Performance of a Chromatic Adaptation Transform based on Spectral Sharpening

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Abstract

The Bradford chromatic adaptation transform, empirically derived by Lam, models illumination change. Specifically, it provides a means of mapping XYZs under a reference light source to XYZs for a target light source such that the corresponding XYZs produce the same perceived color.

One implication of the Bradford chromatic adaptation transform is that color correction for illumination takes place not in cone space but rather in a 'narrowed' cone space. The Bradford sensors have their sensitivity more narrowly concentrated than the cones. However, Bradford sensors are not optimally narrow. Indeed, recent work has shown that it is possible to sharpen sensors to a much greater extent than Bradford.

The focus of this paper is comparing the perceptual error between actual appearance and predicted appearance of a color under different illuminants, since it is perceptual error that the Bradford transform minimizes. Lam's original experiments are revisited and perceptual performance of the Bradford transform and linearized Bradford transform is compared with that of a new adaptation transform that is based on sharp sensors. Perceptual errors in CIELAB ΔE, ΔE_{CIE94}, and $\Delta E_{CMC(1:1)}$ are calculated for several corresponding color data sets and analyzed for their statistical significance. The results are found to be similar for the two transforms, with Bradford performing slightly better depending on the data set and color difference metric used. The sharp transform performs equally well as the linearized Bradford transform: there is no statistically significant difference in performance for most data sets.

1. Lam's Experiment

In his experiment to derive a chromatic adaptation transform, Lam [1] used 58 dyed wool samples. His main objectives when choosing the colors were that the samples represent a reasonable gamut of chromaticities corresponding to ordinary collections of object colors (see Figure 1), and that the samples have various degrees of color constancy with regard to change of illuminant from D65 to A.

To evaluate the samples, Lam used a memory matching experiment where observers are asked to describe the color appearance of stimuli in relation with a memorized color ordering system. Lam trained the observers on the Munsell system. Each observer was asked to describe the appearance of the samples in Munsell hue, chroma and value terms. The observers were fully adapted to the illuminant before they began the ordering. He used five observers with each observer repeating the experiment twice, resulting in ten color descriptions for each surface and for each illuminant, respectively.

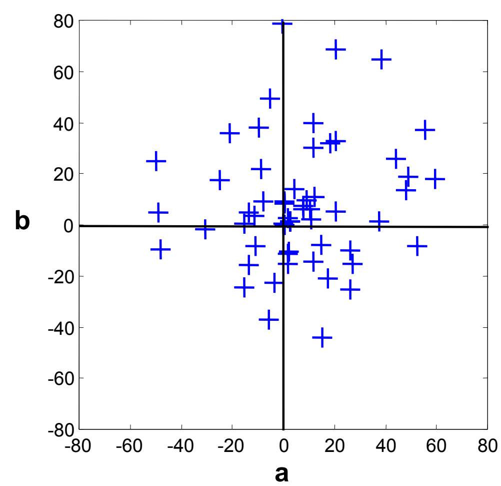

Figure 1: Distribution of Lam's 58 samples in CIELAB space, measured under D65

Lam converted the average Munsell coordinates of each sample under illuminant D65 and A to CIE 1931 Y, x and y values so that any color difference formula can be applied to the data. He calculated tristimulus values using the 1931 CIE equivalents of Munsell samples under illuminant C [2]. To calculate Munsell equivalent values under D65, he used the Helson et al. [3] chromatic adaptation transform to correct for the illuminant change from C to D65. This correction assumes that the Munsell chips are virtually color constant when changing illuminants from C to D65. It should be noted that he used the same illuminant to transform the Munsell coordinates of samples estimated under both D65 and A, justified as he trained the observers on the Munsell coordinate set using D65.

Lam observed systematic discrepancies between the measured sample values under D65 and those obtained from visual inspection under D65. Newhall et al. [4] found similar effects in their comparisons of successive (i.e. memory) matching with simultaneous color matching experiments. To calculate the correct corresponding colors under illuminant D65, he therefore added the difference between the measured sample value and the observed sample value under D65 to each observed sample value using additive correction in CIELAB space.

Lam was now in a position to derive a chromatic adaptation transform, i.e. to find a mapping that related his corresponding color data. In his derivation he adopted the following set of constraints: (1) the transform should maintain achromatic constancy for all neutral samples, (2) it should work with different adapting illuminants, and (3) it should be reversible (i.e. when a particular color is transformed from A to D65, and back to A again, the tristimulus values before transformation and after transformation back to A should be the same). The Bradford chromatic adaptation transform, called KING1 in his thesis, is based on a modified Nayatani transformation [5] and is as follows:

Step 1: Transformation from X, Y, Z to R, G, B.

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \mathbf{M}_{\text{BFD}} * \begin{bmatrix} X/Y \\ Y/Y \\ Z/Y \end{bmatrix} \tag{1}$$

where

$$\mathbf{M}_{\text{BFD}} = \begin{bmatrix} 0.8951 & 0.2664 & -0.1614 \\ -0.7502 & 1.7135 & 0.0367 \\ 0.0389 & -0.0685 & 1.0296 \end{bmatrix}$$

Step 2: Transformation from R, G, B to R', G', B'.

$$\begin{aligned} R' &= R'_w (R / R_w) \\ G' &= G'_w (G / G_w) \\ B' &= B'_w (B / B_w)^p \end{aligned} \tag{2}$$

where $p = (B_w / B'_w)^{0.0834}$

Quantities R_w, G_w, B_w and R'_w, G'_w, B'_w are computed from the tristimulus values of the reference and test illuminants, respectively, through equation (1).

Step 3: Transformation from R', G', B' to X', Y', Z'.

$$\begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix} = [\mathbf{M}_{\text{BFD}}]^{-1} * \begin{bmatrix} R'Y \\ G'Y \\ B'Y \end{bmatrix} \tag{3}$$

2. Linearized Bradford Transform

In some color management applications, the non-linear correction in the blue of the Bradford transform is considered negligible and is not encoded [6]. The linear Bradford transform is simplified to:

$$\begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix} = [\mathbf{M}_{\text{BFD}}]^{-1} * \mathfrak{D} * [\mathbf{M}_{\text{BFD}}] * \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{4}$$

where

$$\mathfrak{D} = \begin{bmatrix} R'_w / R_w & 0 & 0 \\ 0 & G'_w / G_w & 0 \\ 0 & 0 & B'_w / B_w \end{bmatrix}$$

Quantities R_w, G_w, B_w and R'_w, G'_w, B'_w are computed from the tristimulus values of the reference and test illuminants by multiplying the corresponding XYZ vectors by $\mathbf{M}_{\text{BFD}}$.

3. Spectral Sharpening

One implication of the Bradford chromatic adaptation transform is that color correction for illumination takes place not in cone space but rather in a ‘narrowed’ cone space. The Bradford sensors (the linear combination of XYZs defined in the Bradford transform) have their sensitivity more narrowly concentrated than the cones (see Figure 2). Additionally, the long and medium Bradford sensitivities are more de-correlated compared with the cones. However, Bradford sensors are not optimally narrow. Recent work has shown that it is possible to sharpen sensors to a much greater extent than Bradford [7]. These ‘sharp’ sensors are the most appropriate basis for modeling and/or computing adaptation of physical quantities (raw XYZs) across illuminants, i.e. for solving the non-perceptual adaptation problems when treating XYZs as the important units.

Though perceptual data was not used to derive spectrally sharpened sensors, spectral sharpening does appear to be psychophysically relevant. Indeed, sharp sensors have been discovered in many different psychophysical studies. Foster [8] observed that when field spectral sensitivities of the red and green response of the human eye are determined in the presence of a small background field, the resulting curves are more narrow and

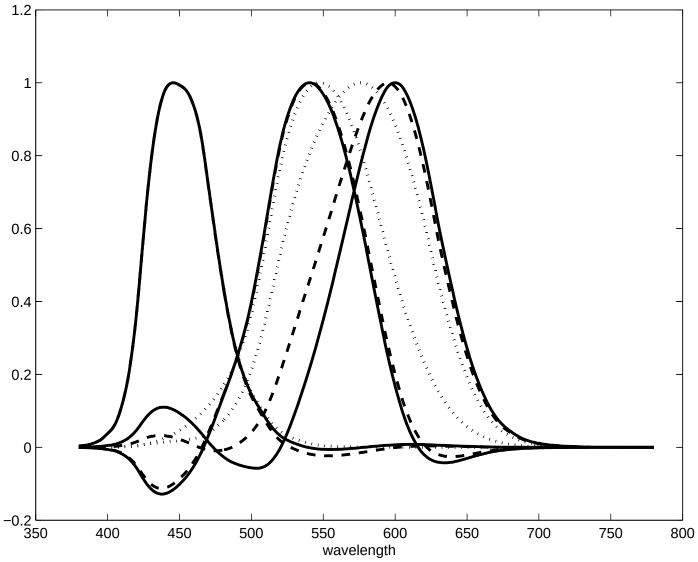

Figure 2: Normalized white-point preserving sharp transform (solid) from A to D65, derived from Lam's experimental data, compared with the Bradford transform (dash), and normalized L,M,S cone responses (dot).

de-correlated than the regular cone responses. These sharpened curves tend to peak at wavelengths of 530 nm and 605 nm, respectively.

Poirson and Wandell [9] studied the color discrimination ability of the visual system when targets are only briefly presented in a complex display. The spectral sensitivities derived from their experimental data peak relatively sharply around 530 and 610 nm.

Thornton [10] postulated that the visual response consists of sharp sensors with peak wavelength around 448, 537, and 612 nm by comparing the intersections of the spectral power distributions of matching light sources. He found that light sources designed with these peak wavelengths minimize metamerism.

Brill et al. [11] discussed prime-color wavelengths of 450, 540, and 605 nm. They proved that monitor primaries based on these wavelengths induce the largest gamut size, and that these monitors are visually very efficient. The color matching functions derived from these primaries, when linearly related to the CIE 1931 2º color matching curves, are sharp and de-correlated.

5. The Sharp Adaptation Transform

The sharp adaptation transform used for this experiment is derived from the spectral sharpening algorithms described by Finlayson et al. [7]. The performance of diagonal-matrix transformations that are used in many color constancy algorithms can be improved if the two data sets are first transformed by a sharpening transform **T**.

Using Lam's experiment, the prediction of the corresponding colors under D65 should approximately equal

$$\mathbf{ST} \approx \mathbf{PT}\mathfrak{D} \quad (5)$$

where **S** is a 58 x 3 matrix of corresponding color XYZs under illuminant D65, **P** is a 58 x 3 matrix of the measured XYZs under illuminant A and $\mathfrak{D}$ is the diagonal matrix formed from the ratios of the two sharpened white-point vectors RGB_{D65} and RGB_A, derived by multiplying vectors XYZ_{D65} and XYZ_A with **T**.

The matrix **T** is derived from the matrix **M** that best maps **P** to **S** minimizing least-squares error [12].

$$\mathbf{M} = (\mathbf{P}^T\mathbf{P})^{-1}\mathbf{P}^T\mathbf{S} \quad (6)$$

However, while **M** calculated using equation (6) results in the smallest mapping error, it will not fulfill the requirement that particular colors are mapped without error, i.e. preserving achromaticity for neutral colors. Therefore, **M** was derived using a white point preserving least-squares regression algorithm [13]. The intent is to map the values in **P** to corresponding values in **S** so that the RMS error is minimized subject to the constraint that, as an artifact of the minimization, the achromatic scale is correctly mapped. For completeness, the mathematical steps are summarized below to allow the interested reader to implement the method. However, it is possible just to assume that such a transform exists and skip over the next two equations.

In order to preserve white:

$$\mathbf{M} = \mathbf{D} + (\mathbf{ZN}) \quad (7)$$

where **D** is the diagonal matrix formed from the ratios of the two white point vectors XYZ_{D65} and XYZ_A respectively. **Z** is a 3 x 2 matrix composed of any two vectors orthogonal to the XYZ_A vector. **N** is obtained by substituting **Z**, **N** and **D** in equation (6) and solving for **N**.

$$\mathbf{N} = [\mathbf{Z}^T \mathbf{P}^T \mathbf{P}\mathbf{Z}]^{-1}[\mathbf{Z}^T \mathbf{P}^T \mathbf{S} - \mathbf{Z}^T \mathbf{P}^T \mathbf{P}\mathbf{D}] \quad (8)$$

The sharpening transform **T** can be derived through eigenvector decomposition of the general transform **M**.

$$\mathbf{M} = \mathbf{U}\mathbf{D}_{iagonal}[\mathbf{U}]^{-1} \quad (9)$$

where **T** is equal to **U**.

The predicted corresponding colors under illuminant D65 of Lam's 58 samples, using the sharp transform, are calculated as follows:

$$\mathbf{S} \approx \mathbf{P}\mathbf{T}\mathcal{D}[\mathbf{T}]^{-1} \quad (10)$$

6. Comparison of the Bradford and Sharp Transforms

Applying the resulting sharp transform, derived via data-based sharpening of the corresponding colors of the 58 Lam samples under illuminants A and D65 minimizes the RMS error between corresponding XYZs. It also yields sensors that are visibly sharper than those implied by the Bradford transform (see Figure 2). However, what we are most interested in is to compare the *perceptual error* between actual appearance and predicted appearance of a color under different illuminants using both the Bradford and the sharp transform.

Several corresponding color data sets were used to compare the performance of the Bradford, linearized Bradford and the sharp transform. Together they form a set accumulated by Luo and Hunt for the purpose of deriving and evaluating color appearance models and chromatic adaptation transforms [14]. Table 1 lists the characteristics of the data sets used in this study.

The actual and predicted XYZ values were converted to CIELAB space. Three perceptual error prediction methods, ΔE_{Lab}, ΔE_{CIE94}, and $\Delta E_{CMC(1:1)}$ were applied. One-tail student-t tests [20] for matched pairs were used to compare the Bradford, the linearized Bradford and the sharp data sets to find if the variations in errors are statistically significant. The null hypothesis was that the mean of the difference between the Bradford or linearized Bradford and sharp prediction error is equal to zero. The alternative hypotheses were that either one or the other prediction is better. For comparison between the Bradford and the sharp transforms, the RMS and mean color differences, and the t-test results for 95 and 99 percent confidence levels are listed in Tables 2, 3, and 4. Tables 5, 6, and 7 list the results for the linearized Bradford and the sharp transforms.

For Lam's corresponding color data, the Bradford transform does perform better than the sharp transform when the color error metric applied is ΔE (Table 2). However, there is *no statistically significant difference* at the 95 or 99 percent confidence level in using either Bradford or sharp to predict corresponding colors under illuminant D65 using either ΔE_{CIE94} or $\Delta E_{CMC(1:1)}$ (Tables 3 and 4). That is, the sharp transform works equally well as the Bradford transform.

For the other 15 data sets, Bradford outperforms sharp for 3 or 5 sets, depending on the color difference metric applied. Sharp performs better for one of the sets. For the other data sets, there is no statistical difference between the two transforms.

Comparing the sharp and the linearized Bradford transform (Tables 5, 6, and 7), the sharp transform performs either equally well, or better for 2 or 3 out of the 16 data sets, depending on the color difference metric used.

Table 1: Characteristics of the corresponding color data sets used in this study [1, 3, 15, 16, 17, 18, 19].

Data Set	No. of Samples	*Approx. Illuminant* Test	*Approx. Illuminant* Ref.	Sample Size	Medium	Experimental Method
Lam	58	D65	A	L	Refl.	Memory
Helson	59	D65	A	S	Refl.	Memory
CSAJ	87	D65	A	S	Refl.	Haploscopic
Lutchi	43	D65	A	S	Refl.	Magnitude
Lutchi D50	44	D65	D50	S	Refl.	Magnitude
Lutchi WF	41	D65	WF	S	Refl.	Magnitude
Kuo&Luo	40	D65	A	L	Refl.	Magnitude
Kuo&Luo TL84	41	D65	TL84	S	Refl.	Magnitude
Braun&Fairchild 1	17	D65	D93	S	Monitor&Refl.	Matching
Braun&Fairchild 2	16	D65	D93	S	Monitor&Refl.	Matching
Braun&Fairchild 3	17	D65	D30	S	Monitor&Refl.	Matching
Braun&Fairchild 4	16	D65	D30	S	Monitor&Refl.	Matching
Breneman 1	12	D65	A	S	Trans.	Magnitude
Breneman 8	12	D65	A	S	Trans.	Magnitude
Breneman 4	12	D65	A	S	Trans.	Magnitude
Breneman 6	11	D55	A	S	Trans.	Magnitude

Table 2: RMS and mean ΔE_{Lab} and student t-test results for BFD and sharp transform.

ΔE_{Lab}	RMS ΔE_{Lab}		Mean ΔE_{Lab}		95% confidence			99% confidence		
	BFD	Sharp	BFD	Sharp	Better than BFD	Same as BFD	Worse than BFD	Better than BFD	Same as BFD	Worse than BFD
Lam	4.7	5.1	4.2	4.5			X			X
Helson	6.2	6.2	5.4	5.3		X			X	
CSAJ	5.3	5.6	4.9	5.1			X		X	
Lutchi	6.7	7.6	5.9	6.8			X			X
Lutchi D50	6.9	6.8	6.3	6.3		X			X	
Lutchi WF	8.9	8.7	7.8	7.8		X			X	
Kuo&Luo	7.0	7.7	6.1	6.9			X			X
Kuo&Luo TL84	4.7	4.7	4.2	4.3		X			X	
Braun&Fairchild 1	4.0	4.0	3.8	3.8		X			X	
Braun&Fairchild 2	6.8	6.6	6.1	5.9	X			X		
Braun&Fairchild 3	7.6	7.3	7.2	7.1		X			X	
Braun&Fairchild 4	6.1	6.0	5.9	5.9		X			X	
Breneman 1	9.0	10.8	8.4	10.5			X			X
Breneman 8	14.0	14.0	12.9	12.1		X			X	
Breneman 4	14.6	14.9	12.9	12.3		X			X	
Breneman 6	7.9	8.3	7.2	7.9		X			X	

Table 3: RMS and mean ΔE_{CIE94} and student t-test results for BFD and sharp transform.

ΔE_{CIE94}	RMS ΔE_{CIE94}		Mean ΔE_{CIE94}		95% Confidence			99% Confidence		
	BFD	Sharp	BFD	Sharp	Better than BFD	Same as BFD	Worse than BFD	Better than BFD	Same as BFD	Worse than BFD
Lam	3.3	3.4	2.9	2.9		X			X	
Helson	4.0	4.0	3.5	3.4		X			X	
CSAJ	3.9	4.1	3.6	3.7			X			X
Lutchi	3.9	4.5	3.5	4.0			X			X
Lutchi D50	4.0	4.0	3.6	3.6		X			X	
Lutchi WF	4.2	4.2	3.9	4.0		X			X	
Kuo&Luo	4.0	4.2	3.7	4.0			X			X
Kuo&Luo TL84	2.8	2.9	2.6	2.7			X		X	
Braun&Fairchild 1	2.9	3.0	2.7	2.8		X			X	
Braun&Fairchild 2	5.3	5.2	4.6	4.5	X			X		
Braun&Fairchild 3	4.7	4.5	4.5	4.3	X				X	
Braun&Fairchild 4	4.3	4.1	4.1	4.0		X			X	
Breneman 1	5.2	5.9	4.8	5.6			X			X
Breneman 8	7.4	7.9	6.6	6.8		X			X	
Breneman 4	8.4	8.9	7.1	7.2		X			X	
Breneman 6	4.3	4.9	4.0	4.7			X			X

Table 4: RMS and mean ΔE_{CMC} and student t-test results for BFD and sharp transform.

$\Delta E_{CMC(1:1)}$	RMS ΔE_{CMC}		Mean ΔE_{CMC}		95% Confidence			99% Confidence		
	BFD	Sharp	BFD	Sharp	Better than BFD	Same as BFD	Worse than BFD	Better than BFD	Same as BFD	Worse than BFD
Lam	4.1	4.2	3.5	3.5		X			X	
Helson	4.7	4.7	4.0	4.0		X			X	
CSAJ	4.3	4.5	4.0	4.1			X			X
Lutchi	4.5	5.2	4.0	4.6			X			X
Lutchi D50	4.5	4.4	4.1	4.1		X			X	
Lutchi WF	5.3	5.2	4.8	4.8		X			X	
Kuo&Luo	4.6	4.9	4.2	4.6			X			X
Kuo&Luo TL84	3.4	3.5	3.1	3.1		X			X	
Braun&Fairchild 1	3.6	3.7	3.3	3.4		X			X	
Braun&Fairchild 2	6.5	6.4	5.7	5.5	X			X		
Braun&Fairchild 3	5.9	5.7	5.6	5.4		X			X	
Braun&Fairchild 4	5.5	5.4	5.2	5.0		X			X	
Breneman 1	6.4	7.1	5.7	6.7			X			X
Breneman 8	8.9	9.3	7.9	7.9		X			X	
Breneman 4	10.2	10.6	8.6	8.5		X			X	
Breneman 6	5.8	6.4	5.1	5.9			X			X

Table 5: RMS and mean ΔE_{Lab} and student t-test results for linearized BFD and sharp transform.

ΔE_{Lab}	RMS ΔE_{Lab}		Mean ΔE_{Lab}		95% Confidence			99% Confidence		
	BFD_{lin}	Sharp	BFD_{lin}	Sharp	Better than BFD_{lin}	Same as BFD_{lin}	Worse than BFD_{lin}	Better than BFD_{lin}	Same as BFD_{lin}	Worse than BFD_{lin}
Lam	5.3	5.1	4.4	4.5		X			X	
Helson	6.7	6.2	5.6	5.3		X			X	
CSAJ	5.9	5.6	5.4	5.1	X				X	
Lutchi	7.6	7.6	6.9	6.8		X			X	
Lutchi D50	6.9	6.8	6.3	6.3		X			X	
Lutchi WF	9.9	8.7	8.9	7.8	X			X		
Kuo&Luo	7.0	7.7	6.4	6.9		X			X	
Kuo&Luo TL84	5.0	4.7	4.6	4.3	X			X		
Braun&Fairchild 1	3.9	4.0	3.6	3.8		X			X	
Braun&Fairchild 2	6.7	6.6	6.0	5.9		X			X	
Braun&Fairchild 3	7.4	7.3	7.1	7.1		X			X	
Braun&Fairchild 4	5.8	6.0	5.7	5.9		X			X	
Breneman 1	9.9	10.8	9.1	10.5		X			X	
Breneman 8	16.1	14.0	14.0	12.1		X			X	
Breneman 4	17.1	14.9	14.7	12.3		X			X	
Breneman 6	8.2	8.3	7.7	7.9		X			X	

Table 6: RMS and mean ΔE_{CIE94} and student t-test results for linearized BFD and sharp transform.

ΔE_{CIE94}	RMS ΔE_{CIE94}		Mean ΔE_{CIE94}		95% Confidence			99% Confidence		
	BFD_{lin}	Sharp	BFD_{lin}	Sharp	Better than BFD_{lin}	Same as BFD_{lin}	Worse than BFD_{lin}	Better than BFD_{lin}	Same as BFD_{lin}	Worse than BFD_{lin}
Lam	3.5	3.4	3.0	2.9		X			X	
Helson	4.2	4.0	3.5	3.4		X			X	
CSAJ	4.2	4.1	3.8	3.7	X			X		
Lutchi	4.0	4.5	3.7	4.0			X		X	
Lutchi D50	3.9	4.0	3.5	3.6			X		X	
Lutchi WF	4.8	4.2	4.4	4.0	X			X		
Kuo&Luo	4.1	4.2	3.9	4.0		X			X	
Kuo&Luo TL84	3.0	2.9	2.8	2.7		X			X	
Braun&Fairchild 1	2.9	3.0	2.7	2.8		X			X	
Braun&Fairchild 2	5.2	5.2	4.5	4.5		X			X	
Braun&Fairchild 3	4.8	4.5	4.5	4.3	X			X		
Braun&Fairchild 4	4.2	4.1	4.0	4.0		X			X	
Breneman 1	5.6	5.9	5.0	5.6			X		X	
Breneman 8	8.4	7.9	7.2	6.8		X			X	
Breneman 4	9.6	8.9	7.9	7.2		X			X	
Breneman 6	4.4	4.9	4.2	4.7			X		X	

Table 7: RMS and mean ΔE_{CMC} and student t-test results for linearized BFD and sharp transform.

$\Delta E_{CMC(1:1)}$	RMS ΔE_{CMC}		Mean ΔE_{CMC}		95% Confidence			99% Confidence		
	BFD_{lin}	Sharp	BFD_{lin}	Sharp	Better than BFD_{lin}	Same as BFD_{lin}	Worse than BFD_{lin}	Better than BFD_{lin}	Same as BFD_{lin}	Worse than BFD_{lin}
Lam	4.3	4.2	3.6	3.5		X			X	
Helson	4.9	4.7	4.1	4.0		X			X	
CSAJ	4.7	4.5	4.3	4.1	X			X		
Lutchi	4.5	5.2	4.2	4.6			X		X	
Lutchi D50	4.4	4.4	4.0	4.1			X		X	
Lutchi WF	6.0	5.2	5.5	4.8	X			X		
Kuo&Luo	4.7	4.9	4.4	4.6		X			X	
Kuo&Luo TL84	3.6	3.5	3.3	3.1	X				X	
Braun&Fairchild 1	3.5	3.7	3.2	3.4		X			X	
Braun&Fairchild 2	6.4	6.4	5.5	5.5		X			X	
Braun&Fairchild 3	6.0	5.7	5.8	5.4	X			X		
Braun&Fairchild 4	5.3	5.4	5.0	5.0		X			X	
Breneman 1	6.7	7.1	5.9	6.7			X		X	
Breneman 8	10.0	9.3	8.5	7.9		X			X	
Breneman 4	11.4	10.6	9.5	8.5		X			X	
Breneman 6	5.7	6.4	5.2	5.9			X		X	

7. Conclusions

These results are very interesting. A sharp transform, derived through white point preserving data based sharpening of an arbitrary set of corresponding colors, performs almost as well as the current most popular chromatic adaptation transform, and slightly better than its simplified version that is used in many color management applications.

More broadly, we believe, the experimental results reported here are significant for a number of reasons. First, the chromatic adaptation transform in CIECAM97 is based on the Bradford transform. Second, the Bradford transform is being considered for standardization (CIECAT). Perhaps one can do better than Bradford? Third, sharp sensors have been discovered in many different psychophysical studies so it seems entirely plausible that sharp sensors are used in color vision. Yet, to the authors' knowledge, the appearance of the Bradford sensors is unique to Lam's original study. Sharp sensors also have the advantage that they are close to sRGB [21] color matching curves. So basing adaptation on sharp sensors meshes well with standard color correction methods used in digital color cameras.

In writing this article, we are not in anyway trying to invalidate the Bradford transform. Rather, we want to draw attention to the fact that the optimality of the Bradford color space for chromatic adaptation has never been experimentally proven. While it is clear that the Bradford sensors perform better than cone space, they perform no better than sharp sensors. This said, it is our opinion that the standardization of the Bradford transform is premature.

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