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An App-based Assessment of SiChaRDa, an Image Enhancer for Color-Blind People

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Abstract. *It is estimated that about 5–10% of the male population has some kind of color vision deficiency (CVD). For them, it is difficult or even impossible to distinguish certain colors. Many image enhancers exist, mostly based on hue changes, since CVDs are usually modeled at spectral level. In this article, the authors consider another point of view, investigating the role of luminance contrast to treat CVD. In the following, the authors present a test, administered as a mobile application, to assess the performance of SiChaRDa, a recently proposed image enhancer, inspired by a model of the human visual system, that modifies the lightness of the image. The results indicate a role of contrast and edges in the readability of images for color vision-deficient people; however, they do not support a clear and unambiguous interpretation.*
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INTRODUCTION

Color vision deficiency (CVD), also referred to as color blindness, is a condition of altered color perception, or inability to discriminate color. The most frequent cause of CVD is the alteration in the genes that encode information on the opsin molecules of photoreceptors, leading to anomalous trichromacy, dichromacy or monochromacy.

Anomalous trichromacy is attributed to deviation or abnormality in the peak sensitivity in one of the three classes of cone photopigments L, M and S, leading to *protanomaly*, *deuteranomaly* and *tritanomaly*, respectively. Dichromacy is a more severe form of CVD, defined by the total absence of one of the three classes of cones: it takes the form of *protanopia*, *deuteranopia* and *tritanopia*, respectively. Tritan phenotypes are also associated with progressive S-cone dystrophy and accompanied by disruption in the regularity of the cone mosaic, caused by the loss of S cones.[1] *Monochromacy* is an alteration resulting in loss of two or all three cone pigments and is by far the rarest form of CVD. The cases of loss of function of all the three classes of cones are referred to as *achromatopsia*.[2]

Image processing techniques used to improve images for people with CVD are called *Daltonization methods*: they consist of a series of color correction algorithms that modify content in order to make it accessible for CVD observers. The general approach to correct the images operates by the changing of the hue (see Related Works section). However, we are convinced that the edges play a fundamental role in the generation of chromatic sensation, both for normal and for CVD people.[3]

This idea has been adopted and developed by some scholars from Norwegian University of Science and Technology (NTNU) in Gjoevik who wrote several very interesting works based on this point of view. In particular, a novel method[4] proposed by Simon-Liedtke and Farup, suggests to work on the lightness channel to increase the contrast without changing the hue or changing it only slightly. Their Spatial Intensity Channel Replacement Daltonization (SiChaRDa) algorithm is based on Spatio-Temporal Retinex-inspired Envelope with Stochastic Sampling (STRESS),[5] a spatial color algorithm[6] that mimics some characteristics within the human visual system (HVS). The application of their method aims at improving color image readability by enhancing the luminance contrast.

We consider this an interesting and promising approach and, since they presented only qualitative tests on four images and on a set of users with no color-deficient vision, we decided to test it on a wider set of users and images.

When we refer to the term contrast without distinction between luminance and chromatic contrast, we refer to spatial changes of image values. This is done on purpose, since the separation between luminance and chromatic contrast is a cognitive issue linked with the way we rationalize color. In the HVS there is not such a distinction: each contrast is detected within the relative channel of the LMS color space. However, when we need to refer to one of these aspects of contrast such distinction will be specified.

Here, we present an app-based test of the work developed by Simon-Liedtke and Farup, based on a larger number of enhanced images and displaying the resulting pictures to a great number of color-deficient and normal-vision observers, so as to have a wider sample.

Interestingly, the results obtained using a larger number of participants and reported here, are different from the results shown by Simon-Liedtke and Farup,[4] where no improvement was found for the Ishihara plates.

The article is organized as follows: the second section presents the related works, the third section explains the method used to enhance the images, in the fourth section we describe the app development and evaluation methodology,

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the fifth section presents the results and the sixth section concludes the article.

RELATED WORKS

In 1996, Atkinson[7] deposited a US Patent in which a computer system can test a user for any CVD and apply a compensatory color palette to the computer display. Since then, a multitude of approaches have been taken to help color-blind people, either via algorithms, applications or physical commercial products.

Daltonize[8] is a user-assisted recoloring technique for protanopes and deuteranopes based on the algorithm proposed by Brettel et al.[9] Users have to provide three parameters that specify the stretching of the red–green channel and its projection into the luminance channel and the yellow–blue channel. In 2007, a Daltonization algorithm for protanopes is proposed[10] featuring an iteration technique for the selection of adaptation parameters and a color clustering method to avoid color matching between the original and daltonized image. In the same year, Huang et al.[11] developed a recoloring method for red–green color blindness that, contrary to other previous works, aims to preserve the original colors of the base image as much as possible, producing images that appear to have more natural look to the color-blind users. This approach was also taken by Kuhn et al.,[12] which presented a deterministic image-recoloring technique for dichromats based on mass–spring optimization.

In 2010, Machado and Oliveira[13] developed a real-time contrast enhancement technique for dichromats that uses Gaussian pairing and predominant component analysis. Their approach is based on the observation that whenever dichromats experience some significant loss of color contrast, most of this contrast can be recovered by working on a perceptually uniform color space, and orthographically projecting the original colors onto a plane aligned with the direction that maximizes contrast loss.

In 2012, Kotera[14] proposed a spectral-based image Daltonization algorithm for the dichromats. It extracts the visible and invisible spectra to dichromatic vision, and shifts invisible spectra to a visible spectral region, reintegrating it into the fundamental spectra of source image.

Due to their nature, mobile phone apps can be used to help people with CVDs in various ways. There are countless apps, designed with color-blind people in mind, which offer various tools to help with daily tasks. Some of them also implemented user-driven Daltonization algorithms.[15] The tools implemented by mobile phone apps usually have different purposes: they can help identify a color from an image or a live picture from the camera, adjust or shift colors to make them easily recognizable by people with color blindness, find colors on a picture that match a chosen color and highlight them or help in finding harmonizing colors.

In the last few years, wearable devices have started to be developed in order to assist people with abnormal color vision. The EnChroma[16] glasses, for example, use a series of optical filters in their lenses to modify chromatic and luminous aspects of the color appearance of light to human vision. By acting like a multi-band filter that cuts out specific wavelengths of light, they increase red–green color discrimination for protanomalous and deuteranomalous observers. In 2014, Tanuwidjaja et al.[17] developed Chroma, an augmented-reality wearable support for color blindness implemented on the Google Glass device. It can operate on four distinct modes: highlighting a range of colors, comparing and contrasting two different colors, applying a Daltonization algorithm and outlining areas strongly affected by the person's color blindness.

Many of these recoloring/Daltonization tools are tested with user-study-based evaluations. In 1997, Olson and Brewer[18] published an experiment based on the choice of map colors, to accommodate people with red–green color vision problems. The subjects had to read from seven pair of maps, with each pair presenting a rendition with colors potentially confusing for people with red–green impairment, and the other rendition with colors selected specifically to accommodate this group.

Sajadi et al.,[19] in 2013, developed the first content-independent method to overlay patterns on colored visualization contents that not only minimizes ambiguities but also allows color identification for individuals with CVD, in particular, for dichromats. They validated the method with two user studies: one including 11 subjects with CVD and 19 normal trichromats, and focused on images that use colors to represent multiple categories; another one including 16 subjects with CVD and 22 normal trichromats, which considered a broader set of images.

In 2012, Flatla and Gutwin developed SSMRecolor,[20] a recoloring tool for CVDs, based on situation-specific models of color differentiation. It was tested using a custom Java application consisting of a matching task in which the user had to click on a single color that matched a given cue color.

Flatla et al.[21] in 2015 developed three new color identification techniques and evaluated them using desktop and mobile color identification tasks carried out by participants with impaired color vision. The tools were implemented and tested on a single mobile device where the subjects had to identify colored targets printed on plain paper.

Recently, alternative approaches started to consider and investigate the role of edges and contrast in a CVD observer. The basic motivation is that color sensation originates from the retina but involves the whole vision system all the way up to the cortical level. Regarding normal vision, many experiments have shown that the color sensation originated by a point derives not only from the spectral signal at that specific point, but also from the many spectral signals from the points that compose the rest of the image. In this way, by just changing the surrounding, the same spectral value can originate nearly all possible color sensations.[22] Another experiment reported the role of edges in the formation of color sensation, in relation with afterimages.[23] Many other works contributed to the idea that the color sensation is not a straightforward integration of spectral content; among the many, here we report the work from Hofer et al.,[24] a fairly recent one: it reports results very hard to fit in a

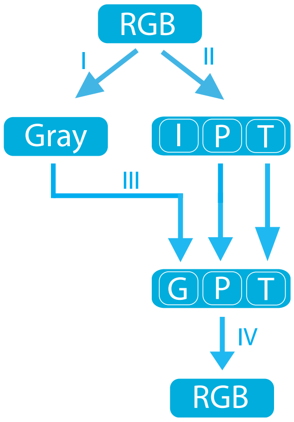

Figure 1. Four steps of the workflow to enhance the images.

point-based model of color sensation. In their work, Hofer and colleagues examined the retinal mosaic of normal-vision males and discovered high variability in L versus M cone ratio and spatial distribution. This remarkable difference did not result in a relative significant change in color matching. Moreover, observers reported from five to seven different color sensations resulting from iterated stimulations of the same point in the retina.

All these evidences suggest the need of a more complex modeling of CVD, where the spatial component of the visual information has to play a role. The first experimental test[3] of this idea started from the observation that all typical tests for CVD contain no chromatic edge. Thus, a set of Ishihara plates has been modified by enlarging the colored dots to form chromatic edges. This affected detection percentage both for normal and CVDs.

Several works from NTNU followed in this direction[4,25–28]; among them we have chosen SiChaRDa[4] for its simple but promising approach.

IMAGE ENHANCEMENT

The enhancement workflow used, shown in Figure 1, is composed by four steps:

I. The original RGB image is converted into a gray-level image using the GIMP function *c2g*. This function implements a specific version of STRESS that converts from color to gray scale.
II. The same original RGB image is converted in the IPT space (passing through XYZ). Three channels compose this color space: one devoted to the lightness, the others to the chromaticity (red–green and blue–yellow).
III. The I channel of the new image is replaced by the gray-level image obtained in the first step.
IV. The new image is converted back in RGB space. We refer to the final image as *filtered image*.

This method ensures that the original chromaticity of each point is preserved, while the lightness component is changed using a method based on STRESS,[5] a spatial color algorithm inspired by some mechanisms of human vision. STRESS calculates the local maxima (reference white) and the local minima (reference black) for each pixel, and then stretches the target pixel values accordingly. Performing this procedure leads to increase of the local contrast with preservation of the edges, and maximization of the luminance dynamic range. In the algorithm, this process is achieved independently on the three RGB channels to remove possible color-cast and mimic color constancy. In the *c2g* version, only one channel, obtained by averaging the three of the STRESS filtered image, is used to summarize the output, leading to a gray-scale image whose luminance contrast has been spatially enhanced. The parameters used to run the algorithm included 10 samples and 100 iterations to have a good compromise between contrast improvements and quality (absence of noise) in the images.

The result replaces the lightness channel of the original image converted in the IPT image (steps II–III) and keep the chromaticity as much as possible similar to the original one.

We tested two kinds of images: a set of Ishihara plates, and a set of natural images. Both the original and the enhanced (from now on, we will referred to these as *filtered*) images are presented in fifth section together with the results.

EVALUATION METHODOLOGY

To evaluate the proposed method, we developed a mobile app to be run on users' portable devices. (As the aim of the app is to collect data to assess the performance of the image enhancer, at the end of the test we avoid to give the score and warn the user that the app does not have clinical validity.) The app is available for iOS and Android on iTunes and Play Store. (Links to the stores pages are available at https://homes.di.unimi.it/mascetti/research/CPT/.) In order to minimize the differences between the two operating systems, the app was developed with a cross platform technique (Apache Cordova).

The app collects the users' answers as well as other information, including device model, screen size, and so forth. Information is then transmitted to a remote server where it is stored for analysis. Filtered images are generated off-line in advance.

At the beginning of the test, users have to fill out a questionnaire collecting personal data, like age, gender, and so forth, as well as if they have CVD or not. As described in the following, to categorize users, in addition to asking them whether they have CVD, we take into account their behavior. After the questionnaire, a set of images is shown (see Figure 2) where each is associated with a question: the users select the answer from a multiple-choice list (see Figure 3). A set of five possible answers (one of which is correct) is pre-determined for each image; they are chosen to reflect the possible answers provided by a user with normal color vision (i.e., the correct answer) and by users with various forms of CVDs.

For example, Ishihara plate number 2 depicts the "number 8." According to his book,[29] CVD people should

Figure 2. Example of task.

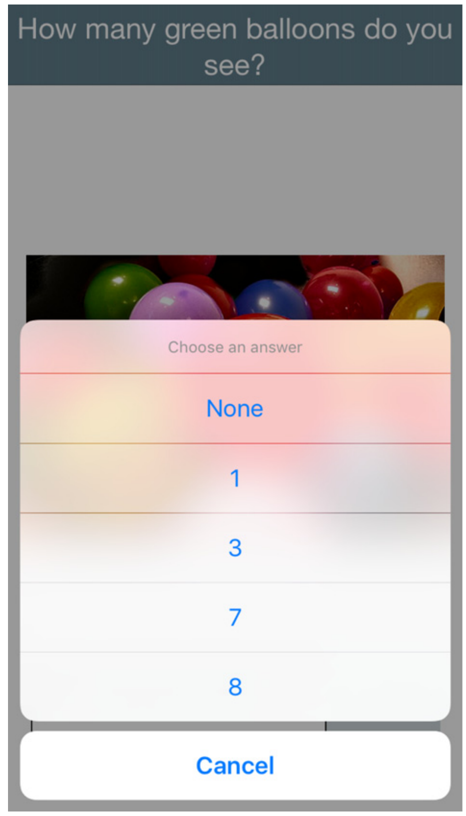

Figure 3. Example of possible answers.

see the "number 3." The answers presented by the app were: None, 3, 6, 8 and 2, with the assumption that the shape of the digit representing the other answers could be challenging for CVD people.

Images are organized into three fixed sequential groups, while within a group images are presented in random order. The images in the first group aim at classifying the user, that is, to distinguish between users with CVD and normal-vision viewers (from now on referred to as *no-CVD*). The first presented image is always Ishihara Plate #1, a control plate, where the number 12 should be visible to both no-CVDs and CVDs. The rest of the group is composed of five Ishihara plates, presented in random order and help us to classify the user as CVD or not. This subset of color plates from Ishihara book is enough for a short-version examination. In a clinical domain, the full series should be used to diagnose red–green deficiency.

We are aware that the different gamuts of the many possible devices used to run the app can have a high variance and can make the digital version of the Ishihara plates less applicable. However, this first group of images is reinforcement assessment of the initial declaration made by the user about his/her type of CVD. The gamut differences, however, do not have a crucial role in the final result. In fact, as explained in the following, the interesting part of the results reported here is extracted in a differential way from the images present in the two other groups. What has to be considered is the difference in response between the same image on the same device, filtered and not by the method under test. Gamuts surely have a variance which is impossible to estimate here and out of the scope of the test. However, we remind that any Daltonization method has to deal with unknown devices.

The images in the other two groups (group #2 and #3) aim at evaluating the effect of the Daltonization method. In each group a set of pair images is stored: a pair is composed by the original image and the filtered one, obtained by applying the procedure presented in Image Enhancement section. Only one image of this pair is randomly chosen and presented to the user. The other image will not be shown to the same user during the test, to avoid any kind of memory effect.

Group #2 is composed by Ishihara images (Figure 4, first column: original image, second column: filtered image), and group #3 by natural images (Figure 5). In this case too, the subset of color plates in group #2 is enough for a short-version examination. The rationale beyond the choice of images in group #3 is the presence of clearly distinguishable different colors.

We decided on purpose to use uncalibrated images without a particular chromatic characterization in order to represent the typical web surfing conditions.

Table I reports the questions asked to the user, together with the group number, the image name and the availability or not of the filtered version. The question for the Ishihara

Table I. Questions associated to each group/image.

Group #	Question	Image description	Filtered version
1	Which number do you see?	Ishihara plates (#1, #2, #7, #9, #14, #16)	No
2	Which number do you see?	Ishihara plates (#3, #6, #8, #17, #13)	Yes
3	How many red berries are there?	Natural image — Berry	Yes
3	How many caps of different colors do you see?	Natural image — Caps	Yes
3	How many green balloons do you see?	Natural image — Balloons	Yes
3	How many balls of different colors do you see?	Natural image — Balls	Yes
3	How many colored flowers are there and which are their colors?	Natural image — Flowers	Yes
3	How many balls of different colors do you see?	Natural image — Balls pool	Yes
3	How many climbing holds of different colors do you see?	Natural image — Climbing holds	Yes

plate is always the same: we ask for the number hidden in the plate, while for the natural image, it is related to the image content.

It has to be noticed that the two questions about red berries and green balloons are prone to potential ambiguity in the results for CVDs, for which a color name related to their deficiency could not necessarily carry the standard meaning for them. Thus, regarding these two questions, the difficulty of CVDs to assign the correct meaning to a color name (the one related to their deficiency) is added to the performance of the tested algorithm. Taking a closer look at the data from these two questions, one can notice a moderate shift using the algorithm; this suggests that a potential quantitative bias is not strong enough to affect qualitatively the overall results.

All questions related to color names and differences carries the unavoidable uncertainty associated to the use of color terms, rather than color measurements. We were aware of this problem since the very beginning of experiment setup design. For this reason we have carefully chosen images that minimize uncertainty in color terms by avoiding the use of too near color tones. Some subjects reported ambiguity between counting of different objects and that of different colors. This derived from the translation from the Italian. In all these cases we have pointed out the correct interpretation.

RESULTS

415 people participated in the remote experiment: 299 assessed to be no-CVDs, and 116 to be CVDs. People were recruited with two main approaches. First, by asking colleagues, friend and students to do the test and to share it. This resulted in the great majority of tests by people without CVD. Second, we contacted associations of people with CVD, that helped us finding most people with CVD. Since the application was localized in English and Italian, we contacted associations in Italy, US, UK and Australia.

From this set of experiments, we removed incomplete data and users for whom the results of our classification are highly in contrast to what was self-declared in the initial questionnaire. Therefore, finally, we considered 242 no-CVDs and 84 CVDs. Among no-CVDs the statistics are the following: 52.3% are males, while 47.7% are females. They are divided in these categories: 15–25 years old: 37.2%, 26–35: 29.3%, 36–45: 24.1%, 46–55: 7.7%, 56–65: 1.7%, no one over 65 years old.

Among CVDs the statistics are 95% are males and 6% females. The percentages, by age ranges, for this group are: 15–25: 31.7%, 26–35: 35.6%, 36–45: 17.7%, 46–55: 7.5%, 56–65: 5.8%, over 65: 1.7%.

Table II shows the general results divided by groups.

As expected, the control Plate #1 is correctly seen by the 100% of both no-CVDs and CVDs. The percentages of group #1 are in line with what was expected: the 97.3% of no-CVDs correctly identifies the number inside the Ishihara plates, while only the 26.5% of CVD people succeeds in the task.

More interesting for our purpose are the results of groups #2 (Fig. 4) and #3 (Fig. 5). In general, we note that the application of the filtering:

- Worsens the interpretability of Ishihara plates for no-CVDs, while improves it for CVDs.
- Does not affect the interpretability of natural images for no-CVDs, while worsens it for CVDs.

These comments seem to be valid on a general averaged level. Interesting variability in the data appears when we analyze the results of the single images, according to the group. In Figs. 4 and 5, all the images used to test the presented Daltonization method are shown. The first two columns show the original and the filtered image, while the third and the fourth reports the percentage of correct answers both for no-CVDs and CVDs, respectively.

The error on the proportions of Binomial counts has been computed as follows:

$$\sigma = \sqrt{\frac{pq}{n}} = \sqrt{\frac{k\left(1-\frac{k}{n}\right)}{n}},$$

where p is the estimate of the true ratio and $q = (1 - p)$, whereas k is the correct answer count and n the total number of answers.

The results about group #2 (Fig. 4, Ishihara plates) are presented in Table III, where also the trend is reported

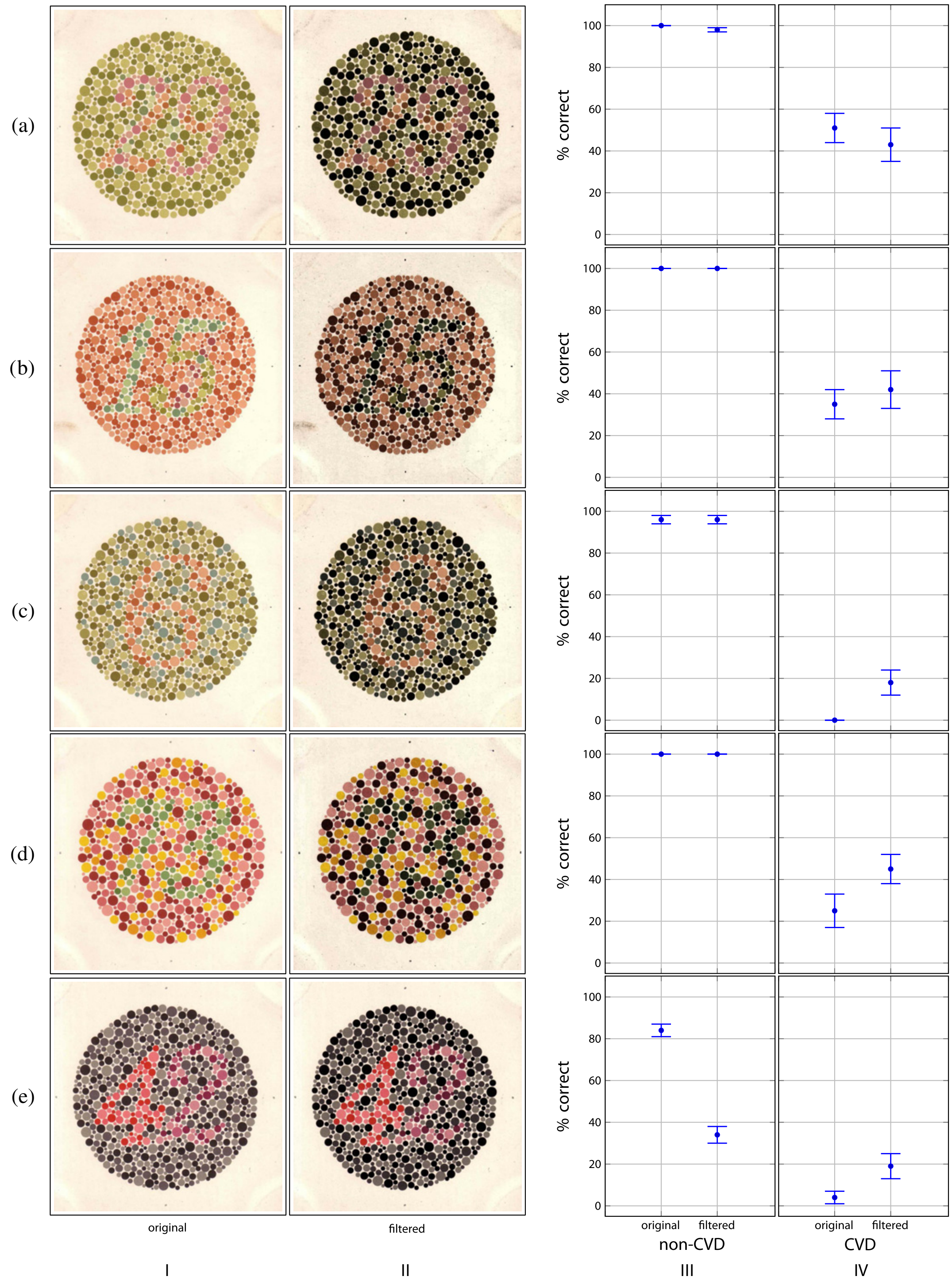

Figure 4. Data related to group #2. Column I: original image, column II: filtered image, column III: percentage of correct answers by non-CVDs, column IV: percentage of correct answers by CVDs. The error bars indicate the 1σ standard error of the frequency estimate.

(where: "=" indicates equality, "↘" and "↗" indicate a decrease or increase of correct answers from original version to filtered version, respectively) along with their significance level expressed in terms of p-value. The latter has been computed by performing the Student-t test for the comparison of two proportions. This test is appropriate because the samples were independent, and the sample size was large. We adopted as null hypothesis the hypothesis that the two population proportions are the same; furthermore, we used one-tailed (directional) tests, since an extreme value on one side of the sampling distribution would be sufficient to reject the null hypothesis, at the same time confirming a trend.

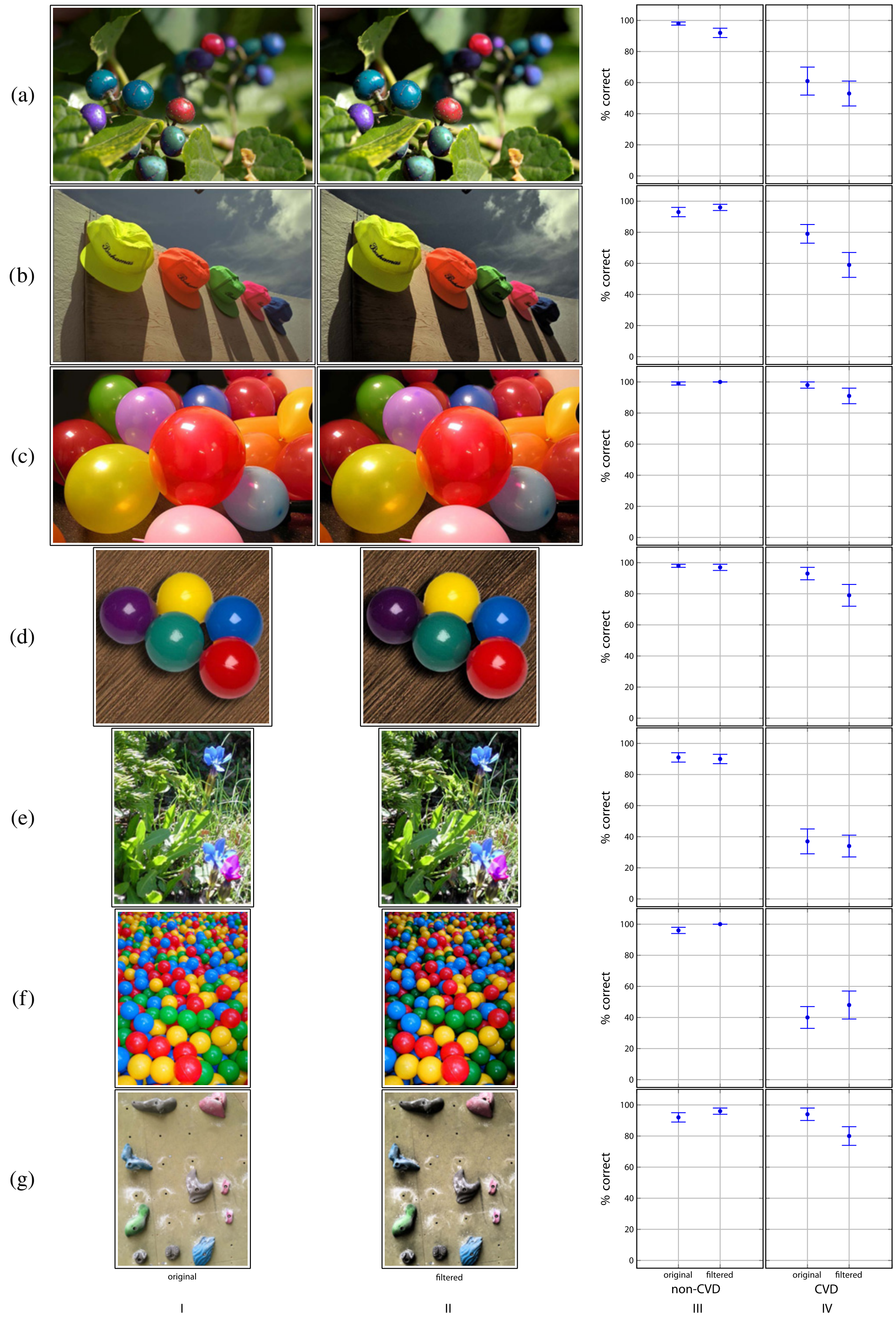

Figure 5. Data related to group #3. Column I: original image, column II: filtered image, column III: percentage of correct answers by non-CVDs, column IV: percentage of correct answers by CVDs. The error bars indicate the 1σ standard error of the frequency estimate.

Results on Ishihara plates are congruent with previous Experiments,[2] when no chromatic border is present: increasing the overall contrast helps CVDs in almost all cases. An important improvement for CVDs takes place in correspondence to three images when the filtering is applied (Fig. 4(c): from 0% to 18.2%; Fig. 4(d): from 25.0% to 44.9%; Fig. 4(e), from 4.4% to 18.9%). From Table III, we note an unexpected decrease in visibility of the last Ishihara plate for no-CVDs (Fig. 4(e), from 84.1% to 33.9%). We do not have a clear explanation for this case: our conjecture is that this could be related to an excessive increment of luminance contrast made by the *c2g* component of the method. Contrast

Table II. General results divided by groups.

	no-CVD				CVD			
	Original		Filtered		Original		Filtered	
Group	Correct/Total	Correct	Correct/Total	Correct	Correct/Total	Correct	Correct/Total	Correct
1-Plate #1	242/242	100%	—	—	84/84	100%	—	—
1	1169/1201	97.3%	—	—	111/419	26.5%	—	—
2	528/550	96.0%	496/577	86.0%	51/211	24.2%	66/189	34.9%
3	632/663	95.3%	685/716	95.7%	198/275	72.0%	162/257	63.0%

Table III. Numerical data and percentages for the comparisons of the original and filtered images for No-CVD and CVD observers; observed trends and corresponding p-values. The p-values greater than 0.95 have been highlighted in bold. Results for group #2 – Ishihara plates (referred to Fig. 4).

	No-CVD					CVD				
	Original		Filtered			Original		Filtered		
Fig. 4	Correct/Total	Correct	Correct/Total	Correct	Observed trend & p-value	Correct/Total	Correct	Correct/Total Total	Correct	Observed trend & p-value
a	104/104	100.0%	118/120	98.3%	↘0.92	23/45	51.1%	16/37	43.2%	↘0.76
b	109/109	100.0%	117/117	100%	=	18/51	35.3%	13/31	41.9%	↗0.72
c	108/112	96.4%	109/114	95.6%	↘0.62	0/38	0.0%	8/44	18.2%	↗**1.00**
d	112/112	100.0%	114/114	100.0%	=	8/32	25.0%	22/49	44.9%	↗**0.97**
e	95/113	84.1%	38/112	33.9%	↘**1.00**	2/45	4.4%	7/37	18.9%	↗**0.98**

Table IV. Numerical data and percentages for the comparisons of the original and filtered images for No-CVD and CVD observers, quoted with two digits accuracy; observed trends and corresponding p-values. The p-values greater than 0.95 have been highlighted in bold. Results for group #3 – natural images (referred to Fig. 5).

	No-CVD					CVD				
	Original		Filtered			Original		Filtered		
Fig. 5	Correct/Total	Correct	Correct/Total	Correct	Observed trend & p-value	Correct/Total	Correct	Correct/Total	Correct	Observed trend & p-value
a	96/98	98.0%	91/99	91.9%	↘**0.97**	20/33	60.6%	23/43	53.5%	↘0.73
b	89/96	92.7%	97/101	96.0%	↗0.84	33/42	78.6%	20/34	58.8%	↘**0.97**
c	95/96	99.0%	101/101	100%	↗0.84	40/41	97.6%	32/35	91.4%	↘0.87
d	93/95	97.9%	99/102	97.1%	↘0.65	40/43	93.0%	26/33	78.8%	↘**0.96**
e	68/75	90.7%	110/122	90.2%	↘0.55	13/35	37.1%	14/41	34.1%	↘0.61
f	96/100	96.0%	97/97	100.0%	↗**0.98**	18/45	40.0%	15/31	48.4%	↗0.76
g	95/103	92.2%	90/94	95.7%	↗0.85	34/36	94.4%	32/40	80.0%	↘**0.97**

increment in STRESS and *c2g* is highly dependent on the image content and in some cases can be excessive. To deal with these cases an automatic measure of contrast can tune the parameters before accepting the result of *c2g* module.

We took the same approach with the natural images, analyzing them individually (Table IV).

For no-CVDs, data confirms the general trend: the interpretability of natural images remains unchanged. For CVDs, it seems that an increment of luminance contrast does not result in an advantage: except for one case, the filtered images are slightly more difficult to interpret than the original ones. Here, the strong increment of luminance contrast due to *c2g* can also have a role and should be better investigated in future works.

As an overall comment, data confirms that contrast plays a role for CVDs, even if in some cases it leads to a decrement rather than an improvement in readability, as indicated by Fig. 5.IV.

CONCLUSIONS

In this work, we presented the results of a test, administered as a mobile application, to assess the performance of SiChaRDa, a novel proposed image enhancer for people with

CVDs that works on the lightness channel, without changing the hue.

The use of a mobile app that allows to reach a large number of participants, in different countries, with different characteristics (age, gender, type of CVD), to collect a great amount of data, has also been shown.

Two different sets of images have been tested: five Ishihara plates and seven natural images. While there is no significant difference in the results for people with a normal color vision, interesting evidences, although contradictory, emerge about CVDs. In fact, the readability of the Ishihara plates filtered with the presented method generally increases. On the other hand, natural images do not seem to benefit from the filtering, and in many cases their readability decreases (as it appears in Fig. 5, column IV).

In conclusion, data indicate a role of contrast and edges for CVDs, but the results do not support an unambiguous interpretation. In CVD research, often the role of edges is underrated: other features are typically investigated. Our hope is that the present work could be a stimulus for further research in this direction.

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