Chromatic Adaptation Transforms with Tuned Sharpening

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Abstract

Traditionally, the chromatic adaptation transforms used in color appearance models are calculated from the tristimulus values of the reference and test illuminants. However, with modern spectroradiometers it is just as easy to measure the spectral power distributions of the illuminants as their tristimulus values so there is no reason to restrict the input parameters to tristimulus coordinates. We propose a new method of calculating chromatic adaptation transforms based on using the extra information available in the illuminants' spectral power distributions. The new method gives comparable results to the current tristimulus-based chromatic adaptation transforms in most cases, and better results in some specific situations such as the McCann-McKee-Taylor experiment [12].

Introduction

While existing chromatic adaptation transforms [7, 8, 10] start with the CIE XYZ tristimulus values of the test and reference illuminants as input, the first processing step is a change of basis to a new coordinate system. One such change of basis is the Bradford transform empirically derived by Lam [7] and another is the spectral sharpening transform derived from Lam's data [7] by Finlayson and Süsstrunk [4] using white-point preserving sharpening. In either case, the same change of basis is applied no matter what the illuminants happen to be. If, instead of restricting the description of the illuminants to the tristimulus values, we describe them in terms of their spectral power distributions, we then can derive an illuminant-specific sharpening transformation. The hypothesis is that tuning the change of basis for each particular illuminant pair will lead to smaller errors in the final chromatic adaptation transform.

Description of the method

Using the Kodak [14] database of spectral surface reflectances which includes 102 DuPont paint chips, 64 Munsell chips (matte collection) and 170 natural and man-made objects, we compute the tristimulus values for each reflectance in the database, under the test and reference illuminants in the standard manner:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = k\sum_{i=1}^{101} S(\lambda_i)\cdot\rho(\lambda_i)\cdot\begin{bmatrix} \bar{x}(\lambda_i) \\ \bar{y}(\lambda_i) \\ \bar{z}(\lambda_i) \end{bmatrix} \qquad (1)$$

$$\text{where} \quad k = \frac{100}{\sum_{i=1}^{101} S(\lambda_i)\cdot\bar{y}(\lambda_i)}$$

The sampling has been performed over 101 wavelengths λ_i in the range from 380 nm to 780 nm in 4 nm intervals. $S(\lambda_i)$ denotes the spectral power distribution of the illuminant and $\rho(\lambda_i)$ represents the spectral surface reflectance at wavelength λ_i.

We find the best transformation T mapping the tristimulus values obtained under the test illuminant to the corresponding tristimulus values under the reference illuminant using the white-point preserving algorithm described by Finlayson and Süsstrunk [4]. This transformation can be used to predict the corresponding tristimulus values X^{ref}, Y^{ref}, Z^{ref} under the reference illuminant from the tristimulus values X^{test}, Y^{test}, Z^{test} under the test illuminant using the chromatic adaptation transformation model:

$$\begin{bmatrix} X^{ref} \\ Y^{ref} \\ Z^{ref} \end{bmatrix} = T^{-1}\begin{bmatrix} R_w^{ref}/R_w^{test} & 0 & 0 \\ 0 & G_w^{ref}/G_w^{test} & 0 \\ 0 & 0 & B_w^{ref}/B_w^{test} \end{bmatrix} T \begin{bmatrix} X^{test} \\ Y^{test} \\ Z^{test} \end{bmatrix} \qquad (2)$$

where the RGB ordinates of the reference and test illuminants are computed respectively as:

$$\begin{bmatrix} R_w^{test} \\ G_w^{test} \\ B_w^{test} \end{bmatrix} = T\cdot\begin{bmatrix} X_w^{test}/Y_w^{test} \\ Y_w^{test}/Y_w^{test} \\ Z_w^{test}/Y_w^{test} \end{bmatrix} \text{ and } \begin{bmatrix} R_w^{ref} \\ G_w^{ref} \\ B_w^{ref} \end{bmatrix} = T\cdot\begin{bmatrix} X_w^{ref}/Y_w^{ref} \\ Y_w^{ref}/Y_w^{ref} \\ Z_w^{ref}/Y_w^{ref} \end{bmatrix} \qquad (3)$$

Testing the model

To the authors' knowledge, most existing corresponding color appearance experiments [1, 2, 5, 6, 7, 9] do not

document the actual spectral power distribution of the test and reference illuminants. One exception is the McCann-McKee-Taylor experiment [12] in which 5 illumination conditions were provided by three projectors with narrow-band filters (630 nm, 530 nm and 450 nm, respectively) having a bandwidth of 10 nm at half-height. Given that the rest of our computations were based on a 4-nm sampling interval, we modeled each peak in the McCann-McKee-Taylor spectra by a simple rectangular signal with a width of 8 nm (2 intervals). The relative power distribution of each illuminant was then computed to accord with the ratios of the reported triplet of radiances from the Munsell white paper for that illuminant. This presumes the Munsell white paper had a uniform surface spectral reflectance.

In most of the other experiments the only information available about the light is the illuminant type (i.e. CIE A, CIE D65, Philips TL84) and its chromaticity. Our proposed method depends on having the actual spectra of the two illuminants, not just their chromaticities. In the present circumstances, the best we can do is to estimate of the actual spectra of the illuminants used in each experiment. We started with the spectral power distributions of the standard sources used to simulate the ideal illuminant spectra A and D65, and measured the Philips TL84 with a PhotoResearch PR650. We then modified these spectra to match the chromaticities reported for the illuminants actually used in the experiments.

To obtain the least distortion in the illuminant spectral power distribution when matching the chromaticity, we solve the following under-determined system with $(S^0–S^1)$ as unknown:

$$\begin{cases} \sum_{i=1}^{101} \overline{x}(\lambda_i)\cdot(S_i^0 - S_i^1) = X_w^0 - X_w^1 \\ \sum_{i=1}^{101} \overline{y}(\lambda_i)\cdot(S_i^0 - S_i^1) = Y_w^0 - Y_w^1 \\ \sum_{i=1}^{101} \overline{z}(\lambda_i)\cdot(S_i^0 - S_i^1) = Z_w^0 - Z_w^1 \end{cases} \quad (4)$$

S^0_i is the spectral power distribution at wavelength λ_i of the measured illuminant with tristimulus values X^0_w Y^0_w, Z^0_w, and S^1_i is the corresponding spectral power distribution of the similar illuminant that has the tristimulus values X^1_w Y^1_w, Z^1_w, as reported in the corresponding experiment. When we solve the under-determined system above using the pseudoinverse method we obtain the solution having the smallest norm, thus having the least deviation from the measured spectral power distribution S^0.

Results

We have used the corresponding color datasets accumulated by Luo and Hunt, available online from the University of Derby [11]. Table 1 summarizes the experimental conditions.

Data set	Number of specimens	Test illuminant type	Reference illuminant type	Experimental method
Helson	59	A	D65	Memory
Lam & Rigg	58	A	D65	Memory
Lutchi (A)	43	A	D65	Magnitude
Lutchi (D50)	44	D50	D65	Magnitude
Lutchi (WF)	41	WF	D65	Magnitude
Kuo & Luo (A)	40	A	D65	Magnitude
Kuo & Luo (TL84)	41	TL84	D65	Magnitude
Breneman 1	12	A	D65	Magnitude
Breneman 2	12	PROJECTOR	D55	Magnitude
Breneman 3	12	PROJECTOR	D55	Magnitude
Breneman 4	12	A	D65	Magnitude
Breneman 6	11	A	D55	Magnitude
Breneman 8	12	A	D65	Magnitude
Breneman 9	12	A	D65	Magnitude
Breneman 11	12	D55	GREEN-B	Magnitude
Breneman 12	12	D55	GREEN-B	Magnitude
Braun & Fairchild 1	17	D65	D65	Matching
Braun & Fairchild 2	16	D65	D65	Matching
Braun & Fairchild 3	17	D93	D65	Matching
Braun & Fairchild 4	16	A	D65	Matching
McCann "blue"	17	BLUE	GREY	Haploscopic
McCann "green"	17	GREEN	GREY	Haploscopic
McCann "grey"	17	GREY	GREY	Haploscopic
McCann "red"	17	RED	GREY	Haploscopic
McCann "yellow"	17	YELLOW	GREY	Haploscopic

Table 1: Experimental conditions for each data set

The results are presented in Tables 2, 3 and 4:

Data set	Mean ΔE_{Lab} Lam sharp	Mean ΔE_{Lab} Spectra sharp	RMS ΔE_{Lab} Lam sharp	RMS ΔE_{Lab} Spectra sharp
Helson	5.3	6.4	6.1	7.6
Lam & Rigg	4.4	5.8	5.1	6.8
Lutchi (A)	6.8	8.5	7.6	9.6
Lutchi (D50)	6.3	6.6	6.8	7.1
Lutchi (WF)	7.8	5	8.7	5.8
Kuo & Luo (A)	6.9	7.7	7.7	8.5
Kuo & Luo (TL84)	4.3	4.4	4.7	4.9
Breneman 1	10.5	11.2	10.8	12.1
Breneman 2	7.1	7.8	7.4	8.1
Breneman 3	12	13.8	14.2	16
Breneman 4	12.3	15.7	14.9	17.6
Breneman 6	7.9	9.6	8.3	10.4
Breneman 8	12	15.5	14	16.8
Breneman 9	17.9	22.1	20.7	24.7
Breneman 11	7.4	6.8	8.2	7
Breneman 12	8.9	9.6	9.1	10.2
Braun & Fairchild 1	3.8	3.4	4	3.8
Braun & Fairchild 2	5.9	6	6.6	6.6
Braun & Fairchild 3	7.1	7.2	7.2	7.3
Braun & Fairchild 4	5.9	6.3	6	6.5
McCann "blue"	21.4	18.7	22.2	19.8
McCann "green"	27.7	23.2	29.7	24.4
McCann "grey"	10.1	10.1	11.2	11.2
McCann "red"	16.9	20.2	17.8	21.6
McCann "yellow"	26.2	19.4	29.6	21
average value	10.5	10.8	11.5	11.8

Table 2: Mean and RMS ΔE_{Lab} error of the full spectra method compared to the sharpening method based on Lam data.

Data set	Mean $\Delta E_{CMC(1:1)}$ Lam sharp	Mean $\Delta E_{CMC(1:1)}$ Spectra sharp	RMS $\Delta E_{CMC(1:1)}$ Lam sharp	RMS $\Delta E_{CMC(1:1)}$ Spectra sharp
Helson	4.4	4.9	5.5	6.2
Lam & Rigg	3.7	4.7	4.6	5.5
Lutchi (A)	4.7	5.5	5.2	6.1
Lutchi (D50)	4.2	4.5	4.7	4.9
Lutchi (WF)	5.2	3.2	5.7	3.6
Kuo & Luo (A)	4.9	5.8	5.4	6.3
Kuo & Luo (TL84)	3.2	3.5	3.7	4
Breneman 1	7.2	8	7.8	9.1
Breneman 2	4.9	5.1	5.5	5.8
Breneman 3	7.5	8.4	9.4	10.1
Breneman 4	8.6	10.7	10.7	12.2
Breneman 6	5.8	6.7	6.2	7.3
Breneman 8	8.2	10.1	9.7	11.3
Breneman 9	12.3	14.6	14.1	16.1
Breneman 11	5.1	5	5.6	5.4
Breneman 12	6	6.6	6.7	7.6
Braun & Fairchild 1	3.5	3.2	3.9	3.8
Braun & Fairchild 2	6.4	6.4	7.9	7.7
Braun & Fairchild 3	5.7	5.6	6.1	6
Braun & Fairchild 4	5.2	5.3	5.4	5.6
McCann "blue"	12.7	11.6	13.2	12.3
McCann "green"	18	16	20.2	18.6
McCann "grey"	7.1	7.1	8.6	8.6
McCann "red"	13	13.9	14.5	15.2
McCann "yellow"	15.8	14.7	17.4	17.7
average value	**7.3**	**7.6**	**8.3**	**8.7**

Table 3: Mean and RMS $\Delta E_{CMC(1:1)}$ error of the full spectra method compared to the sharpening method based on Lam data.

Data set	Mean ΔE_{CIE94} Lam sharp	Mean ΔE_{CIE94} Spectra sharp	RMS ΔE_{CIE94} Lam sharp	RMS ΔE_{CIE94} Spectra sharp
Helson	3.5	3.8	4.1	4.5
Lam & Rigg	2.9	3.8	3.4	4.3
Lutchi (A)	3.9	5.2	4.4	5.9
Lutchi (D50)	3.5	3.7	3.9	4.1
Lutchi (WF)	4.1	3.1	4.4	3.5
Kuo & Luo (A)	4.2	5.1	4.5	5.5
Kuo & Luo (TL84)	2.7	3	2.9	3.3
Breneman 1	5.8	6.8	6.2	7.3
Breneman 2	3.9	4.2	4.3	4.6
Breneman 3	5.8	6.5	7.3	7.8
Breneman 4	7	8.6	8.4	9.7
Breneman 6	4.7	5.8	4.9	6.2
Breneman 8	6.7	8.2	7.6	9
Breneman 9	9.5	11.3	10.8	12.3
Breneman 11	4.2	4.1	4.6	4.4
Breneman 12	4.6	5.2	5.1	5.7
Braun & Fairchild 1	2.8	2.7	3.1	3
Braun & Fairchild 2	4.5	4.5	5.1	5.2
Braun & Fairchild 3	4.6	4.6	4.8	4.8
Braun & Fairchild 4	4.2	4.2	4.3	4.3
McCann "blue"	11.3	10.5	12	11.3
McCann "green"	14.5	12.8	15.6	14.3
McCann "grey"	6.1	6.1	7.1	7.1
McCann "red"	10.6	11.3	11.4	12
McCann "yellow"	13.7	12.4	14.9	13.8
average value	**6.0**	**6.3**	**6.6**	**7.0**

Table 4: Mean and RMS ΔE_{CIE94} error of the full spectra method compared to the sharpening method based on Lam data.

For most of the data sets, our method, denoted as "spectra sharp", performs almost as well as the sharpening based on Lam data (noted here as "Lam sharp") which is considered to give among the best results on these data sets [13]. For the Lutchi (WF), Breneman 11, Braun and Fairchild 1 and McCann "blue", McCann "green" and McCann "yellow" data sets, our new method gives more accurate predictions. We have used three different error metrics: ΔE_{Lab} , $\Delta E_{CMC(1:1)}$ and ΔE_{CIE94} to evaluate the predictions.

We speculate that the somewhat better overall results obtained with the full spectra method on the McCann data sets are due to the fact that it contains the actual spectral power distribution of the 5 rather unusually narrow-banded illuminants which differ substantially from the illuminants in the Lam experiment. For the other cases, the full spectra method performs almost as well as the Lam-based sharpening. In fact, given the significant noise in experimental data, which is based on memory matches, magnitude estimation and halposcopic matching, the performance difference between the models is probably not significant. Furthermore, it must be remembered that we have only an imprecise specification of the required illuminant spectra.

We also considered the possible effect of incomplete adaptation [10] by solving for the optimal value of the incomplete adaptation factor, D. While the errors for both methods dropped slightly, the overall results found were qualitatively similar to those in Tables 2-4.

Conclusions

The main hypothesis of this paper is that a better chromatic adaptation transform could be developed if it were to be computed from the spectra of the illuminants rather than simply from their tristimulus values. In the proposed method, the spectral power distribution of the illuminants is used to derive a sharpening transformation that is specific to the adapting illuminant pair. This contrasts with the fixed transformation approach inherent in either the Bradford transform or the Finlayson-Süsstrunk sharpening as it is applied in most current chromatic adaptation transforms. The new full spectra illumination-specific sharpening method performs better on the McCann-McKee-Taylor data, which is the main case where we should definitely expect some improvement. Many of the other experiments involve the same illuminant pairs (A and D65) as used in the Lam-based sharpening or ones similar to them. Two exceptions are the Kuo & Luo TL84-D65 pair and the Lutchi D65-WF. In the former, the errors are both very small relative to the experimental noise; in the latter, the full spectra method does slightly better. These results indicate, but do not prove, the potential of using the full spectra of the illuminants as input parameters for a better chromatic adaptation transform. Since chromatic adaptation transforms are a crucial part of all color appearance models, this could also lead to improved predictions of color appearance. Unfortunately, information about the actual spectral power distribution of the illuminants is lacking for most of the existing

experiments. This means that at this point, it is difficult to evaluate conclusively the relative performance of the method In our opinion, future experiments to obtain corresponding colors under different illuminants should definitely include a record of the spectra of the illuminants involved.

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