Optimising the Choice of Colours of an Image Database for Dichromats

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Abstract. Colour appears to gradually play more and more significant role in the modern digital world. However, about eight percent of the population are protanopic and deuteranopic viewers who have difficulties in seeing red and green respectively. In this paper, we identify a correspondence between the 256 standard colours and their dichromatic versions so that the perceived difference between any pair of colours seen by people with normal vision and dichromats is minimised. Colour dissimilarity is measured using the Euclidean metric in the *Lab* colour space. The optimisation is performed using a randomised approach based on a greedy algorithm. A database comprising 12000 high quality images is employed for calculating frequencies of joint colour appearance used for weighting colour dissimilarity matrices.

1 Introduction

Data mining is an active field of research with significant effort being devoted in the recent years into the problem of content-based image retrieval. A large number of such approaches rely on using the colour content of an image as a cue for similarity with a query image [1]. Although colour is not the single most important characteristic which allows one to describe a scene or an object, colour is often being used to attract attention of the viewer to something, to stress something, or even to entice the viewer to a certain product. Colour appears to gradually play more and more significant role in the modern world, and to become a significant part of modern technology, being vital in applications like e-commerce and the digital entertainment industry. And yet, 8% of the population see colours in a totally different way from the rest [2], [3], [4]. These are the people who suffer from some sort of colour blindness, and they usually can distinguish only two hues. They are the protanopic and deuteranopic viewers who have difficulties in seeing red and green respectively. Such people are collectively known as dichromats. A small fraction of people can only see a single hue, and these are the truly colour-blind people [2].

An important issue then arises, concerning the colour world as seen by these viewers, the way it appears to them, and whether the use of colour conveys to them the same information it conveys to normal viewers [5], [3]. Several studies have been done to answer this question, and indeed we know with pretty high confidence the way the world looks like through the eyes of such viewers (eg [4]). Further, studies have been made in the way colour coded information should be displayed (eg the Paris underground map [5]) so that it is equally useful to all viewers. However, the issue of database search for dichromats using colour as a cue has received much less attention [6]. “An image is a thousand words”, and an image conveys information by the relative colours and contrasts it contains. If a person does not see these contrasts caused by the use of different colours, the person may miss a significant part of the information conveyed by the image. One approach would have been to map all colours in such a way that they will appear as distinct as possible to a dichromat. This, however, might destroy the overall appearance of a picture, as it may create strong contrasts at places where the originator of the picture did not intent them to be. In this paper, we take the view that the perceived difference between the various colours in an image should be preserved by any colour transformation scheme aimed at dealing with the problem of dichromacy. So, we are trying to identify a correspondence between the 256 colours of the standard palette [5], [4], and the 256 colours to which each one of them is transformed by the vision system of the dichromat, so that the perceived difference between any pair of them by a normal viewer and a dichromat viewer is preserved as much as possible. In this work we do not deal with the totally colour blind people who form a very small fraction of the population. Blue-blind people (known as tritanopes), are also extremely rare [2].

At first sight it may seem impossible to map a 3D space to a 2D one and preserve all distances at the same time: The colour space of a normal viewer is 3-dimensional, while the colour space of a dichromat is 2-dimensional, having lost one of the hues. However, one may exploit the differences in perceived saturation to achieve an approximate invariance in perceived difference, and obtain an optimal solution given the constraints of operation. Further, one may consider a weighted approach, where colours that are encountered more often are given more importance than colours that are less frequent. To identify which colours are more frequent we created the normalised 3D colour histogram of each image in a database of natural scenes, and used it as the probability density function for each colour in the standard palette appearing in the image. A cost function was defined, measuring the difference in perceived difference between all possible pairs of colours of the 256 standard colour palette as seen by normals and as seen by dichromats. The perceived difference between any pair of colours was measured using the Euclidean metric in the *Lab* space of normals, and in the *Lab* space of the dichromats [7]. Each term in this cost function was multiplied with a weight which was the minimum value of the probability density function for the two colours as measured from the colour histogram of the corresponding image. This cost function was minimised by using a randomised approach based on a greedy algorithm. This of course does not guarantee the optimal solution, but good sub-optimal solutions could be found. In section 2 we present details of the cost function, the optimisation method, and the image database we used. In section 3 we report the results of our study. Finally, in section 4 we draw our conclusions.

2 Materials and Methods

2.1 Colours Used in This Study

In this study we limit ourselves to the 256 colours considered in [5], [4] together with their dichromatic versions as seen by protanopes and deuteranopes (Figure 1).

Construction of dichromatic versions of the colours is based on the LMS specification (the longwave, middlewave and the shortwave sensitive cones) of the primaries of a standard video monitor [8], [9]. The palette of 256 colours we use includes the 216 standard colours that are common for the majority of recent computer applications and computing environments. Conversion from trichromatic to dichromatic colors is done using the *dichromat* package implemented by Thomas Lumley within the R, a language and software environment for statistical computing and graphics [10]-[11].

Note that everywhere in this work colours that differ from those represented in the palette are mapped onto the perceptually closest colours of the palette using the nearest neighbour rule.

2.2 Image Database

The image database we use comprises twelve thousand color RGB images (computer wallpaper photographs) of wide semantic diversity. By convention they are subdivided into 41 categories such as animals, art, aviation, birds, cars, history, food, fantasy, gifts, insects, money, machines, mountains, people, sea, patterns, trains, etc. The original image size of 1024×768 pixels has been reduced by a factor of two to 512×384 for convenience. This database was also used in work [6] concerned with the problem of content-based image retrieval for colour-blind people.

2.3 The Cost Function

The basic idea for improving colour replacement for dichromats is to optimise the mapping of normal colours to their dichromatic versions so that perceived difference between any pair of normal colours is preserved in colour-blind space as much as possible. Let d_{ij}^{NR} and d_{ij}^{CB} be the perceived difference between colours c_i and c_j in the normal and the colour-blind space respectively. Then the cost function formalising the requirement of a best mapping can be written as:

$$U = \sum_{i=1}^{Nc} \sum_{j=1}^{Nc} \left| d_{ij}^{NR} - d_{ij}^{CB} \right|,$$

where Nc is the number of colours (dimensionality of colour space), $Nc = 256$. For measuring colour dissimilarity d_{ij} we use the CIE *Lab* colour space [7]. In this space the L component represents the luminance while a and b are the red/blue and yellow/blue chrominances respectively. In the *Lab* space the dissimilarity between the two colours c_i and c_j is computed as the Euclidean distance:

$$d_{ij} = \sqrt{(L_i - L_j)^2 + (a_i - a_j)^2 + (b_i - b_j)^2}$$

The cost function U defined above represents the requirement of a minimal deviation of colour dissimilarity observed by dichromats from the colour dissimilarity in subjects with normal vision. However, the colour confusion characteristic for dichromats (see Figure 1) reduces the effective number of distinctive colours, which can be potentially used. Thus, it is worth considering a *weighting* scheme that gives certain emphasis to the colours which appear frequently conjointly in real-world situations:

$$U_w = \sum_{i=1}^{Nc} \sum_{j=1}^{Nc} |d_{ij}^{NR} - d_{ij}^{CB}| \omega_{ij},$$

where ω_{ij} denotes the frequency of joint appearance of colours c_i and c_j.

Note that in both weighted U_w and non-weighted U versions of the cost function we measure the deviation of colour dissimilarities in dichromats from those in subjects with normal vision simply as the sum of absolute values (ie the $L1$ norm) but not as the Euclidean or any other distance metric. This is because the $L1$ norm has been demonstrated to have more consistent behaviour in other similar studies (eg [6], [12], [13]).

2.4 Calculating the Joint Colour Appearance Matrix

Calculating the weighted cost function U_w assumes availability of the frequencies of joint appearance ω_{ij} of all possible pairs of colours c_i and c_j. Clearly, a precise calculation of weighting frequencies ω_{ij} is not possible because it requires analysing a universe of images of real-world scenes. However, since the image database we use is reasonably large and of great content variability, it could provide an acceptable estimate of the frequencies of joint colour appearance. Thus, the estimated frequencies ω_{ij} were calculated in the form of a joint colour appearance matrix, ω, the elements of which represent the frequency of joint appearance of all possible pairs of colours in the images of the database:

$$\omega_{ij} = \sum_{k=1}^{N_{IMG}} \min\{A(c_i^k), A(c_j^k)\},$$

where $A(c_i^k)$ and $A(c_j^k)$ are the values of the normalised 3D colour histogram of the $k-$th image for colours c_i and c_j respectively, and N_{IMG} is the total number of images.

Figure 2 shows the joint colour appearance matrix calculated using the database. The matrix element values are colour-coded using the colour scale provided on the right. For illustrative purposes, the large values along the matrix leading diagonal were mapped to the maximum of the remaining values in order to allow the details of the rest of the matrix to be visible.

2.5 Optimisation Method

The cost functions U and U_w were minimised by using a randomised approach based on a greedy algorithm. At each iteration step we choose at random an arbitrary colour c_m^{CB} from the colour-blind palette and replace it by another arbitrary colour c_n^{CB}. The replacement is accepted if it reduces the cost function value. No limitations are applied to the new colour c_n^{CB} except $n \neq m$. This means that colour duplication, colour removal, and transitive restitution of certain colours are possible. The latter operation adds some stochastisity to the algorithm, allowing it to retrace its steps and thus increases its chance to escape from local minima. In general, this algorithm does not guarantee the optimal solution, but good sub-optimal solutions could be found.

The method is implemented using the R language, a free version of S [10] on a P4 3.2GHz PC machine with 2Gb RAM. Depending on the input data, the optimisation procedure takes approximately from 3 to 5 hours to converge.

3 Results

3.1 Optimising Dichromatic Colours Without Weighting

At this stage optimisation was performed without considering the frequency of joint colour appearance. The optimisation procedure was run for protanopes and deuteranopes separately.

In case of protanopia (see Figure 3), the initial cost function value $U = 30.49$ dropped down to $U = 14.04$ during the first quarter of the optimisation process ($N = 1.35 \times 10^5$ iterations) and finally converged to the value $U = 13.89$ in $N = 5.4 \times 10^5$ iterations (Figure 3a). These led to substantial changes of the original colour dissimilarity matrix (Figure 3c,d), which became similar to the colour dissimilarity for normal vision (Figure 3b). An iteration in this case is a proposed change of the mapping of colours either it reduces the cost function and so it is accepted, or it does not and so it is rejected.

Optimisation process for the deuteranopic colours (Figure 4) went in a very similar way with slightly slower convergence. As a result, the initial cost function value $U = 20.37$ was reduced almost twice down to $U = 11.92$. In spite of certain differences that can be noticed in the structure of the original colour dissimilarity matrices for protanopia and deuteranopia (see Figure 3c and Figure 4c), the optimised versions were very similar (Figure 3d and Figure 4d).

It should be pointed out that in both occasions the final cost function value remained noticeably different from zero. This is because reduction of the cost function value is proportional to the reduction of the colour gamut in dichromats relatively to normal vision. Thus, converging to zero is not possible in that case.

3.2 Optimising Dichromatic Colours With Weighting

Finally, the optimisation of dichromatic colours was conducted with consideration of the frequencies of joint colour appearance illustrated in Figure 2. The matrix elements ω_{ij} were treated as weights for colour dissimilarities depicted in figures 3c and 4c and the cost function U_w was minimised for both protanopia and deuteranopia.

As a result of the optimisation, the initial cost function value $U_w = 2.38$ was reduced down to $U_w = 1.42$ for protanopic colours and from $U_w = 1.70$ down to $U_w = 1.10$ in case of deuteranopia. During the optimisation process the cost functions behaved similarly to the non-weighted optimisation reported above. Resultant colour dissimilarity matrices for protanopia and deuteranopia are shown in Figure 5. As it can be seen, the optimised dissimilarity matrices depicted in figures 5a and 5b are clearly distinguishable from their non-weighted versions presented in figures 3d and 4d respectively.

The results of colour optimisation using all the ways explored in this study are summarised in Figure 6, where higher colour dissimilarities are evident, after the proposed method is applied.

4 Conclusions

Results reported with this study allow one to draw the following conclusions:

1. The method of optimising the choice of colours of an image database for dichromats suggested in this paper is computationally efficient and able to deal with colour space distortions caused by different kinds of colour deficiency.

2. Any *a priori* knowledge like statistical information about the frequencies of different colours, and other preferences can be incorporated into the cost function in the form of a weighting matrix.

3. A further study is necessary to investigate the role of an additional optimisation constraint reflecting the (possible) requirement of matching the dichromatic colours with the ones in normal vision in order to minimise psycho-physiological and emotional differences in the perception of real-world scenes.

Acknowledgments

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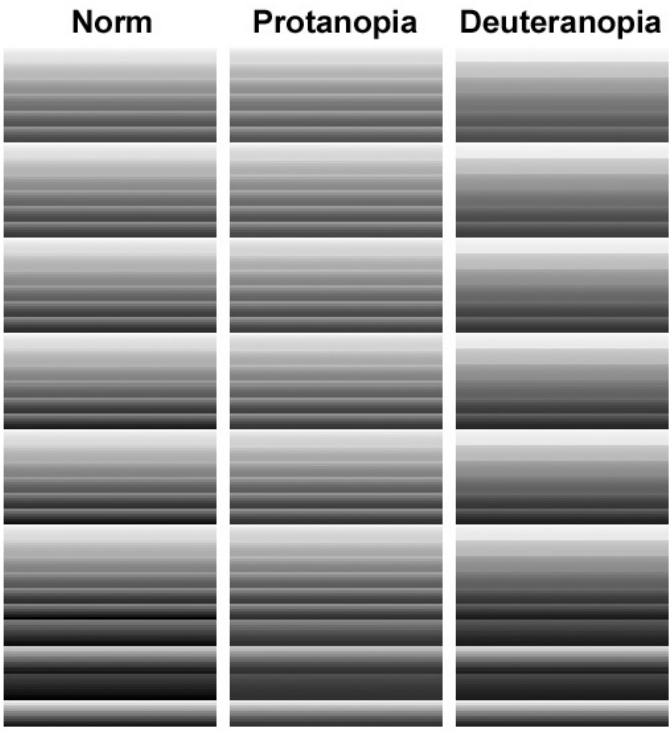

Fig. 1. Palette of 256 colours used in this study as seen by people with normal vision (left column), protanopes (middle column), and deuteranopes (right column)

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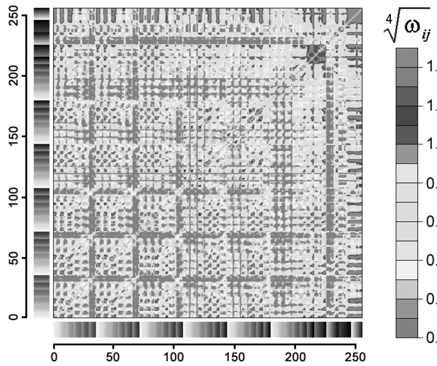

Fig. 2. Matrix of the frequency of joint colour appearance calculated by using the database of twelve thousands images. The matrix element values ω_{ij} are represented by using the non-linear colour scale provided on the right. The high values along the diagonal have been suppressed to show the details in the rest of the matrix.

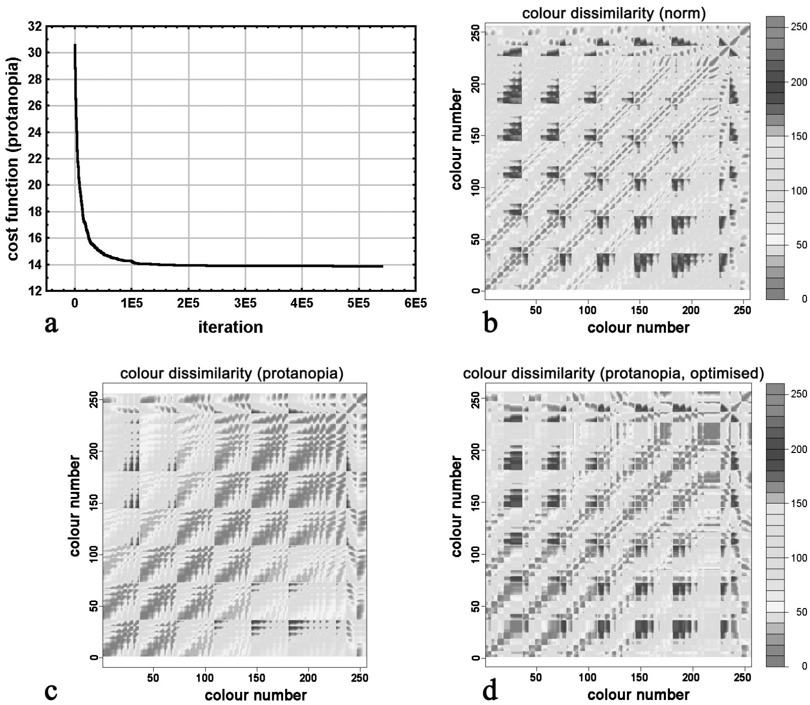

Fig. 3. Optimising protanopic colours without weighting. (a) Changes of the cost function with the iteration steps. (b) Colour-coded representation of the colour dissimilarity matrix for normal vision. (c-d) Colour dissimilarity matrix for protanopia before and after the optimisation. The matrix element values are represented using the linear scale provided on the right.

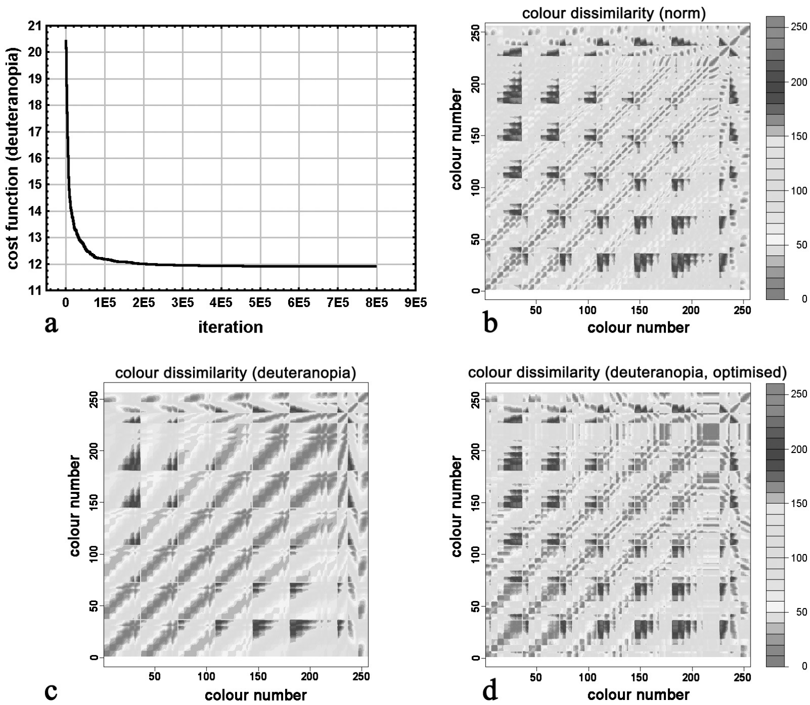

Fig. 4. Optimising deuteranopic colours without weighting. (a) Changes of the cost function with the iteration steps. (b) Colour-coded representation of the colour dissimilarity matrix for normal vision. (c-d) Colour dissimilarity matrix for deuteranopia before and after the optimisation. Matrix element values are represented using the linear scale provided on the right.

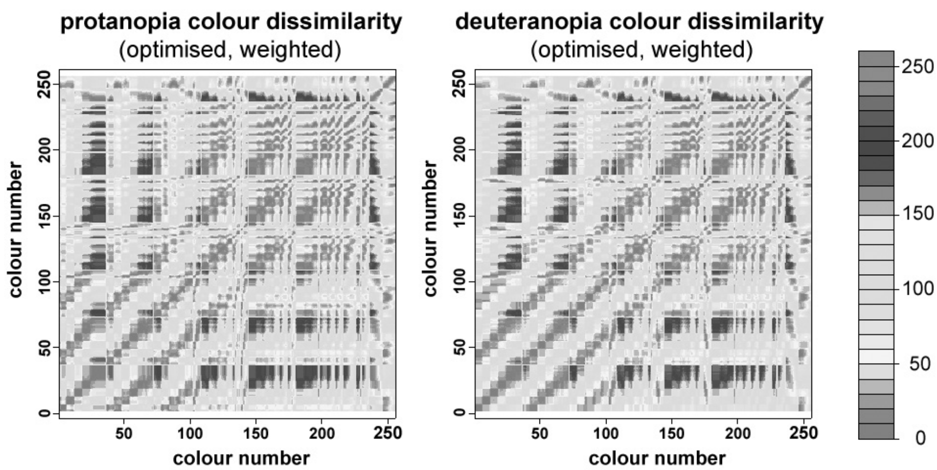

Fig. 5. Colour dissimilarity matrices for protanopia (left) and deuteranopia (right) after colour optimisation with weighting using the frequencies of joint colour appearance ω_{ij}.

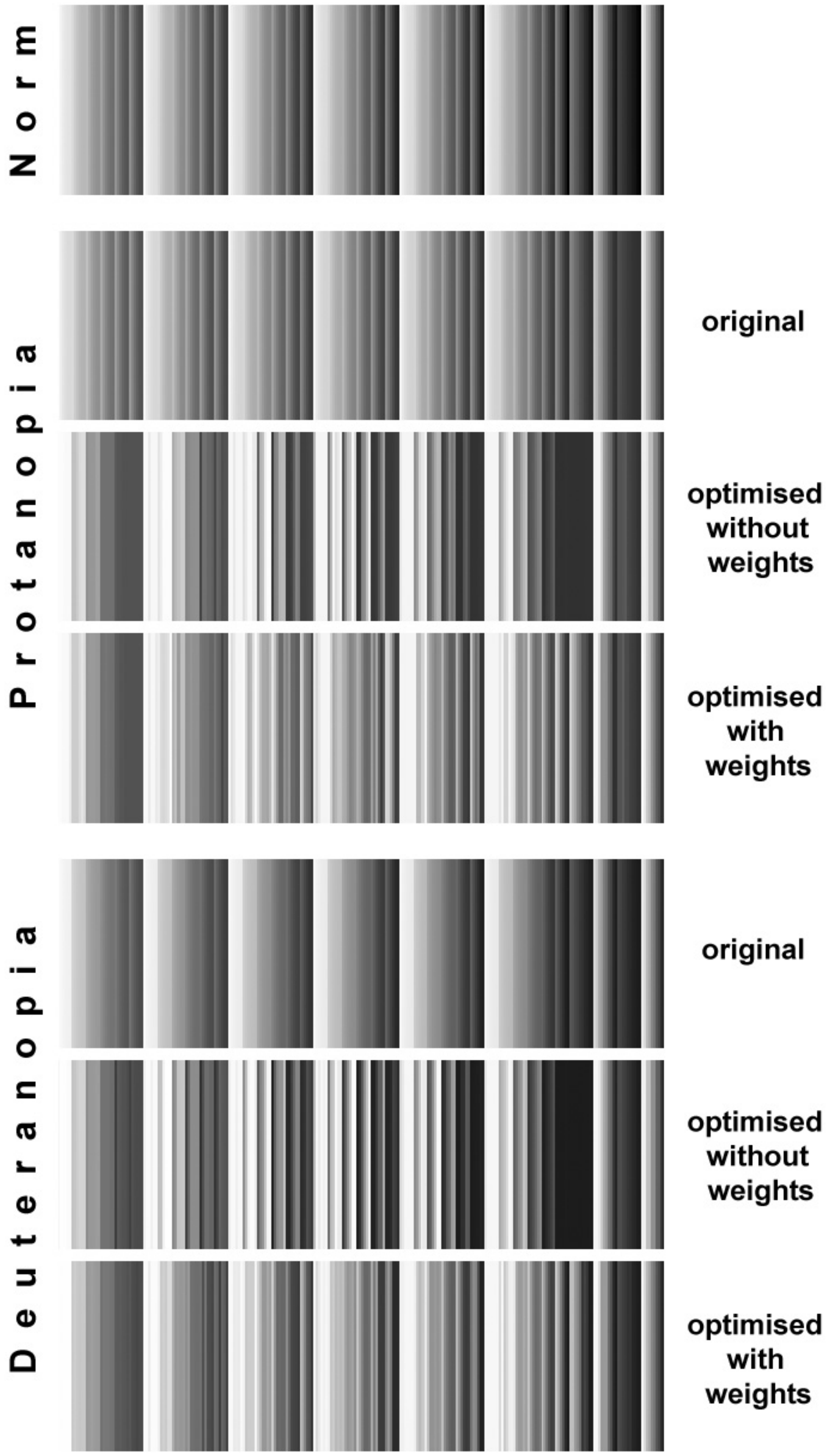

Fig. 6. Results of colour optimisation for all ways explored in this study. Colour palettes which show how much more colours can be distinguishable by colour-blind people after they have been remapped by the proposed methodology.