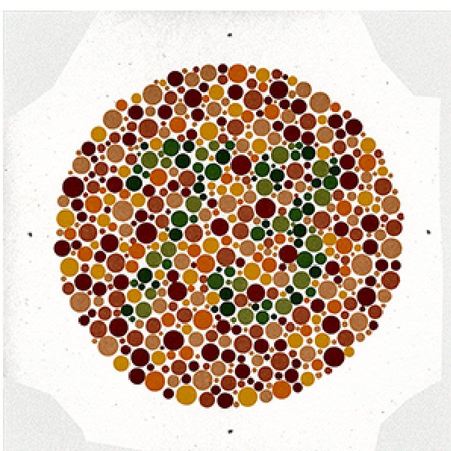
(b) Deutan simulated version



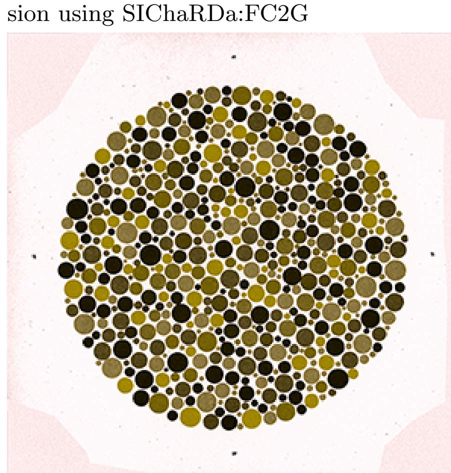
(c) Deutan daltonized version using SIChaRDa:FC2G



(d) Deutan daltonized and simulated version using SIChaRDa:FC2G



(e) Deutan daltonized version using SIChaRDa:STRESS



(f) Deutan daltonized and simulated version using SIChaRDa:STRESS

Figure 3: Original and daltonized versions (left) of the "Ishihara" image, and their simulations using the Brettel method (right). Poor results after daltonization since the color dots do not really overlap. The success of SIChaRDa depends strongly on the images used.

(a) Original version

(b) Deutan simulated version

(c) Deutan daltonized version using SIChaRDa:FC2G

(d) Deutan daltonized and simulated version using SIChaRDa:FC2G

(e) Deutan daltonized version using SIChaRDa:STRESS

(f) Deutan daltonized and simulated version using SIChaRDa:STRESS

Figure 4: Original and daltonized versions (left) of the "holly" image, and their simulations using the Brettel method (right). Somewhat unsatisfying results. However, the output from the color-to-gray image did not represent the red-green contrast adequately either. The success of SIChaRDa depends strongly on the color-to-gray methods used.

(a) Original version

(b) Deutan simulated version

(c) Deutan daltonized version using SIChaRDa:FC2G

(d) Deutan daltonized and simulated version using SIChaRDa:FC2G

(e) Deutan daltonized version using SIChaRDa:STRESS

(f) Deutan daltonized and simulated version using SIChaRDa:STRESS

Figure 5: Original and daltonized versions (left) of the “Mijaín vs. Heiki” image, and their simulations using the Brettel method (right). Copyright by Carl Pilon (Flickr:Pilou@SF). The colors of the jersey become more different from each other after daltonization, especially for the FC2G method.

(a) Original version

(b) Deutan simulated version

(c) Deutan daltonized version using SIChaRDa:FC2G

(d) Deutan daltonized and simulated version using SIChaRDa:FC2G

(e) Deutan daltonized version using SIChaRDa:STRESS

(f) Deutan daltonized and simulated version using SIChaRDa:STRESS

Figure 6: Original and daltonized versions (left) of the “baseball caps” image, and their simulations using the Brettel method (right). The colors of the caps become more distinguishable from each other after daltonization, especially for FC2G.

(a) Daltonized version:
$\alpha = 0.9$ and $\beta = 0.33$

(b) Deutan simulated version:
$\alpha = 0.9$ and $\beta = 0.33$

(c) Daltonized version:
$\alpha = 0.9$ and $\beta = 0.67$

(d) Deutan simulated version:
$\alpha = 0.9$ and $\beta = 0.67$

(e) Daltonized version:
$\alpha = 0.9$ and $\beta = 1.0$

(f) Deutan simulated version:
$\alpha = 0.9$ and $\beta = 1.00$

Figure 7: SIChaRDa:αβP:FC2G – Daltonized versions (left) of the “baseball caps” image, and their simulations using the Brettel method (right). Choosing α and β independently from each other might lead to out-of-gamut colors and over- or underexposure of the image.

(a) Daltonized version:
$\alpha = 0.9$ and $\beta = 0.33$

(b) Deutan simulated version:
$\alpha = 0.9$ and $\beta = 0.33$

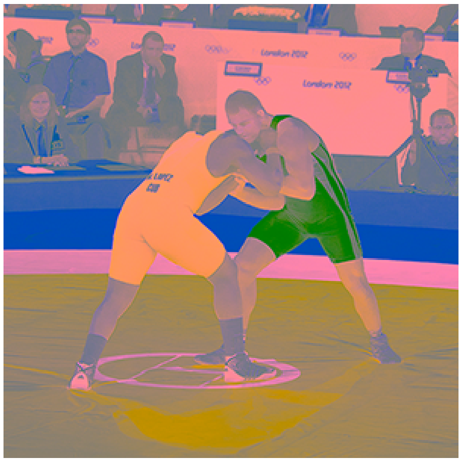
(c) Daltonized version:
$\alpha = 0.9$ and $\beta = 0.67$

(d) Deutan simulated version:
$\alpha = 0.9$ and $\beta = 0.67$

(e) Daltonized version:
$\alpha = 0.9$ and $\beta = 1.0$

(f) Deutan simulated version:
$\alpha = 0.9$ and $\beta = 1.00$

Figure 8: SIChaRDa:αβP:STRESS – Daltonized versions (left) of the "baseball caps" image, and their simulations using the Brettel method (right). Choosing α and β independently from each other might lead to out-of-gamut colors and over- or underexposure of the image.



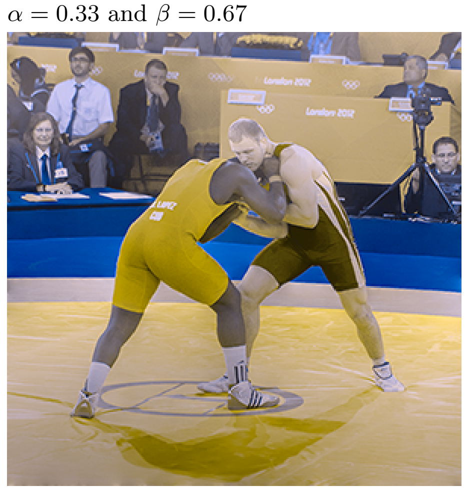
(a) Daltonized version:
$\alpha = 0.0$ and $\beta = 1.0$

(b) Deutan simulated version:
$\alpha = 0.0$ and $\beta = 1.0$

(c) Daltonized version:
$\alpha = 0.33$ and $\beta = 0.67$

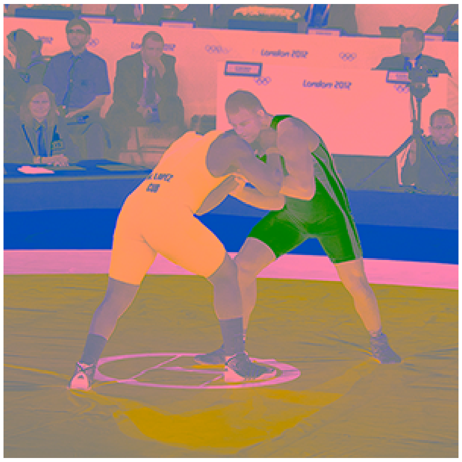
(d) Deutan simulated version:
$\alpha = 0.33$ and $\beta = 0.67$

(e) Daltonized version:
$\alpha = 0.67$ and $\beta = 0.33$



(f) Deutan simulated version:
$\alpha = 0.67$ and $\beta = 0.33$

Figure 9: SIChaRDa:αβP:FC2G – Daltonized versions (left) of the "Mijaín vs. Heiki" image, and their simulations using the Brettel method (right). Copyright by Carl Pilon (Flickr:Pilou@SF). Defining α as function of β might lead to artificial colors and low contrast if α is chosen to low.



(a) Daltonized version:
$\alpha = 0.0$ and $\beta = 1.0$

(b) Deutan simulated version:
$\alpha = 0.0$ and $\beta = 1.0$

(c) Daltonized version:
$\alpha = 0.33$ and $\beta = 0.67$

(d) Deutan simulated version:
$\alpha = 0.33$ and $\beta = 0.67$

(e) Daltonized version:
$\alpha = 0.67$ and $\beta = 0.33$

(f) Deutan simulated version:
$\alpha = 0.67$ and $\beta = 0.33$

Figure 10: SIChaRDa:αβP:STRESS – Daltonized versions (left) of the "Mijaín vs. Heiki" image, and their simulations using the Brettel method (right). Copyright by Carl Pilon (Flickr:Pilou@SF). Defining α as function of β might lead to artificial colors and low contrast if α is chosen to low.