Modelling of Chromatic Contrast for Retrieval of Wallpaper Images

Xiaohong W. Gao,[1]* Yuanlei Wang,[1] Yu Qian,[1] Alice Gao[2]

[1]Department of Computer Science, School of Science and Technology, Middlesex University, London NW4 4NT, United Kingdom

[2]Barts and The London School of Medicine and Dentistry, Queen Mary University of London, London, E1 2AD, United Kingdom

Received 7 November 2013; revised 6 May 2014; accepted 6 May 2014

Abstract: Colour remains one of the key factors in presenting an object and, consequently, has been widely applied in retrieval of images based on their visual contents. However, a colour appearance changes with the change of viewing surroundings, the phenomenon that has not been paid attention yet while performing colour-based image retrieval. To comprehend this effect, in this article, a chromatic contrast model, CAMcc, is developed for the application of retrieval of colour intensive images, cementing the gap that most of existing colour models lack to fill by taking simultaneous colour contrast into account. Subsequently, the model is applied to the retrieval task on a collection of museum wallpapers of colour-rich images. In comparison with current popular colour models including CIECAM02, HSI and RGB, with respect to both foreground and background colours, CAMcc appears to outperform the others with retrieved results being closer to query images. In addition, CAMcc focuses more on foreground colours, especially by maintaining the balance between both foreground and background colours, while the rest of existing models take on dominant colours that are perceived the most, usually background tones. Significantly, the contribution of the investigation lies in not only the improvement of the accuracy of colour-based image retrieval but also the development of colour contrast model that warrants an important place in colour and computer vision theory, leading to deciphering the insight of this age-old topic of chromatic contrast in colour science. Col Res Appl, 40, 361–373, 2015; Published Online 30 May 2014 in Wiley Online Library (wileyonlinelibrary.com). DOI 10.1002/col.21897

*Correspondence to: Xiaohong W. Gao (e-mail: x.gao@mdx.ac.uk)
Contract grant sponsor: JISC, UK.

Key words: colour appearance model; simultaneous chromatic contrast; colour-based image retrieval; computational colour; chromatic adaptation

INTRODUCTION

While content-based image retrieval (CBIR) has been researched for nearly three decades, it remains debatable on whether it can ever meet users' expectations. On the one hand, due to the exponential increase of digital images, the demand for retrieving relevant data in an efficient, sufficient and effective way is high, especially among those images in the internet that are not properly labelled, to complement the current text-based approaches. On the other, the subjectiveness of the interpretation of an image can lead to associations varying considerably between low-level visual contents (notably, colour, texture and shape) and high-level semantics (such as 'children are playing'). To cement this gap, in general, the development of algorithms for extraction of those low-level visual features has been endeavoured to endorse with human vision theories. For example, to represent visual texture information, perceptual texture features coupled with wavelet domain have been established in Ref. [1] to perform pattern-based retrieval, whereas for retrieval of trademark images, deformable models are proposed to retrieve images by shape, the feature that plays a dominant role in determining those images of interest.[2]

More importantly, colour, in many ways, among many visual features presented in an image, tends to be a decisive factor, such as in determining the purchase of clothing or the selection of wallpapers for interior decorations. Additionally, with regard to internet retrieval, colour can be processed faster in real time due to the availability of many well-established colour theories and models, which has led to much wider employment of colour spaces and models in CBIR systems than any other feature models. While colour-based approaches use colour spaces of mainly RGB, HSV, CIELAB and CIELUV, those spaces do not take simultaneous colour contrast into consideration.

Although an image begins by being represented using RGB colour space when it is in a digital form, it is usually converted into HSI (hue, saturation and intensity) colour space to circumvent the dependency nature of RGB space on hardware devices, that is, a colour in one device usually does not appear nor measure the same as the one in another device even with the same RGB values in both devices. This is because the range of R, G or B values are manually set to be the same (such as [0, 255] for an 8-bit computer) for all monitors regardless their physical measurements. Conversely, HSI space agrees more with human vision theories. To improve the fitness between users' perception and retrieved results further, colour appearance based retrieval has been proposed by Qiu[3] and Othman and Martinez.[4] Qiu paid attention to the development of distance formulae, whereas Othman and Martinez, patterned colour is in focus. However, due to the convoluted nature of human vision systems, colour appearance changes with the change of backgrounds. Thereby, although a query image and retrieved images may have similar physical measurements of colour attributes in terms of, say, lightness, colourfulness or hue, perceptually, they do not match, prompting the research conducted in this article. The main intention of this study is to retrieve similar wallpaper images with colour intensive backgrounds by taking considerations of not only dominant background colours but also foreground ones, which leads to the call for a model that can embed both colour appearance and colour contrast spontaneously.

Simultaneous colour contrast, or in short, colour contrast, refers to the phenomenon that colour appearance changes with the change of its surrounding colours, which has played an important part in traditional art and design practices. Although this effect has been investigated for more than a century, it still puzzles researchers who have conducted investigations from various angles. For example, in the 1940s, the effect of chromatic adaptation was studied on achromaticity,[5] which was subsequently quantified by MacAdam who formulated a way to calculate dichromatic white light precisely. In his seminal paper, MacAdam[6] calculated the maximum attainable luminous efficiency for every point in the CIE 1931 chromaticity diagram. More recently, this effect was further explored experimentally by taking a different view at colour induction by Ekroll and coworkers.[7] In their study, they have found the point in achromaticity space that appears grey is different from the point on which lines of constant hue converge while with infields under chromatic surrounds, leading to a number of points confirmed by their experiments. Furthermore, in relation to image processing while taking simultaneous contrast and colour consistency effect into consideration, McCann[8] discusses computational models that mimic human visual image processing, the scope of human colour and the limitations that separate human colour processing from other mechanisms.

Usually, colour effect can be subjectively specified by means of visual percept.[9] By definition given by the CIE (Commission internationale de l'éclairage),[10] the hue, colourfulness and lightness, abstracted from complete visual experiences, are used to represent dimensions along which colour may vary independently. For example, hue is defined as the attribute of a visual sensation according to which an area appears to be similar to one, or to proportions of two, of the perceived colours, red, yellow, green and blue, whereas colourfulness constitutes the attribute of a visual sensation according to which an area appears to exhibit more or less of its hue. Conversely, while brightness implies the attribute of a visual sensation according to which an area appears to exhibit more or less light, lightness refers to the brightness of an area judged relative to the brightness of a similarly illuminated area that appears to be white or highly transmitting.[10]

As an illustration, Fig. 1 elaborates this simultaneous contrast effect by replacing the background colour of an original wallpaper image (top-left) with different hues, that is, yellow, red, cyan, green, blue, purple and white, respectively, while the foreground colours remain the same. Noticeably, the green leaves in the original image can be perceived differently in the subsequent images with varying backgrounds. For example, the leaves pointed by green arrows appear much less colourful under the greenish backgrounds [(d) and (e)] and much greener while against red and purple backgrounds [(b) and (c)] than those appearing in the original image (a).

Traditionally, the effect of simultaneous colour contrast is studied in a three-field centre-surround paradigm[11] as demonstrated in Fig. 2(a). It has shown that the change of lightness, colourfulness and hue of an induction surrounding colour will all contribute to the change of a perceived colour located in the center, the result that holds for both reflection (displayed on a paper) and luminous (presented on a monitor) colour samples. In addition, simultaneous contrast is the change in appearance of a colour through the influence of a contrasting colour in the immediate environment[12] or surround, for example, a larger surrounding colour will influence the appearance of the smaller colour area. If the angular subtending of a colour is not too small (greater than 1°) then the effect of simultaneous contrast usually occurs,[13,14] that is, the colour tends to appear more like the opposite of the surrounding colour. Although chromatic induction has been a subject of prime interest throughout the history of vision research, this phenomenon is only partly understood. In this study, colour contrast is not only revisited from a slightly different perspective, but also has been employed in retrieving a collection of wallpaper images.

As mentioned above, the effect of simultaneous colour contrast is usually studied in a center-surround three-field paradigm[15] consisted of background, induction field and a test colour. To ensure the model developed in this study can be applied to the retrieval of wallpaper images consisted of only foreground and background as shown in Fig. 1, the design of the experiment, tends to be a two-

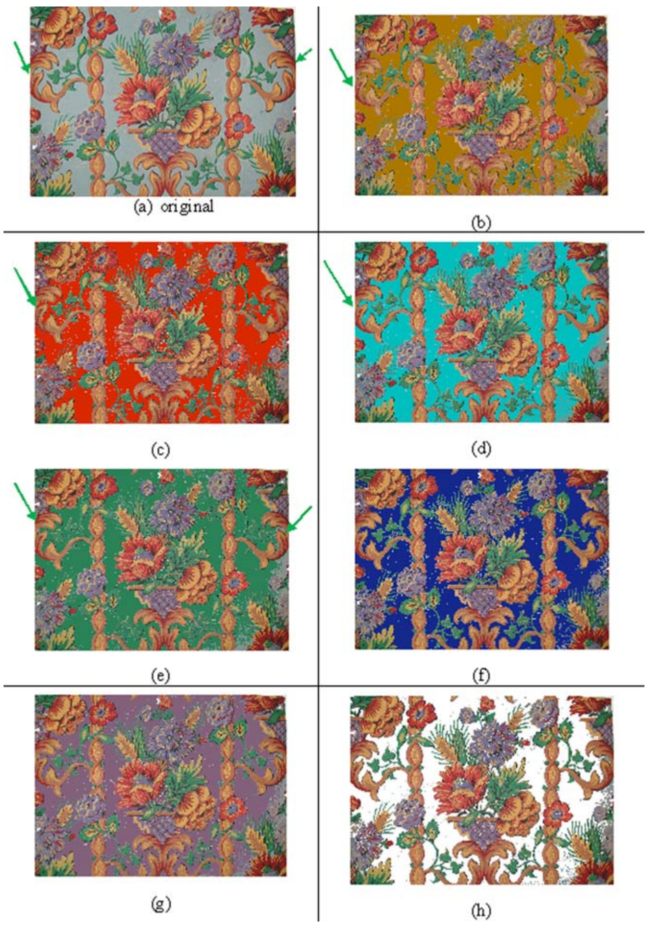

Fig. 1. The effect of simultaneous chromatic contrast is demonstrated by showing the same image with different backgrounds. (a), the original image; (b)–(h), the image in (a) but replaced with different coloured backgrounds.

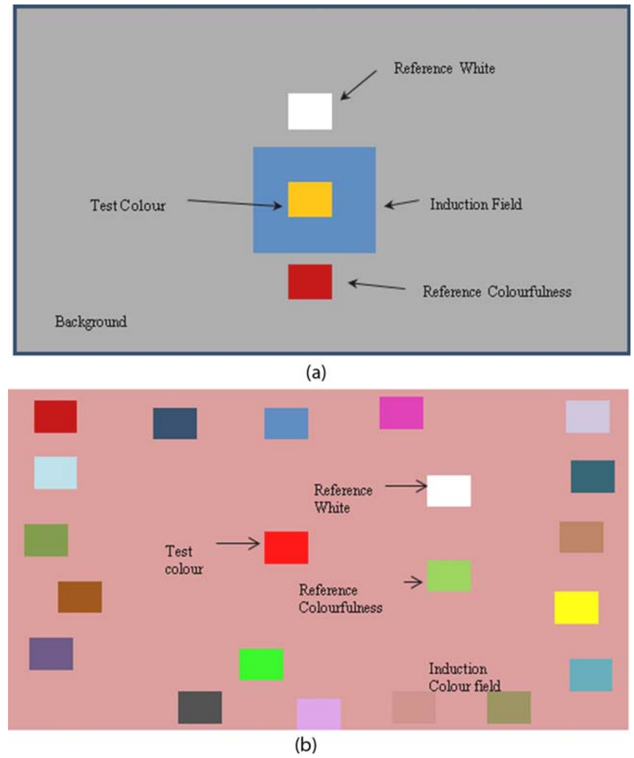

Fig. 2. (a) Traditional three-field experimental setup for studying simultaneous contrast; (b) two-field setup applied in this study. The colours close to the border of the pattern (b) are random surrounding colours.

field paradigm, by merging the induction field with the background as depicted in Fig. 2(b). Hence, this article constitutes two parts with phase 1 establishing a colour contrast model that in turn is applied in retrieving a collection of wallpaper images, to be carried out in phase 2, while contributing to further understanding of this age-old topic in colour science.

The remainder of the article is structured as follows. The Effect of Chromatic Contrast in a Two-Field Paradigm summarizes the psychophysical experiments that are conducted for this study, which is then followed by the establishment of a colour appearance model that embeds colour contrast effect, named as CAMcc, in Embedding Simultaneous Contrast Into Colour Appearance Model CIECAM02. Implementation of Colour Spaces and Models for Colour-Based Image Retrieval details the implementation of CAMcc and several other colour spaces in an attempt to perform colour-based image retrieval, together with the retrieval results. Release of the colour data and Matlab programs originated in this article are discussed in this section as well. Subsequently, last section concludes the work and discusses a number of issues raised in the investigation whereby future direction has been pointed to in its wake. In addition, the calculation of CAMcc is given in Appendix for further references.

THE EFFECT OF CHROMATIC CONTRAST IN A TWO-FIELD PARADIGM

The first part of this project is to study the effect of chromatic contrast in a two-field paradigm as illustrated in Fig. 2(b). Both test and background colour samples are randomly selected from the Munsell colour book while making an effort to cover as much CIE 1931 colour space as possible as depicted in Fig. 3. Psychophysical experiments are performed on a 19″ LCD monitor with its illuminant calibrated to D65. Sixteen coloured backgrounds together with 30 test colours are selected in these experiments, which are illustrated on a CIE $u'v'$ diagram as given in Fig. 3. Throughout all the experiments, the reference white, reference colourfulness and surrounding colours remain the same. As a result, during each individual experiment with a fixed colour background, only test colours change from number 1 to number 30, which is remotely controlled by an operator during the experiment, whereas the order of test colours differs in different experiments. The test field in the centre subtends a visual angle of 2° at a viewing distance of ~60 cm. Ten subjects with normal colour vision are selected to conduct the experiments using the technique of magnitude estimation,[16] which they have been trained in advance to apply skilfully. Specifically, for each test colour, each subject is

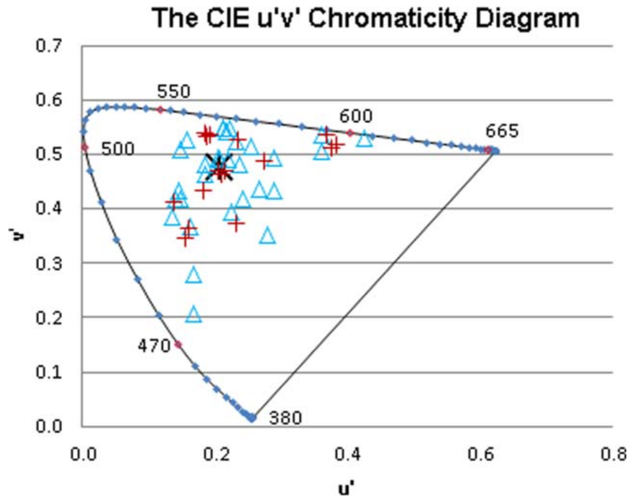

Fig. 3. Sixteen background colours presented on a CIE u′v′ chromaticity diagram (+). The '*' refers to the reference white, whereas the colour closest to the reference white is the grey background. The marks of nonfilled-triangles represent 30 test colour samples used in the study.

asked to estimate its appearance in terms of lightness, colourfulness and hue contents verbally that are then recorded by an operator sitting nearby. Careful consideration has been taken to ensure that the light emitted from the operator's computer does not affect the colour appearance on the subject's computer, whereas the definition of lightness, colourfulness and hue are the same as given in the introduction. In total, 480 ($= 30 \times 16$) test-background presentations are estimated, generating 14,400 ($= 480 \times 3$ estimation $\times$ 10 subject) data. The detailed experimental setting can be found in Ref. [17].

To a certain extent, the effects induced by a chromatic background from a three-field [Fig. 2(a)] are different from that obtained from two-field [Fig. 2(b)] paradigms. For example, in term of lightness, in two-field patterns, although darker background does make colours appear lighter, the effect that presents in three-field paradigms,[18,19] the amount of the shift (= 11–17%) in this study tends to be not significant when it is compared with the variations of estimations within subjects (= 17–21%). This can be reasoned with, by the fact that, in a two-field pattern, the reference white is with a test colour simultaneously against the same background [Fig. 2(b)], which can potentially lead to the coloured background contributing equally to the perceived lightness on both reference white and a test colour.

By contrast, the estimation of colourfulness appears to be effected largely by the change of lightness level of a background, that is, a darker background makes test colours appear more colourful, even though the reference colourfulness is also displayed on the same background with a test colour. In particular, under a red background, colours appear less colourful when the difference of luminance levels between two backgrounds decreases.

Another interesting phenomenon revealed in our psychophysical experiment is that a very colourful background will cause test colours to appear considerably less colourful. In addition, with regard to hue estimation, similar to the effect of simultaneous contrast discovered in a three-field pattern where there is an induction field, a colour shifts towards the opponent hue of the background. In other words, colours appear more reddish while against green surrounds, the phenomenon tends to be similar for the other hues.

EMBEDDING SIMULTANEOUS CONTRAST INTO COLOUR APPEARANCE MODEL CIECAM02

To model colour appearance, CIE has recommended a colour appearance model, CIECAM02.[20] Stemmed from Hunt's early colour vision model[21–23] using a simplified theory of colour vision for chromatic adaptation together with a uniformed colour space, CIECAM02 can predict the change of colour appearance as accurately as an average observer under a number of given viewing conditions. In particular, the way that the model describes a colour is reminiscent of subjective psychophysical terms, that is, hue, colourfulness, chroma, brightness and lightness.

To begin with, CIECAM02 takes into account of measured physical parameters of viewing conditions, including tristimulus values (X, Y and Z) of a stimulus, its background, its surround, the adapting stimulus, the luminance level and other factors such as cognitive discounting of the illuminant. The output of the colour appearance model predicts mathematical correlates of perceptual attributes. Table I summarizes the input and output parameters of CIECAM02.

With regard to the representation of the colour appearance of an image, in this investigation the perceptual colour attributes of lightness (J), colourfulness (M) and hue (H) are used and are detailed in Appendix.

Since the development of CIECAM02 is based on psychophysical experimental data that are obtained under neutral backgrounds, chromatic contrast is not embedded. Conversely to make such a prediction, Hunt[24] has proposed a solution by modifying the responses of ρ_w, γ_w and β_w for reference white by the inclusion of the same responses for both induction field and background using Eq. (1) where subscription p and b indicating ρ, γ and β signals for induction and background, respectively. This equation has been utilized to improve CIECAM02 where three-field paradigm is used.[19] As such, the value of p depends on the size and shape of an induction field and ranges between 0 and -1 for simultaneous contrast. However, in our investigation, both induction field and background are merged into one, that is, $p = 0$, leading to Eq. (2) retaining a constant value of 1 throughout, which in turn produces signals of ρ_w, γ_w and β_w, calculated in Eq. (1), being exactly the same as those of ρ_w, γ_w and β_w. In other words, it is unlikely to predict colour contrast by the modification of reference white in a two-field paradigm.

TABLE I. The input and output information of CIECAM02.

Input	Output
X,Y, Z: Relative tristimulus values of colour stimulus	Lightness (*J*)
X_w, Y_w, Z_w: Relative tristimulus values of white	Colourfulness (*M*)
L_A: Luminance of the adapting field (cd/m*m) = 1/5 of adapted D65;	Chroma (*C*)
Y_b: Relative luminance of the background;	Hue angle (*h*)
Surround parameters: *c*, Nc, *F* = 0.41, 0.8, 0.2, respectively, for luminous colours (i.e., monitor).	Brightness (*Q*)
	Saturation (*S*)

$$\rho'_w=\rho_w\frac{\left[(1-p)P_\rho+\frac{1+p}{P_\rho}\right]^{\frac{1}{2}}}{\left[(1+p)P_\rho+\frac{1-p}{P_\rho}\right]^{\frac{1}{2}}};\quad \beta'_w=\beta_w\frac{\left[(1-p)P_\beta+\frac{1+p}{P_\beta}\right]^{\frac{1}{2}}}{\left[(1+p)P_\beta+\frac{1-p}{P_\beta}\right]^{\frac{1}{2}}};$$

$$\gamma'_w=\gamma\frac{\left[(1-p)P_\gamma+\frac{1+p}{P_\rho}\right]^{\frac{1}{2}}}{\left[(1+p)P_\gamma+\frac{1-p}{P_\gamma}\right]^{\frac{1}{2}}} \tag{1}$$

where

$$P_\rho=\frac{\rho_p}{\rho_b};P_\gamma=\frac{\gamma_p}{\gamma_b};P_\beta=\frac{\beta_p}{\beta_b} \tag{2}$$

A different approach is applied in this investigation. To a large extent, changing to a different background is reminiscent of changing to another chromatic adaptation environment whereby a lighting source is switched from one to another.[25] It is, therefore, under this inspiration that modification of chromatic adaptation response in the CIECAM02 takes place. In CIECAM02, the chromatic adaptation of a stimulus is calculated in Eqs. (3)–(5).

$$R_c=R\left[D\frac{Y_w}{R_w}+1-D\right] \tag{3}$$

$$G_c=G\left[D\frac{Y_w}{G_w}+1-D\right] \tag{4}$$

$$B_c=B\left[D\frac{Y_w}{B_w}+1-D\right] \tag{5}$$

where *R*, *G* and *B* are the values of a stimulus in the RGB space and calculated in Eq. (A1) as given in Appendix, by which the corresponding values for the reference white, that is, R_w, G_w and B_w can be calculated in the similar manner. The degree of chromatic adaption, *D*, is calculated in CIECAM02 as Eq. (6).

$$D=F\left(1-\frac{1}{3.6}e^{-\frac{L_A+42}{92}}\right) \tag{6}$$

Similar to CMCAT2000 that is developed in Ref. [25] for chromatic adaption, in this study, the new chromatic adaptation formulae under the reference of coloured background are formulated in Eqs. (7)–(9), where R_b, G_b and B_b are added to the chromatic response formulae, which are obtained from a coloured background, giving rise to the newly modified model named as CAMcc, short for Colour Appearance Model with Colour Contrast. In our case, a background is interpreted as an adopted white in a test illuminant whereas the value of the original reference white is treated as the reference white in the reference illuminant for the calculation of R_w/Y_w, G_w/Y_w and B_w/Y_w.

$$R_c=R\left[D\frac{Y_b}{R_b}\frac{R_w}{Y_w}+1-D\right] \tag{7}$$

$$G_c=G\left[D\frac{Y_b}{G_b}\frac{G_w}{Y_w}+1-D\right] \tag{8}$$

$$B_c=B\left[D\frac{Y_b}{B_b}\frac{B_w}{Y_w}+1-D\right] \tag{9}$$

Specifically, the degree of discounting adaptation *D* in the above equations adopts the one calculated for CMCAT2000 as given in Eq. (10).

$$D=F\left\{0.08\log_{10}[0.5(L_A+L_{A\text{-}bg})] +0.76-0.45\frac{(L_A-L_{A\text{-}bg})}{L_A+L_{A\text{-}bg}}\right\} \tag{10}$$

where L_A and $L_{A\text{-}bg}$ refer to the luminance for reference white and background in cd/m^2, respectively. *F* is defined in Table I as 0.2 for computer monitors of LCD type.

In this way, the calculations of R_c, G_c and B_c in CAMcc will be the same as those in CIECAM02 under a neutral background where simultaneous contrast is not in place because of $R_b \approx G_b \approx B_b \approx Y_b$ and $R_w \approx G_w \approx B_w \approx Y_w$.

In comparison with subject's estimation in measuring colour appearance, in terms of lightness, colourfulness and hue obtained during our psychophysical experiments, Fig. 4 illustrates the predictions by both CAMcc and CIECAM02 with four different coloured backgrounds, including red, cyan, green and blue, respectively, all with CIELAB $L^* \approx 50$. The left column shows the prediction by CAMcc model whereas the right one by CIECAM02. In each comparison, the data in *y*-axis direction gives predictions by the models whereas *x*-axis presents mean subjects' estimations. The correlation coefficient (*r*) value for each comparison is depicted at the bottom of each graph. Although visually, the difference between the two columns lacks significance, the *r* value does paint better fitness while using CAMcc, especially for hue responses, the key element that resulting from the simultaneous contrast effect.

IMPLEMENTATION OF COLOUR SPACES AND MODELS FOR COLOUR-BASED IMAGE RETRIEVAL

To implement CAMcc for colour-based image retrieval, the treatment to the calculation of background colours

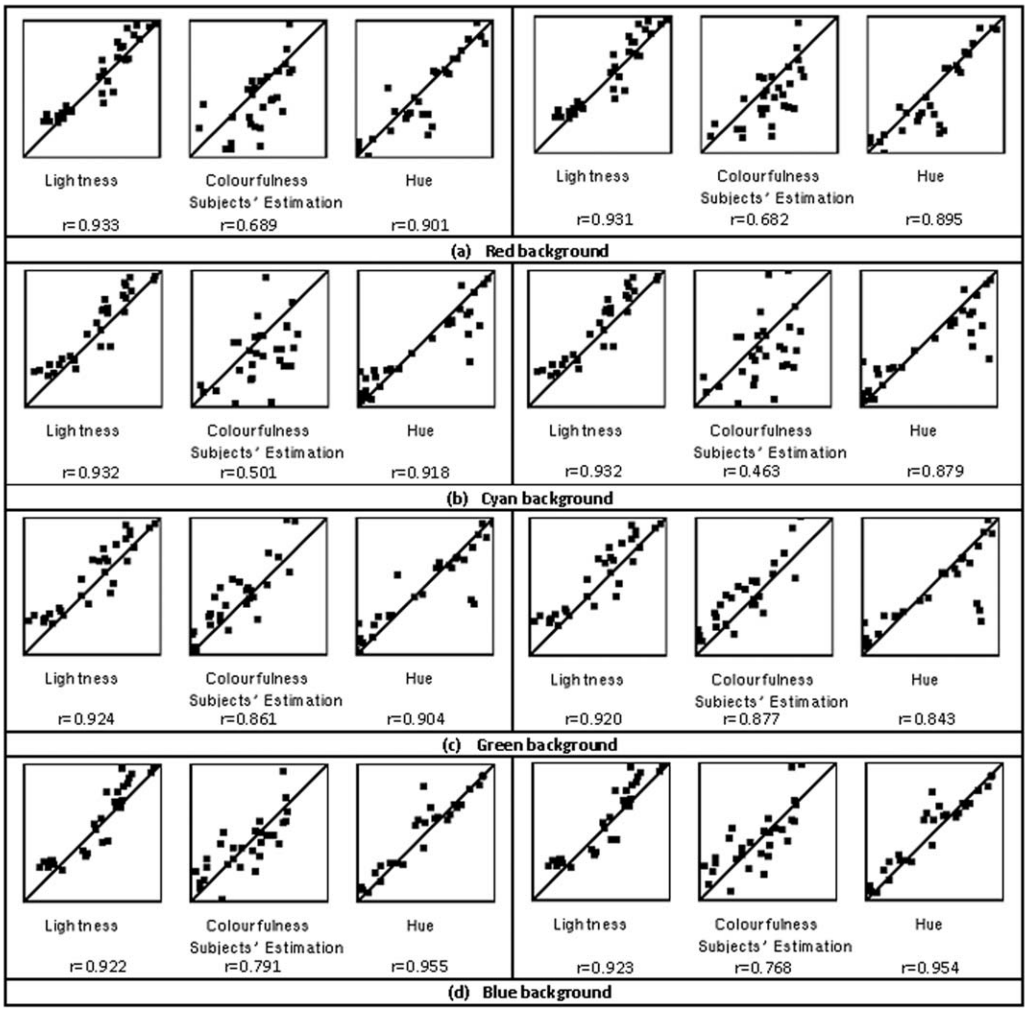

Fig. 4. Predicted responses (y-axis) plotted against mean subjects' estimations of lightness, colourfulness and hue for red, cyan, green and blue backgrounds, respectively, where $L^* = 50$. The left column shows predictions by CAMcc while the right one by CIECAM02.

should be different since a background acts as a reference white as illustrated in Eqs. (7)–(9). Therefore, for processing an image, a background colour is singled out first using the technique of colour histogram map, by which a certain number of bins (e.g., 100) are allocated, whereby the bin number with the peak amount of pixels is considered as the colour of the background.

Subsequently, based on CAMcc that embeds simultaneous contrast, image retrieval is carried out on a database of 654 wallpaper pictures that are collected from the Museum of Domestic Design & Architecture (MoDA) at Middlesex University (www.moda.mdx.ac.uk), which accommodates one of the world's most comprehensive collections of decorative arts for home dating from 1870s to 1960s.

In addition to evaluating CAMcc on colour-based image retrieval, the other three most commonly used colour spaces in CBIR are also investigated, which are CIECAM02, HSI and RGB.

HSI (hue, saturation and intensity)[26] colour space became popular in the computer vision field mainly due to its simplicity while incorporating human vision systems. Conversely, primary colours, red, green and blue (RGB), are the three built-in colour channels within a computer hardware system to represent a digital image in the first instance. As such RGB space has also been widely applied in computer vision fields even though RGB space is device dependent. In other words, a colour represent in a computer as $(R, G, B) = (255, 255, 255)$ might not appear the same as the colour in another computer with the same R, G and B values as explained in the Introduction. To circumvent this, all CIE models, that is, CIELAB, CIECAM02, begin with colour physical tristimulus values of X, Y and Z that can be measured using a colour meter externally. In this way, a formula to convert between XYZ and RGB spaces for each computer has to be worked out first, which prompts a number of users to apply RGB space to avoid conversions between colour spaces. This because that sometimes variations derived from colour space transitions might be larger than the errors of device dependency. Nevertheless, accurate retrieval demands accurate colour models, especially

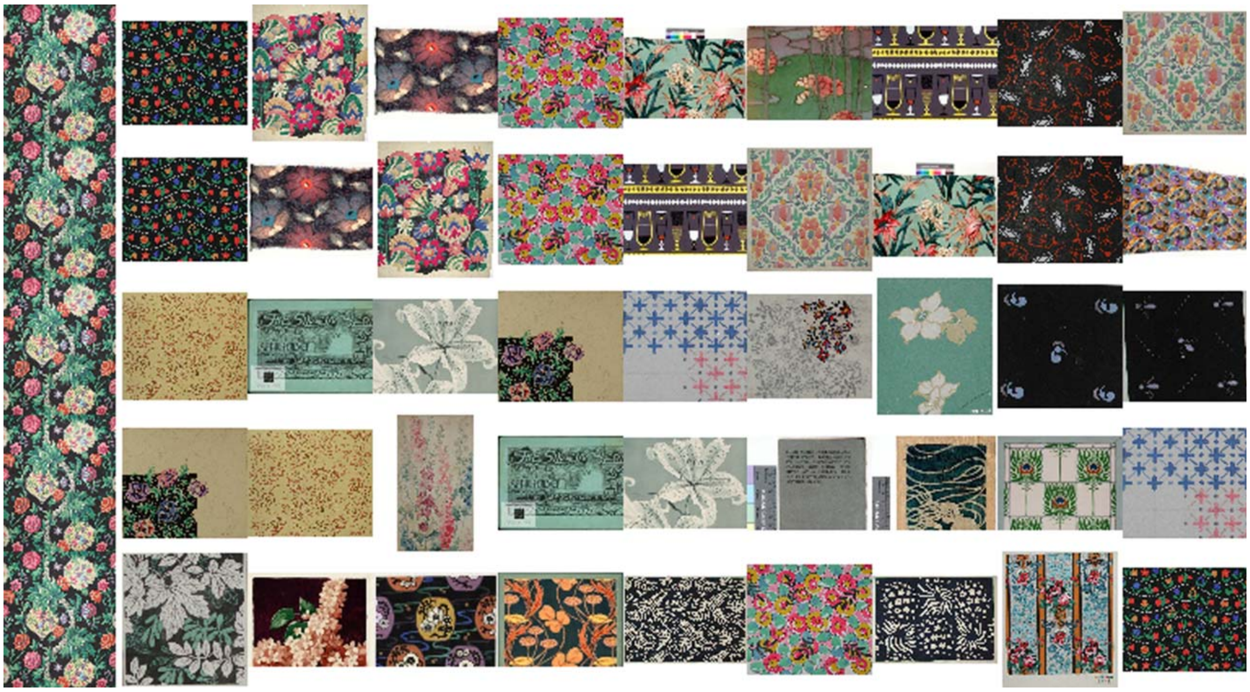

Fig. 5. Dark background. Top nine images retrieved by models of CAMcc, (top row), CIECAM02 (second row), HIS with 20-bin-hue (third row), HIS with 10-bin-hue (fourth row) and RGB (bottom row), respectively. The leftmost column presents the query image for each row.

when a database consists of millions of images (e.g., internet), whereby only first or first few page(s) of retrieved results have the opportunities to be inspected. Computationally, Eqs. (11)–(13) formulate the conversion to HSI from RGB space.[26]

$$H = \cos^{-1}\left(\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right) \quad (11)$$

$$R \neq G \quad or \quad R \neq B$$

$$S = \max(R,G,B) - \min(R,G,B) \quad (12)$$

$$I = \frac{R+G+B}{3} \quad (13)$$

Distance Calculation

All the images that are of JEPG format in a collection are first converted from RGB space to each of the representations dedicated to CAMcc, CIECAM02 and HSI, respectively, using Matlab programs, for example, lightness, colourfulness and hue for CAMcc and CIECAM02 and hue, saturation and intensity for HSI.

When comparing two images, colour attributes are usually grouped into a number of bins. In this way, not only can the number of comparisons be reduced appreciably but also the noises or unintended colours can be restricted to a limited level. When using CAMcc model, however, the shift of hue induced by a background colour can be subtle in a number of cases. As a direct result, considerable reduction of the number of bins will lead to the suppression of the effect. Therefore, with regard to hue attribute, 20 bins, equivalent to every 5% of hue values are retained in this study, whereas the bin numbers for both colourfulness and lightness are set to be in agreement with the literature, that is, 6 and 5 bins, respectively, leading to a total of 600 bins ($20 \times 6 \times 5$). Conversely, to be comparable with HSI, both 20 and 10 bins for hue are given, with the latter being in line with the existing published work, that is those colour attributes being quantized into 300 bins (i.e., $C = 6$ bins, L or $I = 5$ bins and $H = 10$ bins). As for RGB colour space, 216 bins ($R = G = B = 6$) bins are quantized. Finally, colour histograms for each of these four colour spaces are calculated individually for each image in the database. In other words, each image has five colour histograms attached to it, respectively, calculated from CAMcc, CIECAM02, HSI-20 bin, HSI-10 bin and RGB.

When a query is submitted, for each colour space/model, a distance function using the technique of histogram intersection is called for to compare two images of a query Q and an image I from a database, which is formulated as Eq. (14).

$$D(Q,I) = \sum_i \min(Q_i, I_i) \quad (14)$$

where i represents each bin in a histogram and I the image in a database that circulates to all the images one by one, that is, 654 images in this collection. As a result, bigger value of D indicates more similar between

Fig. 6. Pink background. Top nine images retrieved by models of CAMcc, (top row), CIECAM02 (second row), HIS with 20-bin-hue (third row), HIS with 10-bin-hue (fourth row) and RGB (bottom row), respectively. The leftmost column presents the query image for each row.

images of Q and I. Particularly, for each individual colour model, the way that a histogram is calculated is the same for both query and database images. While performing cross-model comparisons, only the rank of retrieved images, say, top 10 most similar images, obtained from every colour model are compared.

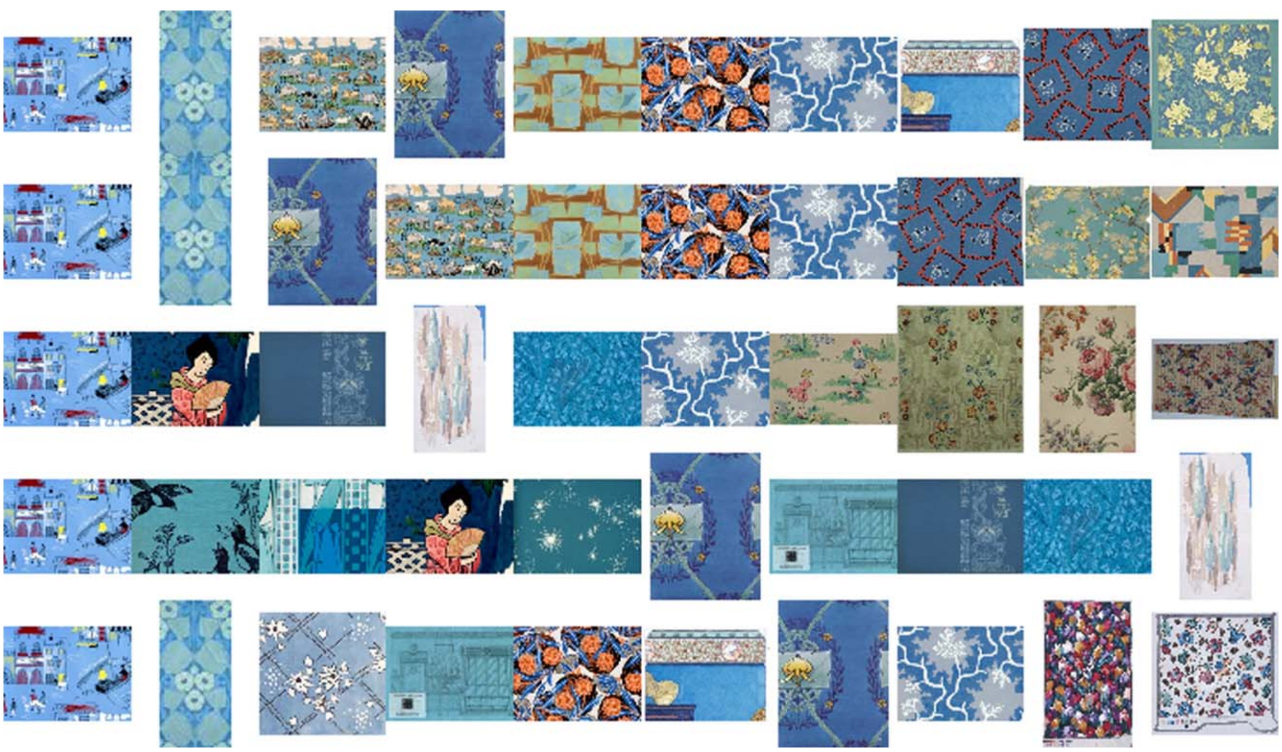

Fig. 7. Blue background. Top nine images retrieved by models of CAMcc, (top row), CIECAM02 (second row), HIS with 20-bin-hue (third row), HIS with 10-bin-hue (fourth row) and RGB (bottom row), respectively. The leftmost column presents the query image for each row.

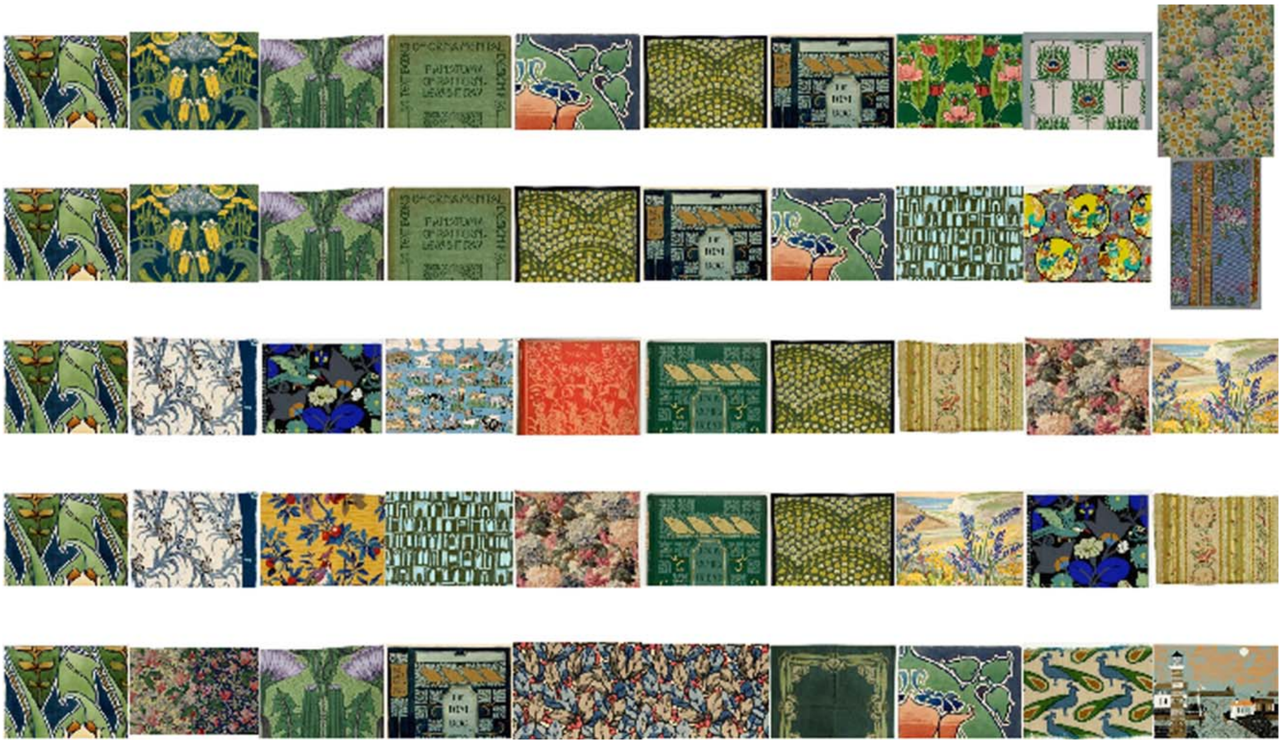

Fig. 8. Green background. Top nine images retrieved by models of CAMcc, (top row), CIECAM02 (second row), HIS with 20-bin-hue (third row), HIS with 10-bin-hue (fourth row) and RGB (bottom row), respectively. The leftmost column presents the query image for each row.

Therefore, there is no need of normalization of image sizes or histogram bin numbers as the ranking number is equivalent to a normalized value.

Retrieval Results and Analysis

The retrieved results are illustrated in Figs. 5–10 that demonstrate several query samples containing varying

Fig. 9. Yellow background. Top nine images retrieved by models of CAMcc, (top row), CIECAM02 (second row), HIS with 20-bin-hue (third row), HIS with 10-bin-hue (fourth row) and RGB (bottom row), respectively. The leftmost column presents the query image for each row.

Fig. 10. Similar retrieval results. Top nine images retrieved by models of CAMcc, (top row), CIECAM02 (second row), HIS with 20-bin-hue (third row), HIS with 10-bin-hue (fourth row) and RGB (bottom row), respectively. The leftmost column presents the query image for each row.

background colours, including dark, pink, blue, green, yellow and unknown. The leftmost column refers to a query image, whereas the remaining nine in each row depict the top nine most similar images to the query by models of CAMcc, (first row), CIECAM02 (second row), HSI with 20-bin-hue (third row), HSI with 10-bin-hue (fourth row) and RGB (fifth row), respectively.

In general, CAMcc and CIECAM02 appear to outperform HSI and RGB models (Fig. 5). Specifically, in terms of mapping foreground colours, CAMcc appears to give much better balanced retrieval results than the other approaches while maintaining similar lightness and colourfulness contrast between foreground and background. For example, in Fig. 6, the query (the leftmost image) contains red, green and orange colours against a pink background. Although the bottom 2 rows (HSI-10 and RGB) maintaining similar background tone, the foreground colours of green and orange are missing in several retrieved results (i.e., row 4, columns 3 and 7 and row 5 columns 5, 7 and 8). For samples in row 2 (CIECAM02), columns 9 and 10, the green and red colours appear a bit too bright than those presented in the query. Conversely, CIECAL02 performs similar to CAMcc (Fig. 7) but seems to have put a bit more weight onto background colours. For example, in Fig. 8, the images in row 2, columns 8 and 10, depict unproportional greenish and bluish hues, respectively.

In Figs. 8 and 9, however, RGB and HIS seem to contain much more foreground colours than those presented in the query image. Since the most appreciable effect while simultaneous contrast occurring lies in the shift of hue, the advantage of CAMcc over the others is that the hue contents of retrieved foreground colours have been very well reserved in all the figures.

In many cases, all four models give very similar results like depicted in Fig. 10, implying that the exact performance of the retrieval that each model details, very much depends on how a user interprets a query image and subsequently justifies the retrieved results. As shown in Fig. 10, there are two contrast patterns, one with dark background and one with light. Users might be more interested in one (row 3, column 2 with dark background) than another or be interested in the combined one (e.g., row 1 column 6 or row 5, column 10 with two backgrounds).

As discussed in Distance Calculation, the final ranking of retrieved images by each model is conducted according to the distance to the query, which is formulated in Eq. (14), that is, an image with the largest distance value indicates that it is the most similar one to the query and, therefore, is ranked as number 1 according to that particular model. Since the calculation of histograms for both queries and all the images in a database is in the exactly same way for each model, the change of bin numbers or any other parameters only affect the ranking order for that particular model, being independent of any other models. Consequently, it is very difficult if not possible to measure the normalized rankings amongst different models. It is anticipated that the developed CAMcc model provides a complement to the existing colour models and benefits image retrieval community, the same way as different colour models being developed to serve different purposes.

Release of Psychophysical Experimental Data and Sample Programs

The 16 sets of psychophysical experimental data estimated by observers are free available at http://www.mitime.org/colour, together with Matlab programs that are used to calculate CAMcc model, the program is built on CIECAM02 model that is originally implemented by Ref. [27]. A number of sample wallpaper images collected from MoDA are also available. More images can be downloaded individually at http://image.mdx.ac.uk/time/demo.php, upon which to select database collection of MODA.

CONCLUSIONS AND DISCUSSION

The aim of this work is to retrieve wallpaper images based on their colour while embedding chromatic contrast, in an attempt to convey the expressionistic culture that may be reflected through differentiated colour contrast,[28] complementing the existing approaches to meet users' varying expectations of retrieval. Towards this end, CAMcc appears to be able to discern feature contents to a certain extent. Specifically, while the other three models pay more attention to the colours of a background, CAMcc focuses on the colour contents on the foreground as well as resembling colour contrast between the two grounds exhibited in a query.

It is well known that colour-based retrieval can vary subjectively very much depending on what content insterests the users most. While global colour constitutes one of the most popular components on which many users are focusing, local changes in perceived hue as a result of chromatic contrast can attribute to the retrieval results noticeably. Therefore, this study extends the current colour appearance model, CIECAM02 into CAMcc by taking into account of chromatic contrast. The subsequent application of CAMcc on image retrieval on a collection of over 650 wallpaper images has shown that CAMcc retrieves more similar images in terms of both lightness and colourfulness contrast between foreground and background patterns than the other three commonly applied colour spaces, that is, CIECAM02, HSI and RGB. In addition, CAMcc outperforms the others by retrieving images with more similar hues to that of a query image. Due to the subjectiveness of the interpretation of an image, the challenge remains to retrieve images based on their content. For example, in our experiments in determining the performance of retrieval results, curators who knew these wallpapers very well were more concerned with style and artists whereas ordinary users who have little knowledge of the collections of these artworks tend to focus on colour, texture or both. In many cases, users apply high level semantics knowledge to retrieve images, for example, flowers, buildings, which at this stage, is difficult to achieve using colour alone. Therefore, future work should elaborate colour-based content coupled with other features, in the hope of leading to semantics-based image retrieval. Furthermore, incorporating with textual descriptions annotated by curators will point to another direction.

For art images, each chronicle generates its own characteristic painting techniques that in turn are reflected in its calligraphy. It is, therefore, conceivable to characterize wallpaper images based on their rich colour contents.

As for the implementation of the CAMcc for CBIR, discerning of the background colour should be addressed first. At present, the background is calculated using the approach of histogram, whereby the bin number with the peak value is considered to contain the background colour. Thereafter the remaining colours constitute the foreground content. Although in most cases, there is only one peak value, singling out the background colour. In some cases, the differences between the first and the second (or even the third) peaks are not significant, leaving the uncertainty of the background colours and thereafter affecting the calculation of CAMcc. Hence further study will be conducted to investigate what constitutes the coverage colour of a background. For the current collection, the bins with peak values containing more than 4% of overall number of pixels are classified as background colours of the image under consideration.

As it happens, the CAMcc model, which we developed, works effectively only for colour intensive images where chromatic contrast usually occurs. Otherwise, the retrieved results will be exactly the same as by the model of CIECAM02. For example, for those images amassed online and bearing large distinguishable colour context, all four models behave nearly the same when it comes to retrieving by colour. Additionally, the work concluded here results only from the study conducted on a LCD monitor. Further work is in need to evaluate the CAMcc for any other media, for example, reflection or CRT.

APPENDIX: THE STEPS OF CALCULATION OF CAMCC MODEL

1. First, the measurement using a colour meter for luminance, reference white, background, test colour samples take place to obtain L_A, $L_{A\text{-bg}}$ and X, Y, Z values.
2. View conditions and notations where λ is newly introduced factor in the CAMcc model for the calculation of simultaneous contrast.

Surround	F	C	Nc
Average	1.0	0.69	1.0
Dim	0.9	0.59	0.95
Dark	0.8	0.525	0.8
Luminous computer monitor	0.2	0.41	0.80
L_A	Luminance of reference white in cd/m^2		
$L_{A\text{-bg}}$	Luminance of background in cd/m^2		
Y_b	Y value for background ranging within [1,100].		
Y_w	Y value for reference white and close to 100.		

$k=\frac{1}{5L_A+1}$

$F_L=0.2k^4(5L_A)+0.1(1-k^4)^2(5L_A)^{1/3}$

$n=\frac{Y_b}{Y_w}$

$N_{bb}=N_{cb}=0.725\left(\frac{1}{n}\right)^{0.2}$

$z=1.48+\sqrt{n}$

3. Chromatic adaption

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = M_{CAT02}\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{A1}$$

$$M_{CAT02}=\begin{bmatrix} 0.7328 & 0.4296 & 0.1624 \\ 0.7036 & 1.6975 & 0.0061 \\ 0.0030 & 0.0136 & 0.9834 \end{bmatrix} \tag{A2}$$

$$\begin{aligned} D=F\ \Big\{&0.08\log_{10}\left[0.5\left(L_A+L_{A\text{-bg}}\right)\right] \\ &+0.76-0.45\frac{\left(L_A-L_{A\text{-bg}}\right)}{L_A+L_{A\text{-bg}}}\Big\} \end{aligned} \tag{A3}$$

$$R_c=R\left[D\frac{Y_b}{R_b}\frac{R_w}{Y_w}+1-D\right] \tag{A4}$$

$$G_c=G\left[D\frac{Y_b}{G_b}\frac{G_w}{Y_w}+1-D\right] \tag{A5}$$

$$B_c=B\left[D\frac{Y_b}{B_b}\frac{B_w}{Y_w}+1-D\right] \tag{A6}$$

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = M_H M_{CAT02}^{-1}\begin{bmatrix} R_c \\ G_c \\ B_c \end{bmatrix} \tag{A7}$$

$$M_{CAT02}^{-1}=\begin{bmatrix} 1.0961 & 0.2788 & 0.1827 \\ 0.4543 & 0.4735 & 0.0720 \\ 0.0009 & 0.0056 & 1.0153 \end{bmatrix} \tag{A8}$$

$$M_H=\begin{bmatrix} 0.3897 & 0.6889 & 0.0786 \\ 0.2298 & 1.1834 & 0.0464 \\ 0.0000 & 0.0000 & 1.0000 \end{bmatrix} \tag{A9}$$

4. Nonlinear response compression

$$R'_a=\frac{400\left(\frac{F_L R'}{100}\right)^{0.42}}{27.13+\left(\frac{F_L R'}{100}\right)^{0.42}}+0.1 \tag{A10}$$

$$G'_a=\frac{400\left(\frac{F_L G'}{100}\right)^{0.42}}{27.13+\left(\frac{F_L G'}{100}\right)^{0.42}}+0.1 \tag{A11}$$

$$B'_a=\frac{400\left(\frac{F_L B}{100}\right)^{0.42}}{27.13+\left(\frac{F_L B'}{100}\right)^{0.42}}+0.1 \tag{A12}$$

5. Perceptual attribute correlates

$$a=R'_a-\frac{12G'_a}{11}+\frac{B'_a}{11} \tag{A13}$$

$$b=\frac{1}{9}(R'_a+G'_a-2B'_a) \tag{A14}$$

Hue angle:

$$h=\tan^{-1}\left(\frac{b}{a}\right) \tag{A15}$$

Eccentricity factor:

$$e_t=\left[\frac{12500}{13}N_cN_{cb}\right]\left[\cos\left(h\frac{\pi}{180}+2\right)+3.8\right] \tag{A16}$$

$$t=\frac{50(a^2+b^2)^{\frac{1}{2}}100e_t\left(\frac{10}{13}\right)N_cN_{cb}}{R'_a+G'_a+\frac{21}{20}B'_a} \tag{A17}$$

Hue response:

$$H=H_i+\frac{\frac{100(h-h_i)}{e_i}}{\frac{h-h_i}{e_i}+\frac{h_{i+1}-h}{e_{i+1}}} \tag{A18}$$

where $h_i \le h < h_{i+1}$ and if $h > h_5$, $h=h-360$.

	Red	Yellow	Green	Blue	Red
i	1	2	3	4	5
h_i	20.14	90	164.25	237.53	380.14
e_i	0.8	0.7	1.0	1.2	0.8
H_i	0	100	200	300	400

Achromatic Response:

$$A=\left[2R'_a+G'_a+\left(\frac{1}{20}\right)B'_a-0.305\right]N_{bb} \tag{A19}$$

Lightness:

$$J=100\left(\frac{A}{A_w}\right)^{cz} \tag{A20}$$

where A_w is the A value for reference white.

Brightness:

$$Q=\frac{4}{c}\left(\frac{J}{100}\right)^{0.5}(A_w+4)F_L^{0.25} \tag{A21}$$

where A_w is the A value for reference white.

Chroma:

$$C=t^{0.9}\left(\frac{J}{100}\right)^{0.5}(1.64-0.29^n)^{0.73} \tag{A22}$$

Colourfulness:

$$M=CF_L{}^{1/4} \tag{A23}$$

Saturation:

$$s=100\sqrt{\frac{M}{Q}} \tag{A24}$$

ACKNOWLEDGMENTS

The authors would like to thank Ms. Zoë Hendon, Senior Curator at MoDA, who has kindly provided those images for our research. Thanks also go to those observers who have helped conducting a number of psychophysical experiments. The financial support from JISC, UK is gratefully acknowledged.

1. Basher MK, Ohnishi N, Matsumoto T, Takeuchi Y, Kudo H, Agusa K. Image retrieval by pattern categorization using wavelet domain perceptual feature with LVQ neural network. Pattern Recognit Lett 2005;26: 2315–2335.
2. Jain AK, Vailaya A. Shape-based retrieval: A case study with trademark image database. J Pattern Recognit 1998;31:1369–1390.
3. Qiu G. Indexing chromatic and achromatic patterns for content-based colour image retrieval. Pattern Recognit 2002;35:1675–1686.
4. Othman A, Martinez K. Colour appearance descriptors for image browsing and retrieval. In Proceedings of SPIE Electronic Imaging: Multimedia Content Access: Algorithms and Systems, San Jose, SPIE, 2008.
5. Helson H, Michels WC. The effect of chromatic adaptation on achromaticity. J Opt Soc Am 1948;38:1025–1032.
6. MacAdam DL. Maximum attainable luminous efficiency for various chromaticities. J Opt Soc Am 1950;40:120.
7. Ekroll V, Faul F, Niederée R, Richter E. The natural cebter of chromaticity space is not always achromatic: A new look at color induction. Proc Natl Acad Sci USA 2002;99:13352–13356.
8. McCann JJ. Simultaneous contrast and color constancy: Signatures of human image processing. In: Davis S, editor. Color Perception: Philosophical, Psychological, Artistic, and Computational Perspectives (Vancouver Studies in Cognitive Studies). Oxford University Press; New York, USA, 2000. p 87–101.
9. Judd, DB. Color appearance. Die Farbe 1965;14:2–26.
10. CIE: Publication No. 17. International Lighting Vocabulary, Paris: Commission Internationale de l'Ec1airage, 1970.
11. Gerritsen F. Theory and Practice of Color. London: Studio Vista; 1975.
12. Takasaki H. Von-Kries coefficient law applied to subjective color change induced by background color. J Opt Soc Am 1969;59:1370–1376.
13. Jameson D, Hurvich LM. Theory of brightness and color contrast in human vision. Vision Res 1964;4:135–154.
14. Blackwell KT, Buchsbaum G. The effect of spatial and chromatic parameters on chromatic induction. Color Res Appl 1988;13:166–173.
15. Wang Y, Gao A, White A, Gao X. Colour Contrast Re-Visit. In Proceedings of AIC Midterm Meeting, Zurich – Interaction Of Colour & Light In The Arts And Sciences, Zurich: pro/colore, 2011, p 808–811.
16. Luo MR, Clarke AA, Rhodes PA, Scrivener SAR, Schappo A, Tait CJT. Quantifying colour appearance. Part 1. LUTCHI colour appearance data. Color Res Appl 1991;16:166–180.
17. Gao X, Qian Y, Wang Y, White A. Colour based image retrieval with embedded chromatic contrast. In Proceedings of IS&T's 6th European Conference on Colour in Graphics, Imaging Springfield VA: IS&T, 2012, Universiteit van Amsterdam, Amsterdam, the Netherlands, Curran Associates, Inc., USA., p 143–150.
18. Luo MR, Gao XW, Scrivener SAR. Quantifying colour appearance, Part V. Simultaneous contrast. Color Res Appl 1995;20:18–28.
19. Wu RC, Wardman RH. Proposed modification to the CIECAM02 colour appearance model to include the simultaneous contrast effects. Color Res Appl 2007;32:121–129.
20. Moroney N, Fairchild MD, Hunt RWG, Li C, Luo MR, Newman T. The CIECAM02 Color Appearance Model. In Proceedings of the Tenth Color Imaging Conference, Springfield VA: IS&T, 2002, p 23–27.
21. Luo MR, Gao XW, Phodes PA, Xin HJ, Clark AA, Scrivener SAR. Quantifying colour appearance - Part IV. Transmissive media. Color Res Appl 1993;18:191–206.
22. Luo MR, Gao XW, Phodes PA, Xin HJ, Clark AA, Scrivener SAR. Quantifying colour appearance - Part III. Supplementary LUTCHI colour appearance data. Color Res Appl 1993;18:98–113.
23. Luo MR, Gao XW, Phodes PA, Xin HJ, Clark AA, Scrivener SAR. Quantifying colour appearance - Part IV. Transmissive media. Color Res Appl 1993;18:191–206.
24. Hunt RWG. Revised colour-appearance model for related and unrelated colours. Color Res Appl 1991;14:146–165.
25. Li C, Luo MR, Rigg B, Hunt RWG. CMC 2000 Chromatic adaptation transform: CMCAT2000. Color Res Appl 2002;27:49–58.
26. Ford A, Roberts A. Colour space conversions, August 1998. Available at: http://www.poynton.com/PDFs/coloureq.pdf, Accessed on June 2012.
27. Green P, MacDonald L, editors. In: Colour Engineering: Achieving Device Independent Colour, London: Wiley; 2004.
28. Hpskins L, editors. In: The Papered Wall: History, Pattern, Technique, London: Harry N. Abrams; 1994.