NON-DIAGONAL COLOR CORRECTION

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ABSTRACT

A new color correction method is introduced which predicts how changing the color of the scene illuminant will affect a camera's RGB response. Like diagonal transformation color correction methods, the new method requires only 3-parameters. It therefore requires only the RGB color of the two illuminants be known. The method models the 9-parameters of a 3-by-3 linear transformation using a 3-dimensional linear model composed of 3 basis transformations. Experiments show that the method works better than the standard diagonal model unless the camera sensors are very sharply peaked, in which case the performance is essentially unchanged.

1. INTRODUCTION

A color image taken under an illuminant that differs in spectral composition and color from the illuminant for which a digital still camera is designed may have an objectionable color cast. Generally, the task of color balancing the image to eliminate the color cast can be subdivided into stages: (a) estimating the scene illumination, and (b) correcting the image colors based on the estimated illuminant. In this paper we address the latter, color-correction stage.

We present a new 3-parameter method of color correcting digital still camera images in order to compensate for the changes in image white point caused by changes in the illumination. This method is an extension of our previous work [6] on modeling the human chromatic adaptation transform.

One standard way to adjust the white point is to apply a diagonal transformation to the camera RGB, which applies an independent scaling to each of the R, G and B signals separately. It is often referred to as the von Kries method [7] since von Kries proposed independent scaling of the cone signals as a model of human chromatic adaptation.

In some cases the diagonal model can be improved by introducing a sensor sharpening transform [5] prior to the diagonal transformation. A sharpening transform is tuned to a particular illuminant pair and is not guaranteed to improve the results in all cases [2].

Another alternative is to use a full 9-parameter 3-by-3 linear transformation mapping RGB under one illuminant to the RGB under a second. The problem with this method is that usually there is insufficient information available to determine the 9 matrix entries. Typically all that is known are the RGB values of a 'white' surface under the two illuminants. Such measurements provide only 3 equations for the 9 unknowns. Of course, for the case of a diagonal transform this suffices since there are only 3 unknowns, which are determined by the ratios of the signals from the white under the two illuminants for each of the color channels taken separately.

Following on our results for the chromatic adaptation transforms [6], we consider here whether or not there is some other non-diagonal 3-parameter model that we could use that would perform better than the diagonal model for color correction of digital imagery. We form a new model by considering the 9-dimensional space of 3x3 transformations that model illuminant change and then finding the 3-dimensional subspace that best approximates the space of transformations. This subspace provides a 3-parameter, non-diagonal model of illuminant change that works better than other models of illuminant change.

There are two main differences between the cases of chromatic adaptation and color correction. The first is the difference in sensor sensitivities. The second is that digital imagery usually is represented in a non-linear fashion relative to the original scene luminance---a 'gamma' function [10] is applied to the linear data. Hence, it would be advantageous for the color correction transformation to apply directly to the non-linear representation.

There is a some similarity between the use of PCA in color correction and its use in color eigenflows [9]; however, color eigenflows are based on applying PCA to vector fields of RGB differences, while here it is applied to transformation matrices.

2. PCA BASED COLOR CORRECTION

To succeed in color correction, we need to estimate the RGB of a surface under different illuminations. In this process, we assume matte surfaces and ignore changes due to shading since by a change of illumination we mean only a change in the spectral composition of the illumination, not a change in the illuminant's position.

The RGB at single point on the surface as determined by the incoming spectrum of the illumination and the surface reflectance is then

$$h_i = \int_\lambda E(\lambda) S(\lambda) R_i(\lambda) d\lambda ,$$

where $E(\lambda)$ is the spectrum of the illumination, $S(\lambda)$ is the percent surface spectral reflectance function, $R_i(\lambda)$, i=1, 2, 3 are the camera sensitivity functions which we assume are normalized to unity.

If the image is nonlinear, we assume the nonlinearity is of the form

$$h^* = h^{1/\gamma} \text{ with a typical value of } \gamma \approx 2.$$

The linear model of the change in RGB induced by a change from illuminant a to illuminant b is $h_b = Mh_a$ where M is 3-by-3. M is independent of the surface reflectance. For the nonlinear case, the form remains the same although M will be different.

If we write the elements of the 3-by-3 M out as a vector, the space of such matrices is 9 dimensional. However, what is the underlying dimensionality of matrices M? Might the 9-dimensional space be embedded in a subspace of dimension as low as three? Since we know that color correction based on diagonal matrix works quite well, it seems reasonable to expect the dimensionality of M to be much lower than 9. Rather than force the 3 parameters to be those of a diagonal matrix, we use principal component analysis to extract the optimal 3-parameters.

To determine the dimensionality of the space of matrices M, we first construct a large set of corresponding RGBs under different pairs of illuminants. These pairs are formed from the 140 illuminants in the Simon Fraser University database [1]. All the illuminants were normalized to unit energy. For each illuminant pair, the corresponding RGBs for 1995 surface reflectances from the Kodak reflectance and Krinov databases [1, 8, 11] are calculated. The best, in the least-squares sense, 3-by-3 illumination transformation matrix, M, mapping one set to the other is then determined. For n illuminant pairs, we obtain n new such matrices M.

We apply principal components analysis to the set of matrices M. To do so, we first write each M as a vector m by scanning it row by row. Arranging all such 9-element vectors as rows in a matrix results in an n-by-9 matrix S. Principal components analysis of S produces basis vectors v_i, $i = 1,...,9$. Let the mean m vector be m_0. These vectors can be reshaped back into corresponding 3x3 matrices V_i and M_0. An illumination transformation matrix M can then be represented as

$$M = \sum_{i=1}^{9} \alpha_i V_i + M_0 ,$$

where $\alpha_i = (m - m_0) \cdot v_i$.

We can also approximate M by truncating the summation and using fewer than 9 basis matrices V_i. Figure 1 shows the residual error in approximating all matrices M as the number of basis matrices is increased.

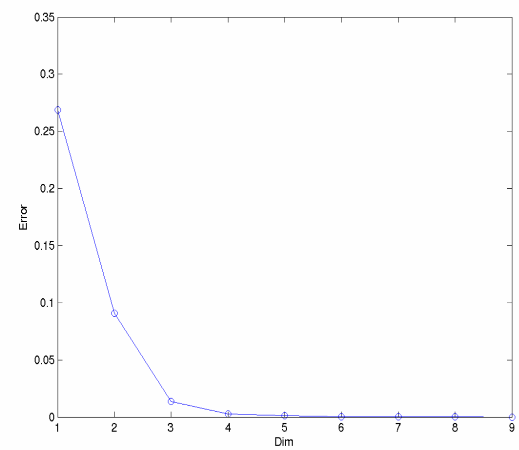

Figure 1. Residual variance versus dimension

More than 99% of the total variance is accounted for in the first 3 dimensions. The remaining issue is how to use this model for color correction. Based on principal component analysis, we have the first three bases matrices V_1, V_2 and V_3. We approximate M :

$$M \approx c_1 V_1 + c_2 V_2 + c_3 V_3 + M_0 .$$

Then given the RGB 3-vectors, l_a and l_b, of white under the two illuminants, the coefficients c_i required to predict RGBs under illumination b from RGBs from corresponding locations under illumination a can be determined as follows. Since $l_b = l_a M$, we have

$$\begin{aligned} l_b - l_a M_0 &= c_1 l_a V_1 + c_2 l_a V_2 + c_3 l_a V_3 \\ &= c_1[l_a V_1(1), l_a V_1(2), l_a V_1(3)] + c_2[l_a V_2(1), l_a V_2(2), l_a V_2(3)] + \\ &\quad c_3[l_a V_3(1), l_a V_3(2), l_a V_3(3)] \\ &= [c_1, c_2, c_3]Q \end{aligned}$$

with

$$Q = \begin{bmatrix} l_a V_1(1) & l_a V_1(2) & l_a V_1(3) \\ l_a V_2(1) & l_a V_2(2) & l_a V_2(3) \\ l_a V_3(1) & l_a V_3(2) & l_a V_3(3) \end{bmatrix}$$

$V_i(j)$ denotes column j of matrix V_i. Letting $c = [c_1, c_2, c_3]^T$, then

$$c = (l_b - l_a M_0)Q^{-1}$$

To color correct an image, we simply calculate the coefficient vector c and use it to construct *M*. *M* is then applied to the RGB of each image in the input image.

Color correcting images that are nonlinear due to gamma is no different from the linear case except that the PCA must be applied to RGB data synthesized to include gamma. We can expect the PCA method to work since previous research [4] showed that color correction using a diagonal transformation on non-linear images had only a slightly higher error than diagonal color correction of linearized images.

3. EXPERIMENTAL RESULTS

To test the proposed color correction method, we measure the error in predicting RGB under illuminant change in terms of relative error and CIE L*a*b* ΔE. The results are tabulated in Table 1. The tests are based on the spectral sensitivity functions of the Kodak DCS 420, Kodak DCS 460 and SONY DXC 930 cameras.

Table 1 shows that the new PCA-based method reduces the CIE $L^*a^*b^*$ ΔE error in all cases. The improvement is greater for the Kodak cameras than the SONY camera. The reason for this is that the SONY sensors have very narrow and sharply peaked sensitivity functions; whereas, the Kodak sensors are much broader. The sensors are compared in Figure 2. Narrow sensors make the diagonal model work very well. In the limit, a sensor with a Dirac delta sensitivity would lead to the diagonal model working perfectly, in which case the PCA method could not yield any improvement. However, there are many tradeoffs in sensor design. For example, narrow sensors let in less light. The PCA method could allow broader sensors without creating color correction problems.

Method/Camera/Data	%R	%G	%B	CIE ΔE
Diag/DCS420/Linear	3.9	4.6	7.3	1.25
PCA/DCS420/Linear	2.0	3.0	2.0	0.80
Diag/DCS420/Nonlin	2.0	2.3	3.7	1.33
PCA/DCS420/Nonlin	1.0	1.6	1.1	0.86
Diag/DCS460/Linear	3.3	3.4	7.6	2.09
PCA/DCS460/Linear	1.4	2.8	1.5	0.75
Diag/DCS460/NonLin	1.6	1.7	3.8	2.58
PCA/DCS460/Nonlin	0.7	1.4	0.8	0.95
Diag/SONY930/Linear	2.6	3.1	2.1	0.41
PCA/SONY930/Linear	2.5	3.4	1.5	0.31
Diag/SONY930/Nonlin	1.3	1.7	0.7	1.15
PCA/SONY930/Nonlin	1.2	1.3	0.8	0.82

Table 1: Average percentage error in R, G, B estimates and average CIE L*a*b* ΔE for each combination of method (simple diagonal, new PCA method), camera type, and linear versus nonlinear (gamma corrected) data.

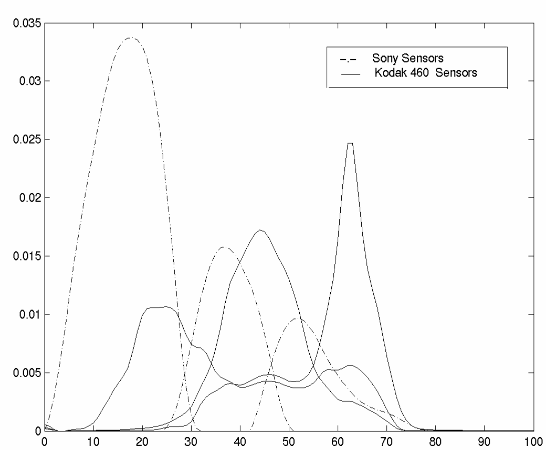

Figure 2. The sensor sensitivities of the SONY DXC 930 camera (dash lines) and the Kodak DCS 460. In

comparison to the Kodak curves, the SONY curves form narrower peaks and have only 1 peak per channel.

4. CONCLUSION

We have shown that color correction can be improved by modeling the 9-parameters of a full linear 3-by-3 transformation by a 3-dimensional linear model. Once the basis matrices have been determined, the additional computational cost of the new model is small. The method works on both linear and nonlinear image data.

5. ACKNOWLEDGEMENT

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