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Fast chromatic adaptation transform utilizing Wpt (Waypoint) based spectral reconstruction

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Abstract

Burns previously showed that a chromatic adaptation transform (CAT) implemented using spectral reconstruction with lightness preserving produces comparable predictive results of corresponding color data sets as optimized linear CATs. A fast spectral reconstruction CAT based on Wpt (Waypoint) spectral reconstruction is proposed that is optimized to take advantage of spectral reconstruction improvements without incurring the performance cost of using spectral reflectance. Comparisons are made, and an implementation using iccMAX profiles is demonstrated.

Introduction

A chromatic adaptation transform (CAT) relies on visual experiments that result in corresponding color data, and therefore, a CAT predicts the sameness of color appearance to the extent that it can be modeled. Corresponding color experiments generally involve asymmetric color matching using techniques including haploscopic viewing, short-term memory matching, or color estimation techniques.[1-3] In such experiments observers are instructed to identify, color in one viewing condition that has the same appearance as the color of an object in a different viewing condition.

Various approaches have been proposed to define CATs in the literature.[4-7] Color appearance models (CAMs) such as CIECAM02 or CIECAM16 utilize linear chromatic adaptation transforms (CATs) that adjust tristimulus values from one viewing condition to another while preserving appearance. These linear CATs first convert tristimulus values to “sharpened” cone responses, then perform vonKries white balancing and finally invert the sharpening to obtain adapted tristimulus values. Public corresponding color datasets can be used to optimize the sharpening filters used to define these CATs.

Recently Burns proposed a method of defining a CAT that predicts results from corresponding color datasets on par with linear CATs used by CAMs without using the datasets for optimizing the prediction.[8] At the core of Burns’s proposed CAT is a new spectral reconstruction method that determines plausible spectral reflectances for a set of tristimulus values, given normalized color matching functions and a spectral power distribution for an illuminant. The proposed reconstruction method results in reflectances for tristimulus values that are smooth, non-negative and spectrally non-selective for neutrals.

The CAT proposed by Burns utilizes four basic steps.

In the first step, spectral power distributions (SPDs) for both the source and destination illuminants are reconstructed using the proposed spectral reconstruction method given the illuminants’ tristimulus values with the equal-energy illuminant used for spectral reconstruction.

In the second step, the spectral reconstruction method is used with the source tristimulus values and reconstructed source illuminant to construct spectral reflection values under the source viewing conditions.

In the third step, the observer color matching functions and destination viewing conditions are then applied to the reconstructed spectra to determine tristimulus values for the destination viewing conditions.

In the last step, the destination tristimulus values are scaled by the value of the Y of the resulting tristimulus values divided by the Y of the source tristimulus values (thus preserving lightness of the source colorimetry in the estimated corresponding color). Without this final step the Burns spectral reconstruction method is not much more than a Material Adjustment Transform (MAT) [10] which predicts how tristimulus values of an object change due to changes in either illuminant and/or observer. It is this final limited optimization step that provides a conversion from a MAT to a CAT.

One challenge that Burns acknowledges is that his proposed method is significantly more computationally intensive than applying a linear transform CAT.

In this paper we propose a CAT that minimizes the overhead of spectral reconstruction by pre-caching the spectral reconstruction and transformation to tristimulus values resulting in similar corresponding color prediction as Burns with significantly less computational overhead, and can easily be implemented as a CAT in iccMAX profiles.

Wpt based spectral reconstruction

A spectral reconstruction method has been proposed [9] that makes use of the linear relationship between Wpt color equivalency [10] and the Chau spectral decomposition. [11]

The Wpt (pronounced “Waypoint”) color equivalency representation utilizes a method that normalizes sensor excitation values (either tristimulus values, cone excitations, or sensor values) for spectral reflectances of non-selective white colors that have constant Munsell Value and Chroma to minimize differences due to observer and illuminant preserving the perceptual correlates of lightness chroma and hue. The determination of Wpt coordinates for an arbitrary indexed observer, object, and illuminant (or light source) can be expressed by the following equivalencies:

$$\mathbf{w}_{i,j,k} = \begin{bmatrix} W \\ p \\ t \end{bmatrix}_{i,j,k} = \mathbf{A}_{i,k}\mathbf{s}_{i,j,k} = \mathbf{A}_{i,k}\mathbf{C}_i\mathbf{O}_j\mathbf{l}_k \qquad (1)$$

Where **w** represents a Wpt vector for the indexed observer, object, and illuminant (having coordinates *W*, *p* and *t*), $\mathbf{A}_{i,k}$ represents a Wpt normalization matrix specific for the observer and illuminant, $\mathbf{s}_{i,j,k}$ represents a vector for sensor excitations of the arbitrarily indexed observer, object and illuminant, $\mathbf{C}_i$ represents a matrix defining the sensor sensitivities or color matching functions for the i^{th} observer, $\mathbf{O}_j$ represents a Donaldson spectral reflectance matrix[12] (with reflectance along the diagonal and off-diagonal entries corresponding to fluorescence) for the j^{th} object, and $\mathbf{l}_k$ represents a vector for the spectral power distribution (SPD) of the k^{th} illuminant.

Example Excel spreadsheets and Matlab code that can be used to determine Wpt normalization matrices are available at (http://www.rit.edu/cos/colorscience/re_IntroducingWptLab.php).

Wpt coordinates can be represented in polar form describing Wpt chroma (c) and hue (h) as follows:

$$\begin{bmatrix} W \\ c \\ h \end{bmatrix}_{i,j,k} = \begin{bmatrix} W \\ \sqrt{p^2+t^2} \\ \arctan2(t,p) \end{bmatrix} \tag{2}$$

The Chau spectral decomposition is as follows:

$$\mathbf{O}_j = s\mathbf{I} + g\mathbf{R}_j \tag{3}$$

Where $\mathbf{O}_j$ is a matrix representing an arbitrary resulting spectral reflectance, $\mathbf{I}$ is an identity matrix representative of a "white" that reflects 100% of the light for all wavelengths, $\mathbf{R}_j$ is a matrix representing a maximally saturated reflectance (also referred to as a characteristic reflectance), g is a scalar of spectral whiteness, and s is a scalar of spectral saturation.

Spectral reconstruction from sensor excitations is performed in the following steps:

1. A Wpt normalization matrix is determined for the source observing conditions and applied to tristimulus values ($\mathbf{s}_{i,j,k}$) to get Wpt coordinates ($\mathbf{w}_{i,j,k}$).
2. $\mathbf{w}_{i,j,k}$ is converted to polar notation using equation (2) resulting in coordinate values $W_{i,j,k}$, $c_{i,j,k}$, and $h_{i,j,k}$.
3. A domain specific function of the $h_{i,j,k}$ (Wpt hue) of step 2 is used to determine a characteristic reflectance ($\mathbf{R}_j$) for the hue.
4. Wch values for the characteristic reflectance ($\mathbf{R}_j$) are determined using equation (1) and equation (2) resulting in coordinate values W_R, c_R, and h_R.
5. The estimated reflectance ($\mathbf{O}_j$) for the sensor excitations starting value ($\mathbf{s}_{i,j,k}$) of step 1 is then determined using equation (3) with the characteristic reflectance ($\mathbf{R}_j$) of step 3 with the scalars g and s being determined directly from $W_{i,j,k}$ and $c_{i,j,k}$ values found in step 2 as follows:

$$\begin{bmatrix} g \\ s \end{bmatrix} = \begin{bmatrix} \frac{1}{W_\mathrm{I}} & \frac{-W_\mathrm{R}}{W_\mathrm{I} c_\mathrm{R}} \\ 0 & \frac{1}{c_\mathrm{R}} \end{bmatrix} \begin{bmatrix} W \\ c \end{bmatrix} \tag{4}$$

Where $\mathbf{M}_\mathrm{R}$ is a matrix associated with the characteristic reflectance $\mathbf{R}_\mathrm{j}$ which leverages the linear relationship between the Wch values associated and $\mathbf{R}_\mathrm{j}$ from step 4 with the following linear regression:

$$\mathbf{M}_\mathrm{R} = \begin{bmatrix} W_\mathrm{I} & W_\mathrm{R} \\ 0 & c_\mathrm{R} \end{bmatrix}^{-1} = \begin{bmatrix} \frac{1}{W_\mathrm{I}} & \frac{-W_\mathrm{R}}{W_\mathrm{I} c_\mathrm{R}} \\ 0 & \frac{1}{c_\mathrm{R}} \end{bmatrix} \tag{5}$$

Where W_I is the Wpt W coordinate for the white point (PRD), W_R is the Wpt W coordinate for $\mathbf{R}_j$, and c_R is the Wpt c coordinate for $\mathbf{R}_\mathrm{j}$.

Determining domain specific characteristic reflectances from Wpt hue

One key point that needs further discussion is the *domain specific function of Wpt hue* mentioned in step 3 in the previous section. This can be implemented computationally using interpolation of a look-up table with the spectral reflectances of each hue determined a-priori. This has the advantage that the computational overhead of determining Wpt hue-based reflectances is separated from the application of these reflectances as part of spectral reconstruction. Additionally, coefficients in equation (5) can also be determined a-priori as well, resulting in a lookup of both hue based reflectances as well as values used to perform spectral reconstruction.

In the domain of color printing the spectral reflectances used in the look-up table can come from direct measurement of reflectances associated with the reproduction of Wpt hues for the most saturated colors (the 'gamut girdle') of the reproduction gamut. Each is scaled and shifted so the maximum reflectances is 1 and the minimum reflectance is zero. Population of reflectances for each Wpt hue in the Wpt hue lookup table is performed using a search of interpolated reflectances between measured hues.

For the purposes of this paper two methods were used to define domain specific reflectances for Wpt based spectral reconstruction. The first method used the Munsell reflectances with constant Munsell Value and Munsell Chroma that are used as part of Wpt normalization. The second method used the spectral reconstruction method proposed by Burns for colors with varying Wpt h and constant Wpt W and Wpt c (which are approximately at the same lightness and chroma of the Munsell colors used in the first method).

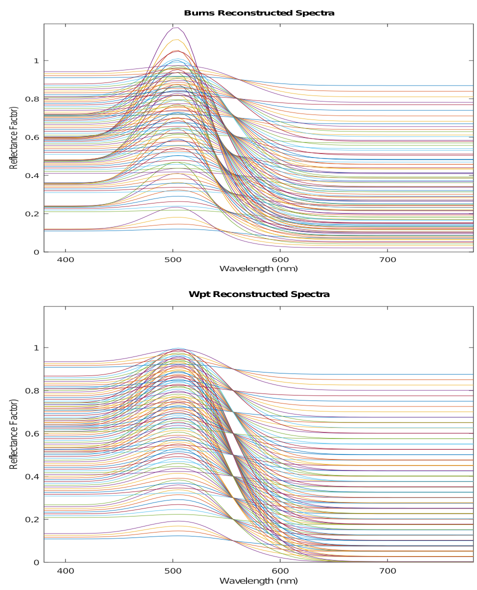

Figure 1. *Example spectral reconstructions using Burns method (top), and Wpt-based reconstruction (bottom) for colors varying in units of 10 Wpt lightness (W) and units of 5 Wpt chroma (c_{pt}) with a fixed Wpt hue (h_{pt}) of 215°*

Spectral Reconstruction Comparisons

For comparison purposes spectral reflectances having constant Wpt hue under a D65 illuminant for the 1931 standard 2° observer were reconstructed using both Burns and Wpt spectral reconstruction. The characteristic reflectance used for Wpt spectral reconstruction was generated for Wch W=40, c=40, and h=215° using the Burns method. Then spectra were generated for varying Wpt W (in units of 10) and Wpt c (in units of 5) for Wpt h=215° using both methods with results shown in Figure 1.

Notice that the shape of the Burns spectra vary in width around the peak while the Wpt spectra share the same general shape.

One of the interesting characteristics of Wpt spectral reconstruction is that reflectances which have the same Wpt hue will share the same Wpt hue regardless of the illuminant or observer used. For comparison purposes Wpt coordinates were determined for the reflectances in Figure 1 under the F11 illuminant and plotted as Wpt chroma versus Wpt hue in Figure 2.

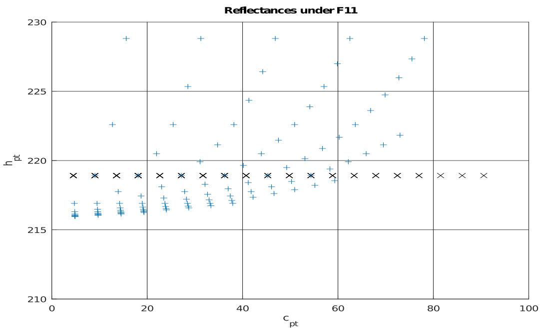

Figure 2. Hue variation of reconstructed reflectances of Figure 1 under an F11 illuminant with blue (+) marks representing points for Burns spectral reconstruction reflectances and black (x) marks representing points for Wpt spectral reconstruction reflectances

As can be seen in Figure 2, the Wpt hue under F11 for the Burns spectra shift significantly while the Wpt based spectra maintain a constant hue relationship (though it is not 215° under F11). The degree of shifting in hue for Burns spectral estimation varies based on the starting Wpt hue as can be seen in Figure 3 showing maximum and minimum relative hue shifts under F11 for planes of reconstructed spectra having constant Wpt hue under D65.

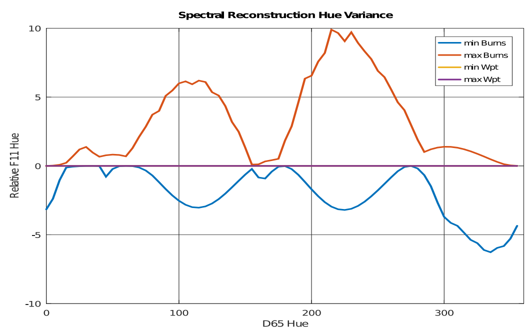

Figure 3. Minimum and maximum variation by hue of Burns reconstructed reflectances under F11 for spectra with constant Wpt hue under D65

Using Wpt based spectral reconstruction in a CAT

A CAT using Wpt based spectral reconstruction generally follows the same four steps as proposed by Burns with a significant performance optimization.

In the first step, SPDs are determined. In situations where the SPDs of the source and destination illuminant are already known then reconstructed SPDs are not needed. For the purposes of utilizing corresponding color datasets (where the SPDs of the source and destination illuminant are not known), two approaches of defining SPDs where used.

- In the first approach the SPD for the closest daylight illuminant or black body illuminant was found varying correlated color temperature. Then Wpt spectral reconstructions were used to adjust this SPD so that tristimulus values for a perfect reflecting diffusor (PRD) under the adjusted SPD match the white point's tristimulus values in the data sets for both illuminants.
- In the second approach the illuminant reconstruction method of Burns was used to determine SPDs for the illuminants in the data sets.

The second overall Wpt based adaptation step provides significant performance optimization by combining Wpt spectral reconstruction (as outlined in previous sections) with the conversion to tristimulus values (essentially combining steps two and three of the Burns method). This is accomplished by combining the sensor excitation conversion indicated in equation (1) using the destination illuminant with the Chau spectral decomposition in equation (3) as follows:

$$
\begin{aligned}
\mathbf{s}_{i,j,Dest} &= \mathbf{C}_i\mathbf{O}_j\mathbf{l}_{Dest} \\
\mathbf{s}_{i,j,Dest} &= \mathbf{C}_i\left(g\mathbf{I}+s\mathbf{R}_j\right)\mathbf{l}_{Dest} \\
\mathbf{s}_{i,j,Dest} &= g\mathbf{C}_i\mathbf{I}\mathbf{l}_{Dest}+s\mathbf{C}_i\mathbf{R}_j\mathbf{l}_{Dest} \qquad (6)\\
&\therefore \\
\mathbf{s}_{i,j,Dest} &= g\mathbf{s}_{i,\mathbf{I},Dest}+s\mathbf{s}_{i,\mathbf{R}_j,Dest}
\end{aligned}
$$

This means that the destination adapted tristimulus vector is the sum of the g scaled tristimulus values for the destination illuminant and the s scaled tristimulus values under the destination illuminant of the characterization reflectance corresponding to the Wpt hue of the source tristimulus values. Thus, steps 3 through 5 of the Wpt spectral reconstruction method are replaced with the following sub-steps:

3b. The $h_{i,j,k}$ (Wpt hue) of Wpt spectral reconstruction step 2 is used interpolate a lookup table to determine destination tristimulus values and corresponding W_R and c_R values associated with the characteristic reflectance for the hue.

4b. Use equation (4) and equation (5) with the W_R and c_R values in the final part of equation (6) to determine the destination tristimulus values

The third adaptation step is the same as step four from the Burns method where the destination tristimulus values are scaled to preserve the lightness of the source tristimulus values.

Corresponding Color Prediction Results

Several experimental data sets of corresponding colors were used to compare the performance of CATs based on HPE[6], CAT02[7] and CAT16[5] cone sharpening, Burns' proposed spectral reconstruction CAT[8], several CATs utilizing the proposed Wpt-based spectral reconstruction, a proposed CAT utilizing a linear Wpt normalization [10] based MAT without lightness scaling (Wpt-MAT) as well as a linear Wpt normalization based MAT with an additional lightness scaling (Wpt-LPMAT) step.

Table 1 – Evaluated Wpt spectral reconstruction CATs

Name	Characteristic Reflectances	Illuminant SPD Estimation
Wpt-MP	40 Munsell Reflectances with Munsell Value 5 and Chroma 6	Adjust nearest black-body / daylight illuminant
Wpt-MB	40 Munsell Reflectances with Munsell Value 5 and Chroma 6	Burns spectral reconstruction
Wpt-BB	360 reflectances using Burns spectral reconstruction with Wpt W=20, and Wpt c=30	Burns spectral reconstruction

The differences between the Wpt-based spectral reconstruction CATs is in the characteristic reflectances, and illuminant estimation with the three combinations chosen for comparison purposes shown in Table 1.

For completeness, comparisons using a Wpt based material adjustment transform (MAT) [10] were included. A Wpt MAT utilizes a pair of Wpt normalization matrices to predict how sensor excitations of an object change with a difference in either observer and/or illuminant as found in the following equation:

$$\mathbf{s}_{2,j,2} = \left(\mathbf{A}_{2,2}\right)^{-1} \mathbf{A}_{1,1}\mathbf{s}_{1,j,1} \tag{7}$$

Where $\mathbf{A}_{1,1}$ is a Wpt normalization matrix for the first observing condition and $\mathbf{A}_{2,2}$ is a Wpt normalization matrix for the second observing condition. The Wpt-MAT transforms evaluated represent the use of a direct linear transform that is predicted by equation (7).

Unlike using spectral reconstruction this results in a linear approximation of the changes in sensor excitations due to changes in illuminant and observer where non-linear relationships between the different illuminants and/or observers are involved. The proposed Wpt-LPMAT method used for predicting corresponding colors in this work first applies the MAT in equation (7) and then adjusts the lightness in similar fashion to the Burns and Wpt spectral reconstruction methods.

Table 2 – Mean ΔE_{94} for corresponding color data set predictions

Dataset	HPE	CAT02	CAT16	Burns	Wpt-MP	Wpt-MB	Wpt-BB	Wpt-LPMAT	Wpt-MAT
CSAJ	4.71	3.66	3.95	3.72	3.83	3.68	3.68	3.72	4.01
Helson	4.52	3.45	4.00	4.10	4.34	4.30	4.22	4.42	3.60
Lam & Rigg	4.31	2.97	3.45	3.22	3.35	3.32	3.38	3.90	3.81
LUTCHI	4.03	3.55	3.43	4.01	4.11	4.07	4.15	4.30	4.84
Kuo & Luo	4.29	3.30	3.41	2.85	2.91	2.83	2.86	3.19	4.09
Breneman	6.61	5.70	5.66	5.48	5.44	5.35	5.64	5.88	6.84
Braun & Fairchild	4.54	4.00	4.24	4.07	4.11	4.08	4.04	4.12	3.81
McCann	10.83	11.52	10.80	9.78	10.54	10.05	10.09	10.23	10.38
Mean (all data sets)	5.54	4.87	4.91	4.74	4.91	4.79	4.85	5.05	5.36
Mean (no McCann)	4.80	3.90	4.04	4.01	4.09	4.02	4.10	4.32	4.74

The mean ΔE_{94} differences between predicted and experimental corresponding colors were calculated for the CSAJ, Helson, Lam & Rigg, LUTCHI, Kuo & Luo, Breneman, Braun & Fairchild (RIT), and McCann data sets[13-14] for the HPE, CAT02, CAT16, Burns, Wpt-MP, Wpt-MB, Wpt-BB, and Wpt-LPMAT adjustment approaches with results shown in Table 2.

Performance comparison between Burns and Wpt-BB methods

An evaluation was made compare the relative speed performance of the Burns and Wpt spectral reconstruction CATs being applied to the same 20000 random XYZ values under D65 finding predicted results under Illuminant A. Both methods used the same reconstructed SPDs for the source and destination illuminants, and the characteristic reflectances for the Wpt estimation method were determined using the Burns reconstruction method. Care was taken to pre-calculate and isolate one-time setup aspects for each method with optimized application of each CAT. The Burns method was significantly slower (about 82 times slower) than the Wpt-BB method. However, the mean ΔE^*_{94} difference in the predicted colorimetry between the two methods was only 0.43 with a maximum difference of 2.65.

Implementing Wpt based spectral reconstruction CATs using iccMAX

Advanced color management systems can take advantage of features in iccMAX profiles[15]. Two significant advances that iccMAX-based color management offers are the ability to work with arbitrary observers and lighting conditions, and to directly encode transform algorithms as scripts within a calculator processing element. When the either the observer is not the 1931 standard 2-degree observer or the illuminant is not D50, then a spectral viewing conditions tag is required that provides the color matching functions and illuminant spectral power distribution. Additionally, two more tags are required that provide conversions of tristimulus values between the custom colorimetry and standard D50/2-degree observer colorimetry. Both the standardToCustomPccTag and customToStandardPccTag are implemented using the multiProcessElements tag type which is usually implemented using a matrixElement with a linear CAT/MAT. However, one can utilize the calculator processing element to perform the transformation of XYZ values between the standard and custom observing conditions. These tags are used whenever profiles that do not share the same observer and illuminant are connected together by an iccMAX-capable Color Management Module (CMM).

Six iccMAX profiles were created for testing to evaluate the predictive capabilities using a CAT02, Wpt-MB, and Wpt-LPMAT with the CSAJ dataset. A pair of profiles was needed for each CAT since connection between non-standard viewing conditions requires an intermediate connection through D50 colorimetry applying the customToStandardPccTag and standardToCustomPccTag as needed. The profiles can be found at (ftp://ftp.onyxgfx.com/p2/md1/ICC-CSAJ-CAT.zip).

Illuminant corresponding to the CSAJ illuminant colorimetry were determined using the Burns spectral reconstruction method for populating the spectralViewingConditions tags in the iccMAX profiles.

The XYZ values for the CSAJ dataset were applied with the iccMAX profiles for each CAT using the iccApplyNamedCMM tool from RefIccMAX, resulting in predicted corresponding colors for each CAT. The resulting data are compared to the corresponding color tristimulus values in Table 3.

Table 3 – Mean ΔE_{94} for corresponding color data set predictions using iccMAX profiles

Dataset	CAT02	Wpt-MB	Wpt-LPMAT
CSAJ	3.70	3.74	3.78

Notice that these values are only slightly different from those found in Table 2. This could be due to the additional intermediate conversion to standard ICC viewing conditions, or to the 32-bit floating point precision in iccMAX profiles relative to the 64-bit floating point precision in the Matlab/Octave evaluations.

Observations and Conclusions

One of the advantages that Burns points out about his purposed spectral reconstruction technique is that it determines spectral reflectances that are never negative thus corresponding tristimulus values for other observing conditions are never negative. The Wpt-based reconstruction method we propose does not have the same guarantee that the spectral reflectances will be non-negative with the possibility of negative corresponding tristimulus values. However, hue relationships are better preserved between observing conditions when using the Wpt-based reconstruction approach.

It was shown that the Wpt-based reconstruction method is flexible in the definition of characteristic reflectances by hue showing that domain specific reflectances or reflectances based on other reconstruction techniques can be applied. Once characteristic reflectances are in place the approach can easily be optimized to achieve nearly the same results as using more complicated reconstruction techniques.

One of the more interesting results is that using lightness preservation in addition to a MAT as proposed by Burns provides a limited optimization that better predicts corresponding color thus turning a MAT into more of a CAT which is something that has not been done previously when making comparisons between Wpt MATs and CATs.

Using the proposed Wpt-based spectral reconstruction CAT approach has at least two sources of improvement - spectral reconstruction as an intermediary (eliminating a linear approximation of the change in illuminant and/or observer that a linear based MAT uses), and lightness preservation.

However, there does seem to be some variability in whether lightness preservation improves the results. In the cases of Helson, Lam & Rigg, and Braun & Fairchild datasets the non-preserving (MAT) approach better predicts corresponding colors than the preserving (LPMAT) approach, and the Wpt-MAT best predicts the Braun & Fairchild CC results overall. This may be due to variability between the data sets in the meaning of "preserving appearance", or in the experimental methods involved.

The use of the proposed method of applying Wpt spectral reconstruction provides improved processing performance without significant average loss in predicting corresponding colors with the added benefit that it can easily be incorporated using advanced iccMAX color management.

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