Color Ratios and Chromatic Adaptation

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Abstract

In this paper, the performance of chromatic adaptation transforms based on stable color ratios is investigated. It was found that for three different sets of reflectance data, their performance was not statistically different from CMCCAT2000, when applying the chromatic adaptation transforms to Lam's corresponding color data set and using a perceptual error metric of CIE ΔE94. The sensors with the best color ratio stability are much sharper and more de-correlated than the CMCCAT2000 sensors, corresponding better to sensor responses found in other psychovisual studies. The new sensors also closely match those used by the sharp adaptation transform.

Introduction

For almost a century, photoreceptor or first-stage adaptation has been proposed as a mechanism for color constancy.[1] Color constancy refers to the invariance of the perceived color of a surface despite changes in the intensity and spectral composition of the light source. The human visual system is able to discriminate very reliably[2] and quickly[3] colored scenes where the spectral composition of the illuminant is changed from colored scenes where surface reflectance is changed. This ability might be based on a visual coding of spatial color relations within a scene. Specifically, the *ratio* of color excitations produced by light from different surfaces is retained and kept constant, rather than absolute excitation values. As a result, due to the multiplicative effect of the spectral power distribution of the light source on the color response of a surface reflectance, the illuminant cancels out.

These ratios are determined within rather than between color classes. That such a model can explain at least partially the phenomenon of color constancy has been investigated and is illustrated in the literature. Dannemiller[4] studied the rank ordering of photon catches from natural objects illuminated with daylight and tungsten light for a model human fovea. He found that the observed rank orderings remained nearly stable across illuminant changes for all three cone classes. Foster and Nascimento[5] have shown that for a large class of pigmented surfaces and for surfaces with random spectral reflectances, color excitation ratios are statistically almost invariant under changes in illumination. The Retinex image processing model[6,7] uses sequential products relating each surface color to one or more bright surfaces, keeping the ratios constant, to produce preferred image reproductions. Brill and West[8] have used color ratios in theoretical studies to set constraints on illuminant and surface reflectance spectra for color constancy.

Image capturing systems, such as scanners and digital cameras, do not have the ability to adapt to an illumination source like the human visual system. To faithfully reproduce the appearance of image colors, it follows that all image processing systems need to apply a transform that converts the input colors captured under the input illuminant to the corresponding output colors under the output illuminant. This can be achieved by using a *chromatic adaptation transform* (CAT). Basically, applying a chromatic adaptation transform to the tristimulus values of a color under one adapting light source predicts the corresponding color's tristimulus values under another adapting light source.

In this paper, we investigate if a chromatic adaptation transform based on stable color ratios performs as well as the newly published chromatic adaptation transform, CMCCAT2000,[9] which was derived by optimizing perceptual error (CIE ΔE) over sets of corresponding color data. The intuition that we apply is as follows: if a CAT is used, then sensor responses are (independently) scaled in some RGB space to account for illuminant change. It follows then that color ratios, computed within a single response channel (R, G or B) must cancel this scaling factor. That is, by looking for a sensor basis that has good ratio stability, we must also be finding a reasonable candidate on which to base a chromatic adaptation transform: stable ratios implies a von Kries CAT and vice versa.

We found that there is no statistical difference at the 95 percent confidence level between CMCCAT2000 and the chromatic adaptation transforms resulting from the sensors that have best color ratio stability for Lam's corresponding color data.

This result is interesting when viewed in the context of theories of human color vision. It is often proposed (e.g. in the Retinex theory) that ratios play a key role in perception. The result here delivers sensor channels that optimize ratio stability. Moreover, our new result helps to explain why previous "physics based" adaptation transforms are quite different from those that are used in color science. Physics based transforms were designed to minimize absolute error of colors "observed" across illumination. As such, these sensors are insensitive to large relative error impinging on small sensor responses (these responses will have small absolute error). The results are sensors that are significantly more peaked than the CMCCAT sensors,[10] which themselves are more peaked than the cones. However, the spectral sharpened sensors also have significant negative lobes, which CMCAT2000 sensors do not. These lobes turn out to be significant in the context of relative error (or ratio error). Indeed, to have stable color ratios across illuminants one should have no lobes or very shallow negative lobes.

Summarizing this argument, if we assume that ratio stability is the rationale for adaptation transforms and that the human visual system optimizes for ratio stability, then we would expect an adaptation transform that is more peaked than the cones but that has minimal negative lobes.

Chromatic Adaptation Transforms

There are several chromatic adaptation transforms described in the literature, most based on the von Kries model.[1] CIE tristimulus values are linearly transformed by a 3x3 matrix $\mathbf{M}_{CAT}$ to derive R'G'B' responses under the first illuminant. The resulting R'G'B' values are independently scaled to get R"G"B" responses under the second illuminant. The scaling coefficients are most often based on the illuminants' white-point R'G'B' and R"G"B" sensor values. If there are no non-linear coefficients, this transform can be expressed as a diagonal matrix. To obtain CIE tristimulus values (X"Y"Z") under the second illuminant, the R"G"B" are then multiplied by $(\mathbf{M}_{CAT})^{-1}$, the inverse of matrix $\mathbf{M}_{CAT}$. Equation (1) describes a matrix formulation of this concept:

$$\begin{bmatrix} X'' \\ Y'' \\ Z'' \end{bmatrix} = \left[\mathbf{M}_{CAT}\right]^{-1} * \begin{bmatrix} R''_w / R'_w & 0 & 0 \\ 0 & G''_w / G'_w & 0 \\ 0 & 0 & B''_w / B'_w \end{bmatrix} * \left[\mathbf{M}_{CAT}\right] * \begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix} \quad (1)$$

Quantities R'_w, G'_w, B'_w and R''_w, G''_w, B''_w are computed from the tristimulus values of the first and second illuminants, respectively, by multiplying the corresponding XYZ vectors by $\mathbf{M}_{CAT}$.

The currently most popular chromatic adaptation transforms are the von Kries CAT operating on cone responses, derived by the Hunt-Pointer-Estevez (HPE) linear transform from XYZ color matching functions to relative LMS[11]; the linearized Bradford CAT[12,13]; the Sharp CAT[14]; and the CMCCAT2000 transform.[9] All are based on the von Kries model as described in equation (1), but they apply the white-point scaling to different RGB sensors (see Figure 1), i.e. they use different transformation matrices $\mathbf{M}_{CAT}$.

CMCCAT2000 has been developed to supersede CMCCAT97. CMCCAT97 is a chromatic adaptation transform included in the CIECAM97s color appearance model. It is based on the Bradford transform,[12] but includes a step to model partial adaptation.[15] CMCCAT2000 was developed by optimizing the transformation matrix $\mathbf{M}_{CAT}$ so that the perceptual error of predicted and actual corresponding colors for a number of corresponding color data sets[16] is minimized. The non-linear correction in the blue of the original Bradford CAT has been omitted to facilitate a reverse transform. It also calculates the degree of adaptation D differently than the previous version. In this paper, the transformation matrix of CMCCAT2000 is used with the chromatic adaptation model described in equation (1), and the degree of adaptation is not considered.

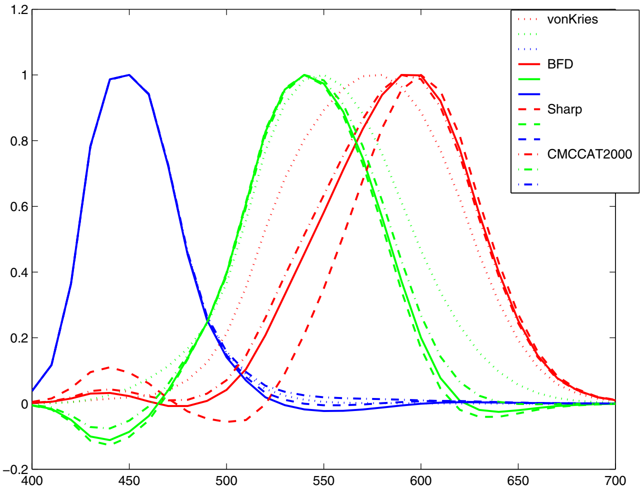

Figure 1. von Kries, Bradford, Sharp and CMCCAT2000 sensors.

Experiment

The experiment consisted of finding the best RGB sensors that result in minimal ratio error between sensor responses of a given set of reflectance data over a range of illuminants. The experiment was done individually for each of the three sensors, under the assumption that ratio stability within one photoreceptor response is independent from the other two.

The "color" or sensor response X for any given reflectance under any illuminant with any sensor can be calculated as follows:

$$X = \int_{\lambda} R(\lambda)E(\lambda)S(\lambda)d\lambda \quad (2)$$

where R is the reflectance factor at a given wavelength, E is the spectral power distribution of the illuminant, and S is the sensor's sensitivity at that wavelength. Using matrix notation, the color x_i for a reflectance vector $\mathbf{r}_i$ (31x1) is given by the inner product of the reflectance times illuminant SPD and the sensor sensitivity:

$$x_i = (\mathbf{r}_i \times \mathbf{e})^T \mathbf{s} \quad (3)$$

where $\mathbf{e}$ (31x1) and $\mathbf{s}$ (31x1) are the illuminant's spectral power distribution and the sensor sensitivity vector, respectively, and ($\times$) denotes an element by element multiplication. The length of the vectors (31) refers to the sampling of the visual spectrum, in our case from 400 to 700 nm at 10 nm intervals.

Let **x** be a (mx1) vector containing the colors for a set of *m* reflectances under the main illuminant with a given sensor. The vector of color ratios **a** is calculated as follows:

$$\mathbf{a} = \left[\frac{x_i}{x_j}; \frac{x_i}{x_{j+1}}; \ldots \right]; \forall x_i, x_j \in \mathbf{x}, x_i \neq x_j \quad (4)$$

a is a component vector of (m/2)x(m−1) entries. If $\mathbf{a}_e$ is a ratio vector of the same set of reflectances under a different illuminant, then the total ratio error ε is given by:

$$\varepsilon = \frac{1}{n} \sum_{e=1}^{n} \frac{|\mathbf{a} - \mathbf{a}_e|}{|\mathbf{a}|} \quad (5)$$

where n is the number of illuminants tested other than the main illuminant. By minimizing ε, we find the optimal sensor $\mathbf{s}_{opt}$ that keeps color ratios most stable:

$$\mathbf{s}_{opt} = \arg\min_{\mathbf{s}_{opt} \in \mathbf{S}} (\varepsilon) \quad (6)$$

The initial sensor set **S** was determined individually for each color response (R, G, and B) using a spherical sampling technique as described in Ref. 17, with the constraint that the sensors are within 30 degrees of either the red, green, or blue Bradford, CMCCAT, and Sharp sensors. Using no constraint, the solution (or optimal sensor) for all three color responses would converge to the blue optimal sensor. The color responses **x** were calculated for seven different illuminants, the main illuminant D65, and six other illuminants: A, D45, D55, D75, D85, and D100. Three different reflectance data sets were used, the Macbeth Color Checker patches (24 reflectances), the Munsell chips (462 reflectances), and Dupont pigments (120 reflectances). The best sensors were derived for each color response and reflectance data set individually. Additionally, an unconstrained non-linear least-squares regression was applied to find a local minimum around the best sensors found through spherical sampling. The resulting sensors $\mathbf{s}_{opt}$ that keep color ratios over changes in illuminants most constant are illustrated in Figure 2.

Now that we have derived sensors that optimize ratio stability, we wish to evaluate their appropriateness for accounting for corresponding color data. A priori, we might expect them to be somewhat appropriate since if ratios, with respect to the derived sensors, were perfectly stable, then this would provide evidence that theoretically a chromatic adaptation transform might perfectly discount illumination.[5] In order to evaluate the optimally stable ratio sensors in the context of chromatic adaptation, we calculated the linear transform mapping XYZs to the ratio stable color responses. We can think of this transform as a chromatic adaptation transform and simply insert it into equation 1.

We now applied this new “chromatic adaptation transform” to Lam's corresponding color data set. Lam had observers predict the appearance of 58 wool samples under illuminants A and D65. The resulting corresponding color data set has been used extensively to test chromatic adaptation transforms and has been found to be quite stable.[9]

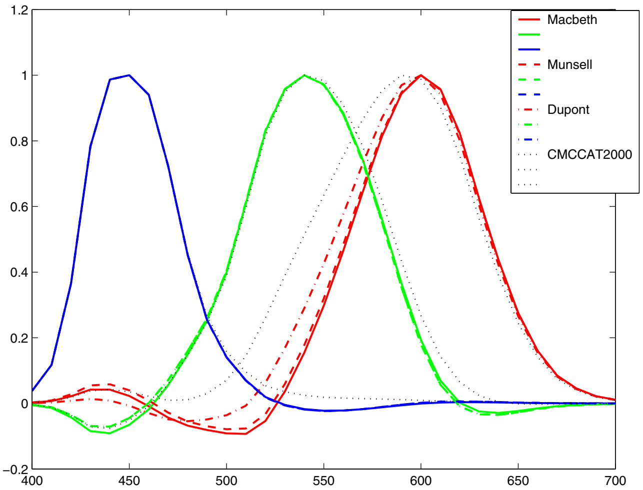

Figure 2. The sensors $\mathbf{s}_{opt}$ *found by minimizing color ratio errors for the Macbeth, Munsell and Dupont reflectance data sets. For comparison, the CMCCAT2000 sensors are also plotted.*

Table 1. Mean CIE ΔE_{94} values for Lam’s data set, and probability (p) values resulting from the t-test evaluation.

	Mean CIE ΔE_{94}	*p* -value
CMCCAT2000	3.03	
Macbeth	3.29	0.06
Munsell	3.20	0.13
Dupont	3.23	0.09

The predicted and actual X”Y”Z” values were converted to CIE Lab, so that the perceptual prediction error (CIE ΔE_{94}) could be considered. One-tail student t-tests for matched pairs[14,18] were calculated to evaluate if the CATs are statistically different from the CMCCAT2000 transform. The results are summarized in Table 1.

At the 95 % confidence level, the ratio optimal sensors deliver the same chromatic adaptation performance as the CMCCAT 2000 sensors. However, the ratio optimal sensors are significantly more peaked than CMCAT 2000 and this better reflects sensors found in other psychophysical experiments. Indeed, so-called sharp sensors derived in[14] were shown to deliver as good of a performance as CMCCAT2000 over many corresponding color data sets.[19] The new ratio optimal sensors are close to sharp sensors.

Perhaps more importantly, we now have a match between minimizing a physical variable and sensors derived through psychophysical means. If we wish to have ratio stability, then we would expect to derive a sharp adaptation transform.

Conclusions

There is no statistical difference at the 95 percent confidence level between CMCCAT2000 and the chromatic adaptation transforms resulting from the sensors that have best color ratio stability. In effect, the different chromatic adaptation transforms will perform equally well. However, as can be seen from Figure 2, the sensors with stable color-ratios are much "sharper," i.e. more decorrelated, than the CMCCAT2000 sensors, which were obtained by optimizing $\mathbf{M}_{CAT}$ over sets of corresponding color data.

The von Kries adaptation model alone cannot totally predict color constancy.[4,20] Therefore, any chromatic adaptation transform based on such a model will result in some error. Additionally, the corresponding color data sets all have some inherent experimental error. Lam calculated that his corresponding colors have a standard error of approximately 2 ΔE.[1] It is therefore possible that there are a number of sensors that will perform equally well using the von Kries adaptation model and tested on corresponding color data sets, as was shown in Ref. 17.

However, the appearance of the CMCCAT2000 sensors is, to our knowledge, unique, while sharp sensors have been found in psychophysical experiments.[21-24] It is therefore plausible that the sensors found by keeping color ratios stable are closer to the "real" sensors used by the human visual system to perform adaptation than the CMCCAT2000 sensors.

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Biography

Sabine Susstrunk is Assistant Professor for Imaging and Visual Representation in the Audiovisual Communications Laboratory, Communication Systems Department, at the Swiss Federal Institute of Technology (EPFL) in Lausanne, Switzerland. Her main research areas are color imaging, image quality metrics, and digital archiving. From 1995-1999, she was the Principle Imaging Researcher at Corbis Corporation in Bellevue, WA. From 1991-1995, she was an Assistant Professor in the School of Photographic Arts and Sciences at the Rochester Institute of Technology (RIT). She received a BS in Scientific Photography from the Swiss Federal Institute of Technology (ETH) and a MS in Graphic Arts Publishing from the Rochester Institute of Technology (RIT). She is an active member of ISO/TC42/WG18 and JWG20-Electronic Imaging standards groups, and a Vice-President of IS&T.