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Colorimetric characterization of imaging device by total color difference minimization

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Abstract: Colorimetric characterization is to transform the device-dependent responses to device-independent colorimetric values, and is usually conducted in CIEXYZ space. However, the optimal solution in CIEXYZ space does not mean the minimization of perceptual error. A novel method for colorimetric characterization of imaging device based on the minimization of total color difference is proposed. The method builds the transform between RGB space and CIELAB space directly using the downhill simplex algorithm. Experimental results showed that the proposed method performs better than traditional least-square (LS) and total-least-square (TLS) methods, especially for colors with low luminance values.

Key words: Colorimetric characterization, Color difference, Imaging device
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INTRODUCTION

With the rapid development of computer system and image processing techniques, color images are widely used in visualization, communication, and reproduction. It is well known that different color devices have their own properties, which make color communication and reproduction difficult. In order to faithfully record and process color images, device characterization algorithms must be developed to minimize the impact of device limitations. Device characterization converts the device-dependent color to device-independent CIE colorimetric values, such as CIEXYZ or CIELAB (CIE Pub, 1986). The methods of device characterization have been intensively investigated and could be approximately classified into 5 categories: linear transform (Green, 2002), polynomial regression (Hong *et al*., 2001), neural network (Kang and Anderson, 1992), lookup table (LUT) (Hung, 1993; Johnson, 1996) and multispectral transform (Shen and Xin, 2004a; 2004b; Shi and Healey, 2002). As the relationship between CIEXYZ values and their corresponding imaging device responses is nonlinear, the direct linear transform is seldom used in practice. Polynomial regression uses high-order and cross terms to represent this nonlinear relationship, and the number of equations is always over-determined to produce reliable characterization results. The performance of neural network is quite good due to its excellent ability of nonlinear mapping. However, when compared with polynomial regression, the neural network method always requires a comparatively large training set and its computational cost is much higher. For LUT transform, it has been reported that the use of 200 color samples was an absolute minimum and that approximately 4000 samples was more typical (Johnson, 1996). The multispectral transform tries to recover the reflectance of physical samples in order to remove the limitation of illuminant dependence and to predict the metamerism. Among these transforms, high order polynomial regression is most straightforward, and is

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usually applied in the CIEXYZ space, although the CIELAB space is used for examining the characterization results. The reason for not applying high order polynomial regression in the CIELAB space is that the direct nonlinear transformation from RGB to CIELAB is beyond the representation ability of polynomial terms. Usually, the polynomial regression is solved using either least-square (LS) (Hong *et al.*, 2001) or total-least-square (TLS) methods (Xia *et al.*, 1999). Due to the extreme non-uniformity of the CIEXYZ space, the performance of the polynomial regression for characterization is evaluated by the color differences between predicted and measured standard samples in the CIELAB space, which requires the cubic root transform of XYZ values. Therefore, the normal way of using LS or TLS independent optimization for X, Y and Z stimulus would not guarantee the global minimization of the color differences. In order to further improve the accuracy of the imaging device characterization, the method of total color difference minimization (TCDM) is proposed in this paper.

ALGORITHM OF TCDM

Suppose the polynomial function has n terms, and there is an over-determined set of m color samples. For each color sample, the device response RGB value can be represented by $1\times n$ vectors $\boldsymbol{a}_i$ (i=1, …, m). Considering the nonlinear relationship between the RGB and XYZ values, high-order and cross term of RGB values should be used. Hong *et al.*(2001) found that 11 polynomial terms could produce satisfactory results in digital camera characterization. In this study, much more color samples are used. We include three additional 3-order terms and find it could produce good color accuracy in characterization. Accordingly, the vector $\boldsymbol{a}_i$, which can be represented in the following (take n=14 for example):

$$\boldsymbol{a}_i=[R,G,B,RG,RB,GB,R^2,G^2,B^2,RGB,R^3,G^3,B^3,1]. \quad (1)$$

Let $\boldsymbol{A}$ denote an $m\times n$ matrix of vector $\boldsymbol{a}_i$, and $\boldsymbol{b}_j$ (j=1, 2, 3) represent the $m\times 1$ vector for the XYZ tristimulus values of the samples. Then the transformation from RGB values to XYZ values can be represented by

$$\boldsymbol{A}\boldsymbol{h}_j=\boldsymbol{b}_j, \quad (2)$$

where $\boldsymbol{h}_j$ is the unknown vector to be solved. By combing the vectors $\boldsymbol{h}_j$ and $\boldsymbol{b}_j$, Eq.(2) can be expressed in the matrix form:

$$\boldsymbol{A}\boldsymbol{H}=\boldsymbol{B}, \quad (3)$$

where $\boldsymbol{H}=[\boldsymbol{h}_1,\boldsymbol{h}_2,\boldsymbol{h}_3]$, $\boldsymbol{B}=[\boldsymbol{b}_1,\boldsymbol{b}_2,\boldsymbol{b}_3]$.

The LS method assumes that the matrix $\boldsymbol{A}$ is free of error, and that all errors are confined to the vector $\boldsymbol{b}_j$. The LS method tries to find a solution $\boldsymbol{h}_j$ which

$$\text{minimizes } \|\boldsymbol{b}_j-\hat{\boldsymbol{b}}_j\| \text{ subject to } \boldsymbol{A}\boldsymbol{h}_j=\hat{\boldsymbol{b}}_j. \quad (4)$$

Any $\boldsymbol{h}_j$ satisfying $\boldsymbol{A}\boldsymbol{h}_j=\hat{\boldsymbol{b}}_j$ is called an LS solution with $\Delta\boldsymbol{b}_j=\boldsymbol{b}_j-\hat{\boldsymbol{b}}_j$ being the corresponding LS correction.

The TLS method, which considers errors in both the vector $\boldsymbol{b}_j$ and the matrix $\boldsymbol{A}$, is a generalization of LS. It tries to give the best estimates (in a statistical sense) when all variables are subject to independently and identically distributed errors with zero mean and common covariance matrix equaling the identity matrix, up to a scaling factor. The TLS method is to find a solution $\boldsymbol{h}_j$ which

$$\text{minimizes } \|[\boldsymbol{A},\boldsymbol{b}_j]-[\hat{\boldsymbol{A}},\hat{\boldsymbol{b}}_j]\|_{\mathrm{F}} \text{ subject to } \hat{\boldsymbol{A}}\boldsymbol{h}_j=\hat{\boldsymbol{b}}_j, \quad (5)$$

where $\|\boldsymbol{M}\|_{\mathrm{F}}$ denotes the Frobenius norm (Golub and Loan, 1989) of matrix $\boldsymbol{M}$. Once a minimizing $[\hat{\boldsymbol{A}},\hat{\boldsymbol{b}}_j]$ is found, any $\boldsymbol{h}_j$ satisfying $\hat{\boldsymbol{A}}\boldsymbol{h}_j=\hat{\boldsymbol{b}}_j$ is called a TLS solution and $[\Delta\hat{\boldsymbol{A}},\Delta\hat{\boldsymbol{b}}_j]=[\boldsymbol{A},\boldsymbol{b}_j]-[\hat{\boldsymbol{A}},\hat{\boldsymbol{b}}_j]$ is the corresponding TLS correction. The difference between LS and TLS can be understood in a geometric interpretation. In the over-determined system, the initial set of equations $\boldsymbol{A}\boldsymbol{h}_j=\boldsymbol{b}_j$ is inconsistent. Geometrically, this implies that the m-dimensional subspace generated by the columns of $\boldsymbol{A}$ does not contain $\boldsymbol{b}_j$. The best approximation of $\boldsymbol{b}_j$ in the LS sense is the orthogonal projection of $\boldsymbol{b}_j$ onto that space. However, if $\boldsymbol{A}$ is also subject to errors, the only correction of $\boldsymbol{b}_j$ in LS is then inappropriate. Therefore, TLS tries to minimize both of the correction $\Delta\hat{\boldsymbol{A}}$ and $\Delta\hat{\boldsymbol{b}}_j$ according to Eq.(5).

The TLS problem can be solved in either one-dimension or multi-dimensions, both using the singular value decomposition technique. More detailed explanation about TLS and its statistical properties can be found in (Huffel and Vandewalle, 1991).

In polynomial regression for device characterization, the LS method for CIEXYZ space fitting is frequently adopted due to its mathematical simplicity. In color printer calibration, it was reported that the TLS method outperforms the LS method as it considers the errors in both the left-side matrix and the right-side vector shown in Eq.(5) (Xia *et al.*, 1999).

Despite the different assumptions, both LS and TLS methods try to find the suitable solution of polynomial regression in CIEXYZ space. In the evaluation process, color difference in CIELAB space is used due to the non-uniformity of the CIEXYZ space. Because of the cubic-root transformation from CIEXYZ to CIELAB, the same errors in different positions in the CIEXYZ space would result in very different errors in the CIELAB space. Given the same error or color difference in CIEXYZ space, the error or color difference in the CIELAB space usually increases with decreasing of luminance values. So the prediction accuracy of the dark color samples is always worse than that of the light color samples. In general, the solution of polynomial regression using LS and TLS methods in XYZ color space does not give best color difference prediction under CIELAB space. Therefore, the ideal and most straightforward way of characterization is to build the direct mapping from RGB to the uniform CIELAB space. However, the complicated non-linear transform from RGB to CIELAB is greatly beyond the fitting ability of a relatively small number of polynomial terms. For the characterization using polynomial regression, the mapping of RGB to XYZ seems unavoidable.

Unlike the LS and TLS methods, at minimization of the errors in XYZ, the new method proposed in this paper tries to optimize the solution of polynomial regression by TCDM of all the color samples in the CIELAB space as follows:

$$\text{minimizes } \sum_{i=1}^{m} \Delta E_i \text{ subject to } \boldsymbol{AH}=\hat{\boldsymbol{B}}, \tag{6}$$

where ΔE_i is the color difference between the measured and predicted color values for the ith sample. It is noted that the vector $\boldsymbol{h}_j$ in matrix $\boldsymbol{H}$ is now not independent of each other, but is optimally adjusted under the objective function of total color difference minimization.

Downhill simplex is used to solve the multi-dimensional minimization problem of Eq.(6), as it does not require the calculation of derivatives of the objective function (Nelder and Mead, 1965; Press *et al.*, 1992). For the N (N=3n) dimensional function, the simplex is the geometrical figure consisting of N+1 fully interconnecting vertices. To start a multi-dimensional minimization, a starting guess is required. For this, the downhill simplex starts with N+1 points defining an initial simplex, which can be represented using an $(N+1)\times N$ matrix $\boldsymbol{P}$

$$\boldsymbol{P}=[\boldsymbol{p}_0\ \boldsymbol{p}_1\ \cdots\ \boldsymbol{p}_N]^{\mathrm{T}}, \tag{7}$$

where $\boldsymbol{p}_i$ (i=0, …, N) denotes a $1\times N$ vector. Let $\boldsymbol{p}_0$ be the initial starting point, with the other N points being defined as

$$\boldsymbol{p}_i=\boldsymbol{p}_0+\lambda\boldsymbol{e}_i, \tag{8}$$

where $\boldsymbol{e}_i$'s are N unit vectors, and λ is a constant representing the characteristic length scale. The downhill simplex algorithm then tries to find the minimum by reflection, expansion, 1D contraction and full contraction. When a tolerance is met, the optimization stops.

As the objective function for minimization in devices characterization is complex (42 dimensions when n=14) and not continuous, a random starting point is not a good selection as the downhill simplex may be trapped in local minima and produces unacceptable color differences. A good and reasonable selection of $\boldsymbol{p}_0$ is the matrix $\boldsymbol{H}$ solved using LS method. In order to avoid the problem of local minima, the simplex algorithm could be run iteratively as follows:

(1) Let the initial starting point $\boldsymbol{p}_0$ be the solution of LS method;

(2) Run downhill simplex algorithm;

(3) If the color difference reduction of two iterations is quite small, stop.

EXPERIMENTS AND DISCUSSION

In this study, two reference targets were used:

Macbeth ColorChecker for digital camera characterization and Kodak Ektacolor IT8.7/2 for scanner characterization. The digital camera used was a Canon model EOS D30 with 3.25-million pixel (2160×1440) sensor with 45/0 illuminating/capturing geometry, and the scanner used was Epson model GT-10000+. The colorimetric values of the two reference targets were measured by Macbeth Color-Eye 7000A spectrophotometer, and the RGB values were obtained from the captured image of the digital camera and the scanner respectively. For imaging devices such as digital cameras and scanners, the raw responses of the senses are always nonlinear transformed to match the inverse of the non-linearity of display system to provide high signal-to-noise ratio. Therefore, the linearization of channel responses was conducted using gray samples before the device characterization by polynomial regression. So the RGB values in Eq.(1) are no longer the original responses, but their corresponding linearized ones. In the experiment, CheckerDC was used for digital camera characterization and IT8 was used for scanner characterization. It should be noted that there are different strategies for the selection of training and testing samples. For example, some researchers (Hong *et al*., 2001; Shi and Healey, 2002) divided the samples into two datasets, one for training and one for testing. Shen and Xin (2004a; 2004b) proposed to select the training samples adaptively according to their positions in color space and excluding the testing samples. In this study, we use all the samples on a color target except the current testing one for training purpose, which is close to our pervious methods in (Shen and Xin, 2004a; 2004b). In addition, the training and testing samples were selected from the same targets in this study. It is expected that there will be severe material metamerism if we use CheckerDC for training and IT8 for testing or vice versa, due to the quite different materials of these two targets (Hong *et al*., 2001; Shen and Xin, 2004b). Therefore, we consider that the training strategy adopted in this study is suitable for industrial applications. Table 1 shows the results obtained for the digital camera and scanner. It is noticed that the TLS based method does not perform better than the LS based method for both the digital camera and the scanner used in this study. This might be due to the fact that the errors in matrix $\boldsymbol{A}$ do not satisfy the conditions required by the TLS method. The proposed method produces the best results for both the digital camera and the scanner. The improvements of the average results are around 14% in terms of color difference $\triangle E_{ab}^{*}$.

Table 1 Characterization accuracy of the method LS, TLS and TCDM in terms of mean, maximum (Max), and standard deviation (*SD*) of color difference

$\triangle E_{ab}^{*}$	CheckerDC, digital camera			IT8, scanner		
	LS	TLS	TCDM	LS	TLS	TCDM
Mean	1.29	1.27	1.10	1.26	1.40	1.09
Max	7.18	3.52	3.97	5.59	7.27	5.58
SD	1.43	0.90	0.98	0.96	1.17	0.84

To further analyze the error distribution of predicted color differences with LS based method, Fig.1 was plotted showing that the large prediction errors of the LS method are mostly associated with the low luminance values with the magnitude of those errors being quite large. To compare the errors and their distribution between the LS method and the TCDM method, Fig.2 was plotted. For the *Y*-axis, the difference in color difference values after prediction by the two methods was used. It can be found that the predicted errors for colors with low luminance values are considerably reduced, while the prediction errors remain almost unchanged for colors with high luminance values.

CONCLUSION

This paper proposes a method for obtaining imaging device characterization by total color difference minimization. The experimental results clearly showed the advantages of using the new proposed method for device characterization over the traditional method of polynomial regression using least-square (LS) and total-least-square (TLS) methods. By minimizing the object function of total color difference using downhill simplex, the proposed method provides consistent and more accurate results in device characterization.

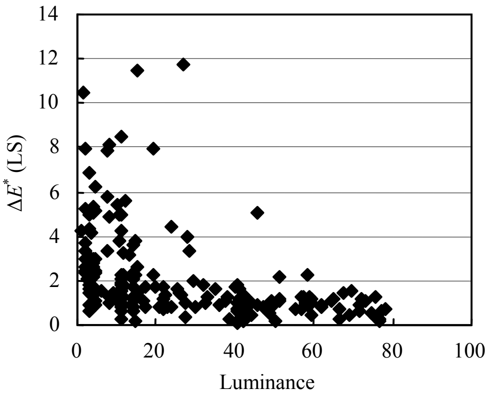

Fig.1 Distribution of color difference using LS method for scanner characterization

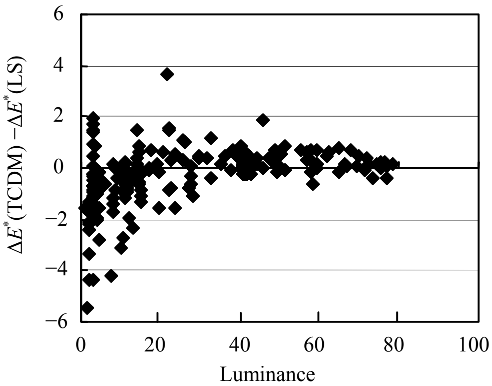

Fig.2 Distribution of color difference changing between TCDM and LS based methods for scanner characterization

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