



Can you imagine a world without colors? The physical and psychological effects of colors contribute to a satisfying and joyful way of life, far beyond aesthetic pleasure, in both natural and man-made environments. Color as an interface connects us with our surrounding environment, and color differentiates the things we need not only to survive, but to indulge in life and to appreciate it.

The aim of the conference is to explore how colors interact with our daily life, to approach the conscious and unconscious influence color may have on individual thought and perception, and how we can identify and apply colors from a healthier and more sustainable perspective. Seven fields of discussion have been selected for discussion: Color and Environment, Color Culture, Art and Design, Color Communication, Color Synesthesia and Visionary Projects, Color Science and Technology, Color Psychology, and Color Education.

"In Color We Live - Color and Environment" hopes to emphasize the importance of a colorful environment for a sustainable and healthy way of life, by addressing both individual and basic human needs, and by giving examples drawn from all aspects of life.

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Intensity Independent RGB-to-XYZ Colour Camera Calibration

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ABSTRACT

In order for a digital colour camera to represent the colours in the environment accurately, it is necessary to calibrate the camera RGB outputs in terms of a colorimetric space such as CIE XYZ or sRGB (Wyszecki 1976). Assuming that the camera response is a linear function of scene luminance, the main step in the calibration is to determine a 3×3 linear transformation matrix M mapping data from linear camera RGB to XYZ. Determining M is usually done by photographing a calibrated target, often a colour checker, and then performing a least-squares regression on the difference between the camera's RGB digital counts from each colour checker patch and their corresponding true XYZ values. In order to measure accurately the XYZ coordinates for each patch, either a completely uniform lighting field is required, which can be hard to accomplish, or the illuminant power spectrum incident on each patch must be measured. In this paper we present an optimization method for camera colour calibration that does not necessitate constant radiance across the scene, yet still determines an accurate colour correction matrix.

1. INTRODUCTION

Due to the fact that the spectral sensitivity functions of most cameras do not correspond to that of the human eye, cameras often need to be calibrated in order to produce outputs that are consistent with standard colour spaces, such as sRGB or CIE XYZ. Assuming for the moment that the camera response is a linear function of scene luminance, the main step in the calibration is to determine a 3×3 linear transformation matrix M mapping data from (linear) uncalibrated camera RGB to XYZ. Non-linear "gamma correction" is then added as a second step.

Determining M is often done by photographing a calibrated target such as the X-Rite Digital ColorChecker SG and then performing a least-squares regression on the difference between the camera's RGB digital counts from each colour checker patch and their corresponding true XYZ values. One difficulty with this method is that it is hard to create an environment in which the lighting is completely uniform. If there is a single light source, then we can assume that the *relative* spectral power distribution of the light is constant; however, its irradiance is likely to vary across the colour checker and this will affect the RGB digital counts. If the amount of variation in the irradiance is unknown, then the "true" XYZ values will not correctly model the scene and so the colour correction matrix (CCM) M computed from them will also be incorrect. A difference in irradiance on a patch changes its luminance and hence results in a scaling of the associated RGB intensities (i.e., digital counts). In other words, treating RGB as a vector, its length changes, but not its direction. In traditional least-squares, the difference between transformed RGBs and XYZs is what is minimized.

One way to account for illumination variation is to measure the irradiance at each patch, but this extra step can be quite time consuming. It would certainly be preferable to measure the illuminant spectrum at only one location and have a method for deriving matrix M that works even when the irradiance is non-uniform. Just such an illuminant-independent method is presented here.

The proposed method deals with illumination variation by minimizing the angle between transformed RGBs and XYZs. Unlike the traditional least-squares method, which takes into account both the direction and magnitude of RGB vectors, and thus is affected by any irradiance-induced scaling; the proposed method seeks the 3×3 linear transform that best aligns the vectors from RGB space with those in XYZ space, without regard to their magnitude. As a result, the effect of irradiance is eliminated from the minimization.

2. BACKGROUND

The camera colour calibration process involves imaging a target with a camera. Let A represent the $3 \times N$ matrix of camera responses for N patches. Similarly, let B represent the $3 \times N$ matrix of the corresponding tristimulus values computed using the measured SPD of the illuminant, the spectral reflectance functions of each patch, and the CIE colour matching functions. Conventional least-squares regression minimizes $E(M) = \|MA - B\|_2$. It is well known that the best mapping is given by the Moore-Penrose pseudo-inverse

$$M = MA^T(AA^T)^{-1}.$$

As is clear from the above equation, both the direction and magnitude of RGB vectors represented in A affect the regression results. We next propose a magnitude-independent regression technique that is especially useful for camera calibration under circumstances where the irradiance cannot be guaranteed to be uniform across the target.

3. INTENSITY-INDEPENDENT REGRESSION

Consider a set of camera RGBs, $\{\vec{a}_i\}_{i=1}^N$, captured from N patches and their corresponding XYZ values, $\{\vec{b}_i\}_{i=1}^N$. The proposed technique finds a 3×3 linear transform M mapping RGB to XYZ by minimizing

$$E(M) = \sum_{i=1}^N \cos^{-1} \left(\frac{M\vec{a}_i \cdot \vec{b}_i}{\|M\vec{a}_i\| \|\vec{b}_i\|} \right)$$

This minimization takes into account only the angles between pairs of vectors. We used the Nelder-Mead (Nelder 1965) nonlinear optimization method to solve for the M . However, since the minimization is performed without regard to the overall vector magnitudes, the resulting transformation matrix M can be arbitrarily large or small in magnitude. To correct for the overall magnitude of M , the matrix is rescaled so that the sum of all its elements is 3 in sRGB space. This constraint ensures that the transformation does not alter the overall image brightness. We next show the results of performing camera calibration using synthesized data by applying least-squares and our proposed intensity-independent regression.

4. EXPERIMENTS

We performed two sets of experiments to study the effectiveness of our proposed method in camera calibration. In the first experiment, we synthesized an image of the interior patches of the X-Rite Digital ColorChecker SG under a non-uniform illuminant (Figure 1a) with irradiance-induced image intensity variation as shown in Figure 1b. The XYZ coordinates of each patch are calculated assuming constant radiance across the scene in both cases.

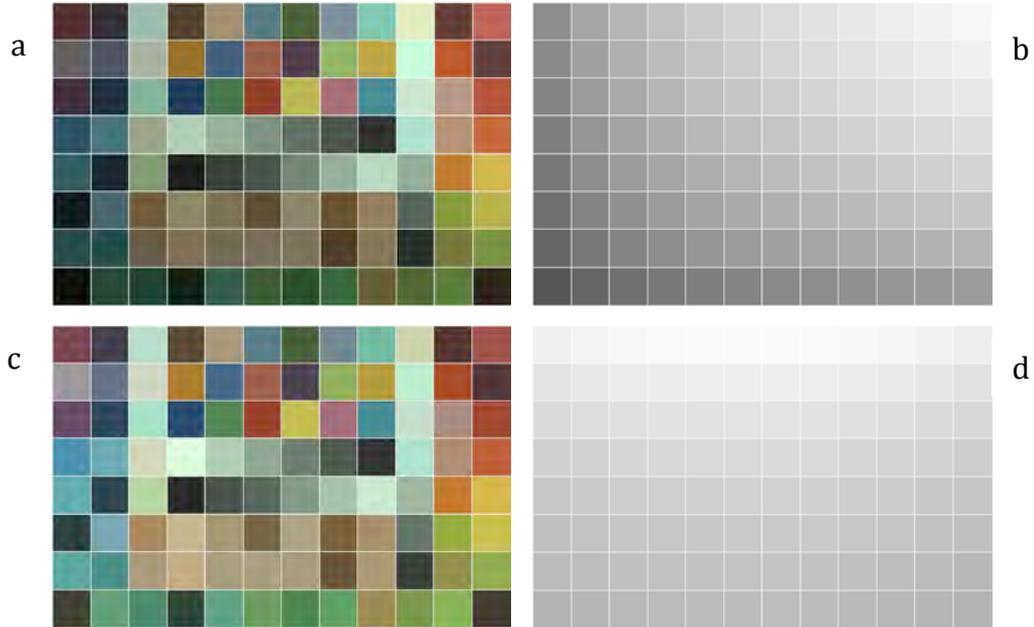


Figure 1: *a) synthesized image of the interior patches of the color checker under non-uniform lighting b) intensity variation in the synthesized image c) captured RGB values of the color checker patches in the light booth d) intensity variation in the captured image. The images here have been modified for visualization. The actual image data is linear.*

If we compute the CCM mapping camera RGB to XYZ space using conventional least-squares minimization, we obtain the following two matrices M_1 and M_2 for the images synthesized under uniform and non-uniform lighting, respectively:

$$M_1 = \begin{pmatrix} 0.6915 & 0.4720 & -0.0126 \\ 0.2476 & 1.0363 & -0.2559 \\ 0.1031 & -0.2840 & 1.5388 \end{pmatrix} \quad M_2 = \begin{pmatrix} 0.2020 & 0.3539 & -0.1059 \\ 0.0612 & 0.5435 & -0.1913 \\ 0.0279 & -0.1356 & 0.7056 \end{pmatrix}$$

The relative difference between the two matrices, measured using the Frobenius norm, is $2 \frac{|M_1 - M_2|_F}{|M_1 + M_2|_F} = 0.893$, indicating that the calibration results are impacted significantly by the irradiance variation. However, using our proposed technique, the camera calibration results are unaffected by the variation in the scene irradiance, and the two CCMs obtained for scenes 1 and 2 are identical:

$$M_1 = M_2 = \begin{pmatrix} 0.5428 & 0.3956 & 0.0232 \\ 0.1765 & 0.9293 & -0.2574 \\ 0.0234 & -0.0727 & 1.1288 \end{pmatrix}.$$

Of course, it is not sufficient for the transform simply to be intensity independent; we are also interested in seeing how well the transform maps colours from camera RGB to XYZ.

For this purpose, we compute the CCM based on the shaded image and measure the error on the uniformly lit image using CIEDE2000. We repeat this process for both methods. The results in Table 1 under “synthesized data” column show that our proposed calibration technique has better colour correction properties than the least-squares method under non-uniform lighting due to the fact that it is not affected by the irradiance variation across the scene.

	Synthesized Image Data		Captured Image Data	
	mean ΔE_{ab}^*	max ΔE_{ab}^*	mean ΔE_{ab}^*	max ΔE_{ab}^*
Least-Squares	8.00	12.41	4.25	7.91
Intensity Independent	3.19	8.86	2.81	7.49

Table 1: ΔE_{ab}^* statistics based on calibrating the camera using an image of the X-Rite Digital ColorChecker SG under non-uniform lighting and testing it on a uniformly lit image.

In addition to using synthesized images, we used a camera to acquire images and then computed the CCM based on the captured image data. To reduce the effects of noise, the camera RGB values for each patch were determined by averaging the values over the whole patch. The resulting values are displayed as the image shown in Figure 1c. To measure the irradiance variation across the colour checker, we replaced it with a grey surface in the same location and captured a second image. The average RGBs from each patch location are shown in Figure 1d. As before we calibrated the camera using the original (non-uniformly lit) image and also an image in which the intensity was adjusted to be uniform using the background irradiance variation map. As expected, the results showed that while the two CCMs computed by the least-squares method based on the original versus intensity-corrected images differed significantly (Frobenius norm of 0.10), our intensity-independent regression resulted in an identical CCM in both cases. The “captured data” column of Table 1 also shows that the proposed method has better correction error than the standard least-squares method.

5. CONCLUSION

We proposed a color calibration technique that does not require uniform irradiance across the calibration target. While conventional methods, such as least-squares regression, take into account both the magnitude and direction of color vectors in mapping uncalibrated camera RGB output to XYZ coordinates, our method eliminates the dependence on the scene irradiance and resulting image intensities by considering only vector directions. The method’s effectiveness was demonstrated on a non-uniformly lit calibration target.

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