Unique Hue Data for Colour Appearance Models. Part II: Chromatic Adaptation Transform

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Abstract: Unique hue settings of 185 observers under three room-lighting conditions were used to evaluate the accuracy of full and mixed chromatic adaptation transform models of CIECAM02 in terms of unique hue reproduction. Perceptual hue shifts in CIECAM02 were evaluated for both models with no clear difference using the current Commission Internationale de l'Éclairage (CIE) recommendation for mixed chromatic adaptation ratio. Using our large dataset of unique hue data as a benchmark, an optimised parameter is proposed for chromatic adaptation under mixed illumination conditions that produces more accurate results in unique hue reproduction. © 2011 Wiley Periodicals, Inc. Col Res Appl, 38, 22–29, 2013; Published online 1 October 2011 in Wiley Online Library (wileyonlinelibrary.com). DOI 10.1002/col.20725

Key words: unique hue; CIECAM02; colour appearance model; chromatic adaptation transform

INTRODUCTION

Colour appearance models is an active research area with the aim to extend basic colorimetry to predict how observers perceive, describe and match colours in a wide range of viewing conditions. Interest in colour appearance models has been greatly stimulated by the need to predict colour inconstancy, evaluate colour rendering properties of light sources and simulate colour reproductions under different lighting conditions.

In the most common form, colour appearance models consist of three stages: a chromatic adaptation transform (CAT), a dynamic response function and a transformation into a uniform colour space.[1] This article focuses on the CAT, which models the ability of the human visual system to adjust to changes in the illumination to preserve approximately the appearance of object colours. In other words, CATs allow the prediction of corresponding colours under different illumination conditions.[2] The CIE TC8-01 has recommended CIECAM02 colour appearance model for colour management applications,[3] which consists of a modified version of the CMCCAT2000 CAT model and equations for computing a set of perceptual attribute correlates.[4,5] In a parallel technical report, CIE TC 8-04 has also recommended a mixed and incomplete CAT model[6] for comparing soft copy images previewed on self-luminous displays and hardcopy images printed on paper by using successive observations. Because of the fairly limited corresponding-colour datasets, the CIE has recommended a set of experiments to evaluate the adopted ratio parameter of the chromatic adaptation model and proposed future research directions towards the formulation of a model that more closely follows the human visual system.[4,5]

The work presented in this article evaluates the performance of the above CIE colour appearance models for the common mixed illumination conditions where users tend to view images on self-luminous displays in rooms with sufficient ambient light for comfortable viewing. In this context, previous studies using achromatic colour matching experiments[7,8] indicated shifts of 10–20% caused by the ambient illumination. To test the hue repro-

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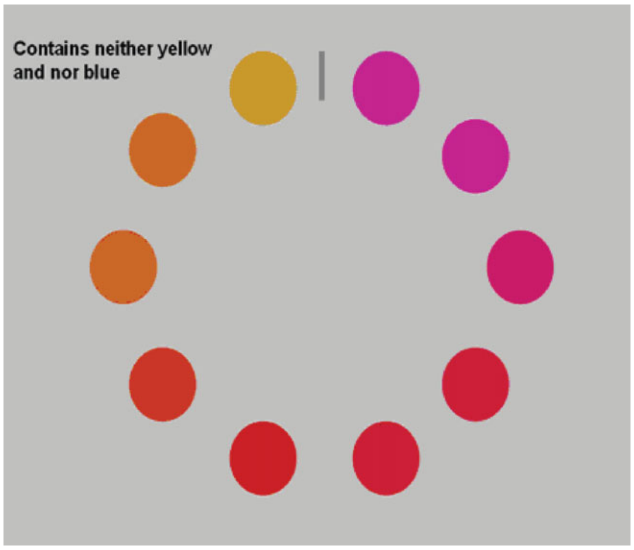

FIG. 1. Viewing patterns used in the experiment.

duction of colour appearance models, it is necessary to assess the appearance of a coloured patch under different adaptation conditions. A widely used assessment method is asymmetric matching, where a test patch seen under a particular chromatic adaptation is matched to a reference patch viewed under a different adaptation; this requires full adaptation of different parts of the retina to different adapting lights (e.g. Ref. 9). An alternative method is to ask observers to provide unique hue settings under different illumination conditions, the advantage being that no reference is necessary.[10]

Unique hues[11] are defined as pure colours such that either a putative red-green channel is at equilibrium, yielding unique yellow (UY) and blue (UB); or a putative yellow-blue channel is at equilibrium, yielding unique red (UR) and green (UG). In this study, we used unique hue settings obtained using a hue selection method[12,13] under three different ambient illumination conditions to test current colour appearance models. In addition to previously reported unique hue data obtained in a dark room,[10] we present two supplementary sets of unique hue data assessed and then measured under mixed illumination conditions. The unique hues under each illuminant were predicted by using both full and mixed CATs embodied in CIECAM02. The performance of each CAT was evaluated by measuring perceptual hue differences between predicted and observed unique hue settings. An optimized adaptation parameter is suggested for mixed chromatic adaptation under mixed illumination conditions, which produces more accurate colour appearance predictions.

EXPERIMENTS

Methods

The experimental setup and the assessment of the unique hues in a dark room have been described in previous articles.[10,14] All stimuli were presented on a 21-inch SONY CRT display driven by a ViSaGe system (Cambridge Research Systems, Kent). In addition to the dark room data (first presented in Ref. 10), unique hue settings were obtained from 185 colour normal observers under two ambient illumination conditions: under a daylight simulator (D65) and cool white fluorescent (CWF) light sources. All three datasets were obtained using the same CRT, the same stimuli and the same 185 colour-normal observers.

Stimuli and Task

The hue selection interface adopted in the previous experiments[10,14] was also used to find the coordinates of the four unique hues under room lighting conditions (Fig. 1). Each patch had a diameter of 2° of visual angle and was presented at an eccentricity of 4°. For example, to obtain unique red, 10 reddish patches of similar luminance and saturation were displayed on an annulus, and the task of the observer was to indicate via a mouse press which of these patches contained neither yellow nor blue. Unique green was assessed in an analogous way. To obtain unique yellow and unique blue, observers chose that patch that contained neither red nor green. All four unique hues were assessed at different lightness and chroma levels to test hue uniformity.[10] The nine particular chroma and lightness combinations were chosen for each unique hue in CIELUV colour space to maximize the available gamut of the display while for each particular trial only the hue attribute was varying to facilitate the task.[10,14] Stimuli were displayed on a CRT under either a D65 simulator or a CWF light source (Fig. 2).

Before the beginning of the experiment, the light sources were equilibrated for at least 15 min, and each observer was adapted to both, display and ambient light for at least 5 min. During the experiments, each observer first assessed unique hue stimuli under D65 and then under CWF. For each lighting condition, 108 unique hue stimuli (four unique hues × nine different lightness-chroma levels × three repetitions) assessed by 185 subjects and

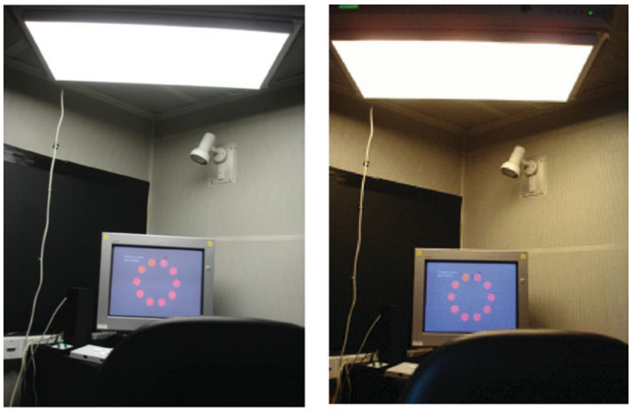
(a) (b)

FIG. 2. Experimental setup under different room lightings. (a) D65 simulator (b) CWF.

TABLE I. Specification of room lighting for experiment.

Room lighting	Lum	*x*	*y*	CCT
D65	41.3	0.3229	0.3453	5917
CWF	136.8	0.3890	0.3887	3866

19,980 assessments were made in total. The experiment lasted ~50 min for each subject. For more details regarding the experimental set up, please consult part I of this study.[10]

Ambient Illumination

A GTI ColorMatcher GLE M5/25 installed in the centre of a soundproof booth was used to provide two lighting conditions: a D65 simulator for daylight and CWF for typical office light. A white tile was placed underneath the light sources and measured by a PhotoResearch PR-650 telespectroradiometer (TSR). Their specifications (luminance, CIE xy chromaticity and Correlated Colour Temperature) are listed in Table I.

Unique Hue Data

After each experiment, the colour patches selected as unique hues were redisplayed on the CRT and measured with the TSR, under identical illumination conditions. The unique hue settings were recorded in CIE XYZ tristimulus values in the unit of cd/m^2 based on the 2-degree standard observer.[15]

Observer Variability

Both inter-observer and intra-observer variabilities were evaluated to measure the reliability of the unique hue data. Inter-observer variability indicates the extent to which individual observers agree with the average observer, whereas intra-observer variability indicates how consistent the individual observer is across different sessions. The CIEDE2000 colour difference formula[16] was used to calculate the mean colour difference to the mean value (MCDM)[17]; for both inter-observer and intra-observer variabilities for each group of experimental data. It is noted that the mean value for inter-observer variability represents the mean results between 185 observers, whereas the mean results of three assessments in a different time are used to calculate intra-observer variability. The inter-observer and intra-observer variabilities results for each unique hue and the overall mean are listed in Tables II and III, respectively. The observer variability for the unique hue data assessed in a dark room from the previous study[10] is also listed for comparison.

TABLE II. Inter-observer variability.

Inter-observer	UR	UG	UY	UB	Mean
CRT (D65)	1.44	0.95	1.76	1.76	1.48
CRT (CWF)	1.58	0.91	1.51	1.63	1.41
CRT (Dark)	2.30	1.17	1.92	1.97	1.84

TABLE III. Intra-observer variability.

Intra-observer	UR	UG	UY	UB	Mean
CRT (D65)	0.77	0.53	0.90	0.91	0.78
CRT (CWF)	0.73	0.46	0.74	0.85	0.69
CRT (Dark)	0.97	0.66	1.07	1.06	0.94

Comparing the intra-observer variability (Table III) for the dark room condition with the mixed illumination condition (D65 or CWF) indicates that observer has a smaller variability for assessing all four hues in the mixed illumination condition. Equally, variability across observers (Table II) was also lower under D65 or CWF compared to the dark room condition. The lowest observer variability was found for unique green, whereas for the other three unique hues, it was found to be similar. The intra-observer variability was roughly 50% of the inter-observer variability.

RESULTS AND ANALYSIS

Using the measured unique hues settings as a reference, the performance of full and mixed CAT models of CIECAM02 was evaluated by predicting the loci of the unique hues under three room-lighting conditions. As the human visual system adapts to the chromaticity of the illumination to preserve the neutral appearance of the white point,[2] for each viewing condition, both CATs were applied to the recorded tristimulus values of the unique hue settings under one adapting light to predict the corresponding unique hue settings under another adapted light.

In CAT method I, it was assumed that subjects were fully adapted to the CRT. The white point of the monitor was measured in each room lighting condition by a TSR (Table IV) and used as the adopted white point. CIECAM02 was used to predict colour appearance attributes for each unique hue stimulus, whereas the full CAT model transformed unique hue data from the test viewing condition to the standard equal-energy white condition. The input parameters for CIECAM02 are given in Table IV. The Surround parameter was defined as "Average" when the CRT was viewed in rooms with sufficient ambient light.

In CAT method II, it was assumed that subjects were adapted to both the white point of the CRT display and to each of the ambient room illumination (Table I). The

TABLE IV. Input parameters for CIECAM02 for unique hue stimuli for full adaptation.

CIECAM02	X_w	Y_w	Z_w	L_w	Y_b	Surround
CRT (D65)	97.4	100.0	138.2	117.1	20	Average
CRT (CWF)	97.7	100.0	134.2	121.4	20	Average

TABLE V. Input parameters for CIECAM02 for unique hue stimuli for mixed adaptation.

CIECAM02	X_n	Y_n	Z_n	X_a	Y_a	Z_a	R_{adp}
D65 (D65)	117.6	120.0	167.6	38.6	41.3	39.7	0.6
CWF (CWF)	117.6	120.0	167.6	136.9	136.8	78.2	0.6

measured peak white in a dark room was used as the main adopted white point (X_n,Y_n,Z_n in Table V), and the measured room lighting was used to represent ambient light (X_a,Y_a,Z_a in Table V). The mixed chromatic adaptation model using the CIE recommendation of R_{adp} value of 0.6[6] was adopted to transform unique hue stimuli from the test mixed illumination condition to the standard equal-energy white condition, and CIECAM02 was used to predict their colour appearance attributes. The remaining input parameters were the same for both methods. The implementation of both colour appearance models is described in detail in the CIE technical reports.[3,6]

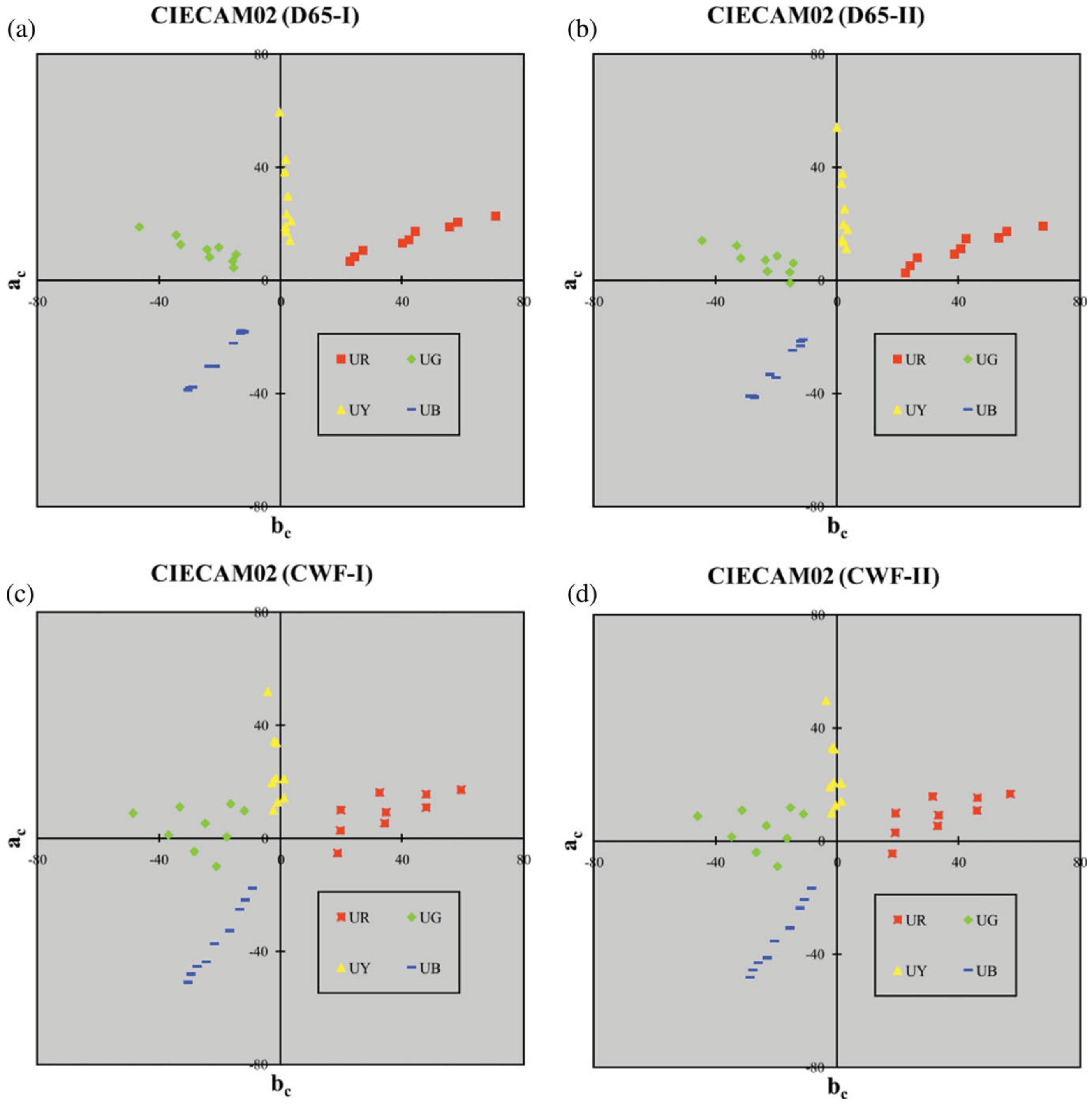

FIG. 3. Unique hue distribution in CIECAM02 chromatic diagram. (a) Unique hue stimuli under D65 predicted by method I. (b) Unique hue stimuli under D65 predicted by method II. (c) Unique hue stimuli under CWF predicted by method I. (d) Unique hue stimuli under CWF predicted by method II.

TABLE VI. Mean hue angle for unique hue settings in CIECAM02.

Mean hue	UR	UG	UY	UB
CRT (D65-I)	18.7	156.6	84.7	234.0
CRT (D65-II)	14.4	165.7	83.3	239.0
CRT (CWF-I)	12.7	171.0	93.6	240.8
CRT (CWF-II)	13.2	170.1	92.5	241.1
CRT (Dark)	14.2	164.6	83.6	235.4

Unique Hue Distribution in CIECAM02

CIECAM02 with two types of CATs was used to predict colour appearance attributes for each unique hue stimulus under corresponding mixed illumination conditions. Figure 3 shows the unique hue data in the CIECAM02 $a_c b_c$ chromaticity diagram. Each point in the diagram represents a grand mean of unique hue settings across 185 subjects in three experimental sessions. Each diagram includes 36 points (nine lightness-chroma levels tested × four unique hue) plotted in four different colours and symbols, red, green, yellow and blue to demonstrate each corresponding unique hue. Unique hue settings under D65 calculated by methods I and II are denoted as D65-I and D65-II respectively [Figs. 3(a) and 3(b)], whereas unique hue stimuli under CWF calculated by methods I and II are denoted as CWF-I and CWF-II [Figs. 3(c) and 3(d)]. The mean of the nine unique hue stimuli in different lightness-chroma levels for each unique hue and each setting are listed in Table VI. In the last row, the results for dark conditions were added for comparison.

Based on the reported variability in Tables II and III, which support the theoretical framework, hue angles of unique hue settings should be similar under different lighting conditions. This is not the case in Fig. 3, where there is clearly a larger scatter for UR and UG under CWF comparing with that under D65, implying the degree of hue differences vary for each CAT method. This indicates that the current form of CAT models might not compensate well for unique hue constancy when colour patches are viewed in different room lighting conditions. Accordingly, in the next section, both CAT methods are evaluated for each unique hue stimulus using our measured unique hue data as a benchmark.

Testing Chromatic Adaptation Transform Models

Conventionally, the average colour difference (ΔE) between observed and predicted data is used to measure the performance of CAT models.[3] In this study, as we focused on the accuracy of the unique hue reproduction, the performance of each CAT was evaluated by the mean perceptual hue difference ($\overline{\Delta H}$) in CIECAM02 between pairs of unique hue stimuli viewed under different lighting conditions.

The unique hue settings obtained in the dark room were used as the reference stimuli and the unique hue settings under D65 and or CWF room lighting were used as the test stimuli. CIECAM02 was used to predict the hue attributes for both reference and test stimuli, and the perceptual hue differences between each corresponding pair of test and reference stimuli were calculated by using Eq. (1). Note that, as recommended by Li *et al.*,[4] because ΔH is not normally distributed, instead of using root mean square, the mean perceptual hue difference ($\overline{\Delta H}$) is used directly to measure the overall predictive hue error.

$$\overline{\Delta H} = \frac{\sum_{i=1}^{9} |\Delta H_i|}{9} \quad \text{where} \quad \Delta H_i = 2\sqrt{C_{Ri}C_{Ti}}\,\sin\left(\frac{h_{Ri} - h_{Ti}}{2}\right) \tag{1}$$

C_R and C_T represent chroma, and h_R and h_T denotes the hue angle of reference and test stimuli.

An Optimized Chromatic Adaptation Ratio

In CAT method II, a mixed CAT with an R_{adp} value of 0.6 was adopted between monitor white point and ambient light based on the recommendation of CIE TC 8-04. In CAT method III, we use our unique hue data to find the best-fitting parameter R_{adp}; we estimated R_{adp} through an optimization routine so that the mean perceptual hue difference [Eq. (1)] between unique hue settings under dark room and under mixed illumination conditions was minimized. It was found that the best performance can be achieved when R_{adp} is equal to 0.75 and 0.80 for D65 and CWF room lightings, respectively. This mixed CAT with an optimized R_{adp} (CAT method III) is then compared with the existing methods I and II.

Comparison of Models

For each chromatic adaptation model, the average perceptual hue difference of the nine stimuli (nine different chroma-lightness levels) for each unique hue is calculated according to Eq. (1) and listed in Table VII. A small hue difference ($\overline{\Delta H}$) indicates a good performance of the CAT method (I, II or III) in terms of unique hue reproduction. Perceptual hue differences are derived for both illumination conditions (D65, CWF) in relation to the dark condition.

For both illumination conditions (D65 and CWF), we performed a two-way ANOVA (factor 1: CAT method-I,

TABLE VII. Mean perceptual hue differences in CIECAM02 for unique hue stimuli under two illuminants.

ΔH	UR	UG	UY	UB	Mean
Dark versus D65-I	3.3	3.3	0.6	0.8	2.0
Dark versus D65-II	1.0	1.6	0.8	2.4	1.4
Dark versus D65-III	1.7	1.2	0.6	0.9	1.1
Mean (Dark vs. D65)	2.0	2.0	0.7	1.4	1.5
Dark versus CWF-I	8.3	9.2	1.3	1.0	4.9
Dark versus CWF-II	3.8	6.4	3.0	4.1	4.3
Dark versus CWF-III	5.3	4.7	1.5	1.5	3.3
Mean (Dark vs. CWF)	5.8	6.8	1.9	2.2	4.2

TABLE VIII. *P* value of comparisons between different models.

P values	UR	UG	UY	UB
D65-I versus D65-II	7.6E-05	9.3E-03	0.54	6.8E-03
D65-I versus D65-III	2.8E-10	1.4E-07	0.31	0.69
D65-II versus D65-III	0.08	0.59	0.21	6.2E-06
CWF-I versus CWF-II	1.4E-02	0.2	7.6E-05	9.0E-03
CWF-I versus CWF-III	7.6E-11	6.0E-09	0.26	0.40
CWF-II versus CWF-III	0.32	0.46	1.7E-04	1.8E-04

-II or -III; factor 2: unique hue – UR, UG, UY, UB) to test whether there are differences in the model performance and whether these differences are specific to particular hues.

For D65, model performances are significantly different [$F(2,48) = 16.34$, $P < 0.0001$). Both mixed adaptation models (D65-II and D65-III) resulted in a significantly smaller perceptual error (mean error 1.4 and 1.1) than method I (D65-I; mean error = 2.0). Method III outperformed method II, but this difference did not reach statistical significance. The observed differences in model performances are not uniform across the four unique hues [i.e., significant interaction between model and hue; $F(6,48) = 17.13$, $P < 0.0001$]. To evaluate this difference in model performance for each of the four unique hues, posthoc *t* tests were performed. Table VIII shows the *P* values for all pairwise model comparisons; significant ($P < 0.05$; Bonferroni-corrected[18]) comparisons are underlined. Mixed-adaptation models (D65-II and D65-II) outperform CAT model I, but only for red, green and blue; for yellow all models perform equally well. Model III yields smaller perceptual errors than model II only for blue.

A similar pattern of results is obtained for illumination CWF; we find again significant model performance differences [$F(2,48) = 4.3$, $P = 0.0192$]. In contrast to the D65 results however, only method III outperforms method I (see Table VII) for CWF. The model performance differences are again specific to particular hues (significant interaction between model and hue: $F(6,48) = 5.5$, $P = 0.0002$. Posthoc pairwise comparisons are shown in Table VIII: Model III outperforms Model I for the red and green

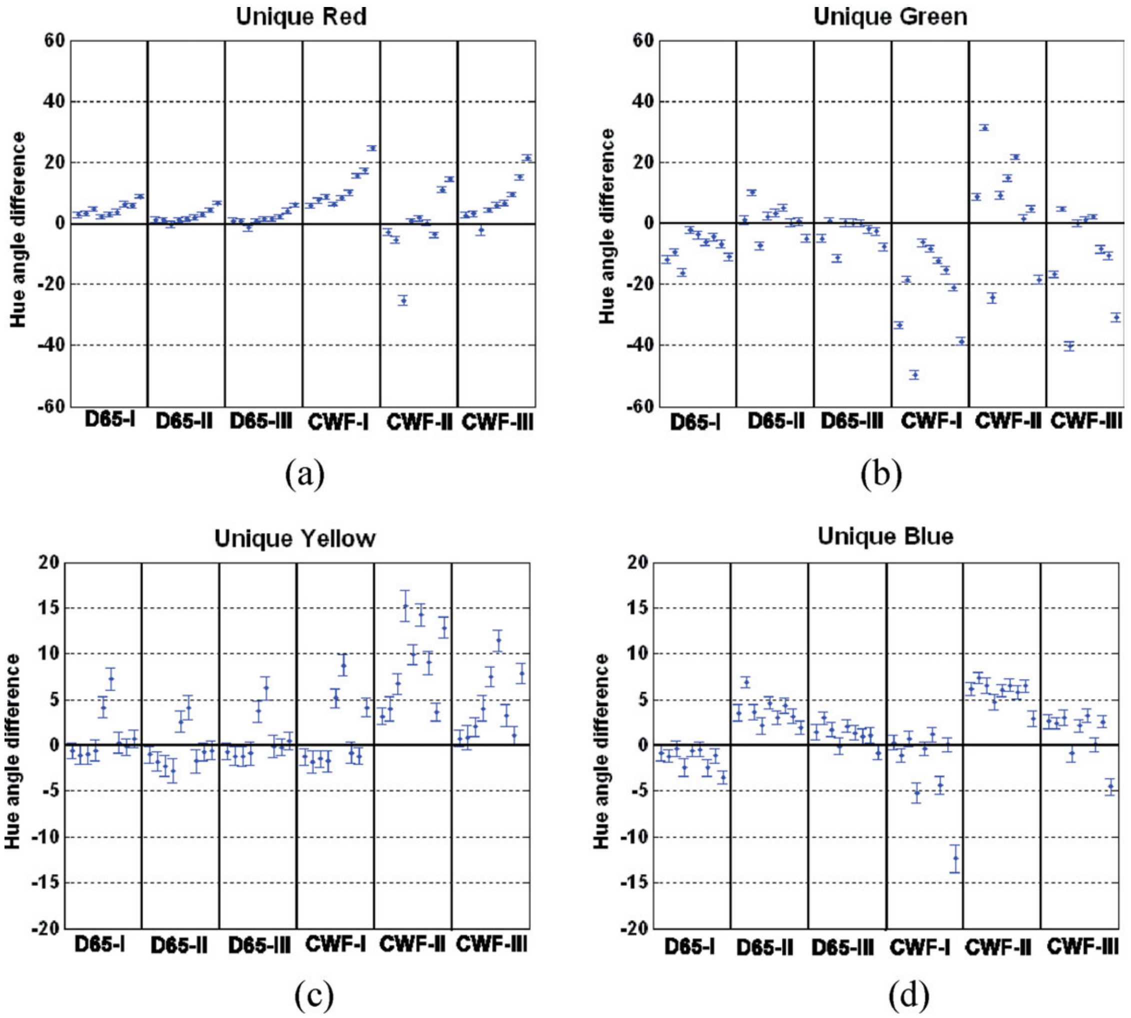

FIG. 4. Predicted hue angle differences [calculated according to Eq. (2)] for all four unique hues and both illumination conditions. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

predictions, whereas no significant difference in model performance is present for yellow and blue. In fact, Model II performs worse than Model I in the latter cases. All significant pairwise differences ($P < 0.05$; Bonferroni-corrected) are underlined in Table VIII.

In summary, for both illumination conditions (D65 and CWF), the mixed chromatic adaptation model with the optimised adaptation parameter (Method III) outperforms method I but depends on the particular hues. The hue shifts were found to be larger for CWF than for D65 room lighting for both methods, which indicates poor performance for both CATs for CRT displays viewed in unfamiliar lighting conditions.

Figure 4 illustrates the hue angle shifts for all four hues at the nine different lightness-chroma levels. The four panels a, b, c and d represent hue shift for UR, UG, UB and UY respectively. For each unique hue, the hue angle difference (Δh) is calculated by Eq. (2) and represents the hue shift between the reference stimulus and the stimulus predicted by the three different CAT methods under both illuminations.

$$\Delta h = h_R - h_T \quad (2)$$

where Δh, h_R and h_T represent the hue angle difference, reference hue angle and test hue angle, respectively.

In total, six sets of predictions were made: three different methods (CAT I, II, III) for two illumination conditions (D65 and CWF). Each data point in the figure represents the mean hue angle shift for a particular unique hue at a specific lightness-chroma level, averaged over 185 observers. A hue angle shift close to zero indicates a good agreement between unique hues in different viewing conditions and therefore implies a good performance of the CAT method in terms of unique hue reproduction. Error bars (95% confidence intervals) are also plotted for each data point to indicate significant differences from zero.

Figure 4 illustrates two main points. First, hue shifts are much smaller for UY and UB than for UR and UG [note the different scales on Figs. 4(a) and 4(b) in comparison to Figs. 4(c) and (d)] when the reference CRT stimulus viewed in a dark room is transformed to either D65 or CWF room lighting. For UR and UG, the predicted hue differences between the two illuminants are always significantly different from zero for all three methods and indicate that current chromatic adaptation models cannot produce satisfactory results for red and green hue reproduction. Second, hue shifts are much larger for CWF compared to D65 for all four unique hues.

The best performance for unique hue reproduction was achieved with CIECAM02 for mixed chromatic adaptation when R_{adp} was equal to 0.75 and 0.8 for D65 and CWF ambient light conditions, respectively. Following the CIE recommendation for a single factor for both viewing conditions the best performance can be achieved when R_{adp} is equal to 0.77.

CONCLUSIONS

Unique hue judgements from a large number of colour-normal observers ($n = 185$) were obtained under three different room-lighting conditions using a CRT display. These unique hue data were used to evaluate the performance of both full and mixed CATs of CIECAM02 for three lighting conditions by measuring the perceptual hue differences between predicted and observed pairs of unique hues stimuli. The evaluation of the performance for both models resulted in large predictive errors particularly when the light source of the room had large deviation from the white point of the monitor.

Our results confirm that incorporation of a mixed adaptation parameter improves the reproduction of unique hues in both viewing conditions (D65, CWF) while it was also found that the adaptation parameter varies for each lighting condition.[19] Specifically, the current CIE recommendation ($R_{adp} = 0.6$) for the mixed adaptation produced better performance than the single adaptation for UR and UB but worse performance for UY and UB. Using our optimized adaptation ratios ($R_{adp} = 0.75$) for D65 and ($R_{adp} = 0.80$) for CWF, the mixed CAT outperformed significantly the full CAT for both room lighting conditions.

This study complements existing research on colour appearance models by presenting a new method to evaluate the performance of mixed and full CAT for colours on display devices without the need of external reference and by proposing two optimized adaptation ratios, which predict more accurately hue attributes on display devices viewed in two different ambient illumination conditions.

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BOOK REVIEW

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The alternative is the Emergence Hypothesis,[8] whereby color terms pop up in the middle of unnamed regions of color space, at first idiosyncratically across speakers, but finally coalescing into well-formed color categories as speakers communicate with one another to reach consensus. The authors report that most languages obey the Partition Principle, although there are a few World Color Survey (WCS) languages, such as Kuku-Yalanji and Murrinh-Patha, both Australian Aboriginal languages, which appear to be exceptions and are more consistent with the Emergence Hypothesis. Other principles are: distinguish black from white; distinguish warm colors (red and yellow) from cool colors (green and blue); distinguish red from all other colors. Further sections describe the methodology, data analysis, and results of their analysis of the WCS dataset.

By far the largest part of the book, and in our view its most important contribution, is the painstaking and in-depth descriptive analysis of the WCS dataset itself, with several full pages of description and figures devoted to each of the 110 WCS languages. Each language receives a narrative description, including where the language fits into the evolutionary sequence, a description of the color terms, a listing of the terms and their frequency of usage, and diagrams showing how the colors are distributed across the array of color samples and the range of usage of each color term. The authors have taken great care to assure that all languages are examined using a single consistent protocol, which assures that the lists of Basic Color Terms have been arrived at using the same criteria in all the languages. For the linguist, who might be interested in the color vocabulary of a given language or group of languages, the description is ideal. The WCS dataset itself is available in tabulated form online for investigators who wish to use it to test other hypotheses about color and language (http://www.icsi.berkeley.edu/wcs/data.html).

Any project of this size must necessarily emphasize some aspects of the data at the expense of others. The analysis offered by the authors does not conceal or attempt to explain away the often prominent differences among speakers of a language, but neither does it take full advantage of the power of the individual differences to test the hypotheses about the universal glossary, the evolutionary sequence, and the four principles they outline in the introductory essays. It is too much to ask of a single book, even a book as long as this one, to carry out every possible analysis of such a comprehensive dataset.

Anyone who is interested in the naming of colors will find *The World Color Survey* to be the perfect companion to the WCS dataset. Together, these will define the debate about the relation between language and cognition for many years to come.

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