Improvement for Spectral Reconstruction Accuracy of Trichromatic Digital Camera

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***Abstract*—Trichromatic digital camera has been used for spectral imaging, but spectral reconstructive accuracy is poor if actual digital responses are directly used in linear imaging model. The linearity of Nikon D700 is analyzed, and a new radiation intensity-based linearization technique is put forward, whose performance is verified and compared with other linearization methods. For nonlinear imaging system, the polynomial regression is verified which is more appropriate than other algorithms based on linear imaging system. Especially, if actual digital camera responses are linearized firstly, the accuracy of model can be improved greatly.**

***Index Terms*—Linearization, spectral reconstruction, polynomial regression method**

I. INTRODUCTION

Compared with the expensive price and complicated working conditions of special multi-spectral imaging device, some of research began to capture multi-spectral images using a conventional trichromatic digital camera combined with either absorption filters or multi-illumination [1, 2, 3]. But the CCD used in consumer digital camera is different from scientific CCD, which are disturbed by noise easily, and the information processed by CCD need complicated transmit and compress and then transport to output device, actual digital camera responses are non-linearity. Frequently-used spectral reconstruction algorithms are built based on linear mode of imaging system, for example, pseudo-inverse, winner estimation, PCA, and so on [4, 5, 6]. If we use directly actual digital responses to reconstruct spectra, the performance of spectral reconstruction and chromatic accuracy is poor. This article investigated techniques for accounting for the nonlinearity of the input-output response of a digital camera system [7, 8]. A new linearization method is put forward based on radiation intensity and verified in experiments with other linearization methods. For nonlinear imaging system, the polynomial regression method has been proven effective, so we expand this method to spectra.

In this paper, the linearity of Nikon D700 is analyzed, and a new radiation intensity-based linearization technique is put forward, whose performance is verified and compared with other linearization methods. For nonlinear imaging system, the polynomial regression is verified which is more appropriate than other algorithms based on linear imaging system. Especially, if actual digital camera responses are linearized firstly, the accuracy of model can be improved greatly.

II. CAMERA RESPONSE MODELS

During the last decade, digital imaging systems such as digital cameras have been widely used to record scenes. A simple trichromatic camera response model can be expressed as:

$$C_i(x,y)=\int_{400nm}^{700nm} E(\lambda)S_i(\lambda)P(x,y,\lambda)d\lambda\,, \tag{1}$$

where C_i is the camera responses, $E(\lambda)$ is the spectral radiant distribution of illuminant, $P(x,y,\lambda)$ is the spectral reflectance of an object piexl, and $S_i(\lambda)$ is the spectral sensitivity of the camera's ith channel (which is the product of spectral transmittance of the optical systems, spectral transmittance of filter and spectral sensitivity of the sensors).

Equation (1) is ideal camera response model. Furthermore, various noise should be considered which usually includes dark current noise, shot noise, read noise and quantisation noise. Equation (1) will be changed (2):

$$C_i(x,y)=\int_{400nm}^{700nm} E(\lambda)S_i(\lambda)P(x,y,\lambda)d\lambda+n_i(x,y)\,, \tag{2}$$

A non-linear relationship between camera input and output responses has often been introduced by the manufacturing or electronic process. In the non-linearity model, the camera response for a pixel of the ith sensor type pixel is given by:

$$\begin{aligned}U&=\Psi(C)\\&=\Psi(\int_{400nm}^{700nm} E(\lambda)S_i(\lambda)P(x,y,\lambda)d\lambda+n_i(x,y))\end{aligned}\,, \tag{3}$$

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where Ψ is a monotonically increasing non-linear function, U is actual camera responses, this is R, G, B values read from photographic image.

Ⅲ. Multi-spectral Image Capture based Trichromatic Digital Camera

Traditional trichromatic imaging systems capture and represent information about real scenes using three sensors which respond broadly in the red, green and blue regions of the visible spectrum. Traditional trichromatic images (or sometimes termed RGB images) are both device and illuminant dependent. Device dependency refers to the RGB values that the device captures are specific to that device and the conditions under which it was used. Illuminant dependency is due to the fact that the RGB values only describe the color of an image when viewed under the light source that was used during capture. Although, these problems can be solved by applying a process called device characterization which is defined as finding the relationship between the device colour space and the CIE system of color measurement. But XYZ color space is metamerism, when two color samples have the same tristimulus values for a specific combination of illuminant and observer, but the reflectance curves are different [9].

It is well known that the only way to assure a color match for all observers across changes in illumination is to achieve a spectral match. Imai and Berns put forward a new spectral restructure system in which a conventional trichromatic digital camera combined with either absorption filters or different light sources [10]. multi-filter or multi-illuminant approach can make the image acquisition easier than the traditional monochrome camera and interference-filter-based multi-spectral acquisition because it can provide three channels per imaging shot. This trichromatic camera approach also has relatively low cost since the cost-performance relation of commercial trichromatic digital cameras has decreased rapidly.

Spectral reconstruction algorithms used in traditional multi-spectral image capture, are also used in spectral restructure based trichromatic digital cameras. the spectral reflectance of each pixel can be estimated using a priori spectral analysis with direct measurement and imaging of color patches to establish a relationship between the digital counts and spectral reflectance. the most frequently-used spectral reconstruction algorithm is the method based on basic vectors, this article will use the method to rebuild spectrum and verify reconstruction accuracy.

Many researches have proved [11, 12, 13] spectrum can be expressed by a linear combination of a set of basic vectors which are linearly independence. That is, the approximate value $\hat{R}$ of the spectral reflectance factor $R(\lambda)$ is linear combination of the p N-dimensions unit basic vectors b_i (1≤i≤p) that is orthogonal to each other.

$$\hat{R} = \sum_{i=1}^{p} b_i w_i = BW , \tag{4}$$

The b_i is eigenvectors. $B = (b_1, b_2, \ldots, b_j)$, w_i is the corresponding weight coefficient to the ith vector, $W = (w_1, w_2, \ldots, w_j)^T$.

Generally, the most common method for the basic vector calculation is PCA. PCA is a multivariate statistics to deal with, compress and extract the data based covariance matrix. And reduce the dimensions by dispelling the linear dependence of the input random vectors and ignoring the unimportant change directions [14, 15]. The basis vectors after the reducing are also named eigenvectors. Therefore, PCA is also named eigenvector analysis. PCA works very well in the data compressing and the dependences dispelling. It's widely used in the feature extraction of the faces and number plates. In recent years, some researchers use the PCA in the color science [16, 17, 18].

The number of basic vectors is decided by cumulative Percent Variance. If the cumulative Percent Variance of the front p eigenvectors is large enough, the spectral reflectance can be regarded as the linear combination of the front p eigenvectors. After determining the required number of eigenvectors according to the cumulative percent variance of eigenvectors, calculate the corresponding coefficient w_i .

Equation (4) is introduced into (1):

$$C = QBW , \tag{5}$$

Because the level of matrix QB is m*j, let $F = QB$, then $C = FW$, suppose the relationship between digital camera responses and coefficient matrix is $W = AC$, By the least square, the transform matrix A can be established by the equation

$$A = F^{+} = WC^T(CC^T) , \tag{6}$$

In actual application, to training samples, the matrix A can be expressed as follows:

$$A = W'C'^T(C'C'^T) , \tag{7}$$

To testing samples, the coefficient matrix is expressed as follows:

$$W'' = AC'' = W'C^T(C'C'^T)C'' , \tag{8}$$

So the reconstruction spectra of testing samples are calculated as follows:

$$\hat{P} = BW'' = BW'C^T(C'C'^T)C'' , \tag{9}$$

where T denotes transpose matrix, matrix W' and W'' are respectively the coefficient matrix of the training and testing samples, matrix C' and C'' are respectively the digital responses of the training and testing samples.

IV. Linearization of Spectral Imaging Device

As analyzed in (3), there is a non-linear relationship between camera input and output responses. Because most of spectral reconstruction algorithms are built based on linear relationship, if we use actual digital response values to reconstruct spectrum in linear relationship, it will produce big errors.

Consider that a spatially uniform surface of known spectral reflectance $P(\lambda)$ is captured under an illuminant with known spectral power distribution $E(\lambda)$ by a three-channel imaging system with spectral sensitivities $S_r(\lambda)$, $S_g(\lambda)$ and $S_b(\lambda)$. Thus, if we represent the variables by discrete samples at uniform intervals of wavelength λ the raw channel responses R', G' and B' for the red, green, and blue channels respectively are given by the following:

$$\begin{aligned} R' &= \sum E(\lambda)S_r(\lambda)P(\lambda) \\ G' &= \sum E(\lambda)S_g(\lambda)P(\lambda), \\ B' &= \sum E(\lambda)S_b(\lambda)P(\lambda) \end{aligned} \quad (10)$$

We assume that the channels are subject to a nonlinearity Ψ to generate the actual output responses R, G and B. Equation (6) shows an example for the blue channel; similar nonlinearities are assumed to exist for red and green channels as follows:

$$B = \Psi(B'), \quad (11)$$

Actually, we know actual output responses R, G and B read from images, and aim to look for raw channel responses which are linearization in Eq (5), so eq (6) is expressed as follows:

$$B' = \Gamma(B), \quad (12)$$

where Γ is a monotonically increasing non-linear function, the aim of linearization is to build Γ function. However, that to compute the raw channel input B', the spectral sensitivity of the channel is required. Actually, in most cases, we don't know spectral sensitivity of the channel, besides methods based on a knowledge (or estimation) of the spectral sensitivities of the channels. Methods based on the luminance were put forward [19]. luminance Y is often used instead of the raw channel responses B' to determine the nonlinearity function Γ.

$$Y = \Gamma(B), \quad (13)$$

where $Y = \sum E(\lambda)V(\lambda)P(\lambda)$, $V(\lambda)$ is the luminous efficiency function of each surface.

Here, we put forward a new linearization based the radiation intensity of a set of neutral samples based on radiation intensity is proportion to raw digital camera responses [20]. Radiation intensity I is often used instead of the raw channel responses B' to determine the nonlinearity function Γ.

$$I = \Gamma(B), \quad (14)$$

where $I = \sum E(\lambda)P(\lambda)$. The nonlinearity can be modeled using a power law function or polynomial regression with least-squares fit as follows:

$$B' = B^r, \quad (15)$$

$$B' = (a + bB)^r, \quad (16)$$

$$B' = aB_i^n + bB_i^{n\ 1} + \ldots + cB_i + d, \quad (17)$$

Here, equation (15) and (16) are both power law functions.

V. Spectrum Reconstruction with Polynomial Regression Method

The reconstruction method based on PCA is to simulate the whole system as a linear system. But as above (3) described, because the limitation of traditional trichromatic imaging system, the light-electronic transform between actual response U and linear response C is non-linear, and it can be fitted by a power law function or high-order polynomial curve, but two models are required, one is a nonlinear model, the other is spectral reconstruction linear model. Can we find a method which is suitable for non-linear imaging system? The polynomial regression method is put forward. Mr. Hong and Luo adopt the usual polynomial regression method to predict the corresponding color tristimulus based on three channels camera responses [21]. Herzog and his colleagues expand the polynomial regression method to spectra [22].

The polynomial regression analysis is the statistic analysis method to research the interdependent relationships between a random variable (usually called the independent variable or the explained variable) and two or more general variables (usually called the independent variable or explaining variable). It can get the best regression models based on the principle of least square method. The theory and experiments had showed that reconstructive spectra by the regression method is workable and effective [23]. In multispectral imaging, camera digital response c_i is the independent variable, it will be expanded high-level polynomials, which can be expressed as:

$$v = \left|1, c_1, \ldots, c_m, c_1^2, c_1c_2, \ldots, c_1c_m, \ldots\right|, \quad (18)$$

The essence of the polynomial regression method is application of l variables multiple linear regression, l is greater than or equal to the numbers of independent variables. The linear regression expression can be expressed as below:

$$p_i(v) = e_1v_{1i} + e_2v_{2i} + \ldots + e_lv_{li}, \quad (19)$$

And the form of matrix is expressed as below:

$$p_i = V_i^TE = E^TV_i, \quad (20)$$

In multispectral imaging, there are k color training samples. If k is greater than or equal to l, VV^T is non-singular and reversible, the coefficient matrix E can be calculated on the basis of the least squares method.

$$E = (VV^T)^{\ 1}VP, \quad (21)$$

Therefore, the reconstructed spectra can be expressed as below:

$$\hat{P} = V''^T E = V''^T (V'V'^T)^{-1} V'P' , \tag{22}$$

$\hat{P}$ is the reconstructed spectral reflectance matrix of testing samples. V' and V'' are respectively the matrix formed by the extended items based on the digital camera responses of the training samples and testing samples. P' is the spectral reflectance matrix of training samples.

The idea of the polynomial regression is the signal vector E is extendible. That is to add more extended items which can affect the accuracy of the characterization. There are many ways for the polynomial expansion. In order to get the better results, the most used one is to add the high order items of the channels in the vector as well as the cross items between the channel responses, such as r^2, g^2 and b^2. However, the capacity of the transferring matrix will become larger with the increasing of the items number.

In order to study reconstruction accuracy caused by the polynomial numbers of V, four kinds of polynomial regression methods (three, six, eight and eleven polynomials separately) are used to reconstruct the spectra in the experiment. Corresponding to the different expansion form of the RGB signals combination, the transferring matrix of the polynomial regression model will be changed with it. Equation (23) is the expression for the four kinds of extended digital camera responses V adopted in the experiment.

$$\begin{aligned} V_1 &= [r, g, b] \\ V_2 &= [r, g, b, rg, rb, gb] \\ V_3 &= [1, r, g, b, r^2, g^2, b^2, rgb] \\ V_4 &= [1, r, g, b, rg, rb, gb, r^2, g^2, b^2, rgb] \end{aligned} , \tag{23}$$

VI. Experiments

In our experiments, we used a Nikon D700 digital camera (4, 256×2, 832 pixels, built-in R, G, B array sensors, 8bits per channel). The spectral radiant power of the illuminant used in this imaging system was measured. We used data measured by Christian Mauer as The spectral sensitivities of each of the color channels in digital camera system (Figure 1).

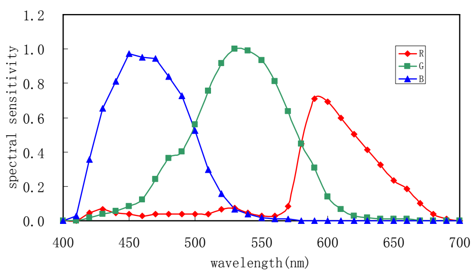

Figure 1. The spectral sensitivities of each of the color channels in digital camera system (measured by Christian Mauer)

Two imaging targets, 140 GretagMacbeth ColorChecker SG (abbreviated in CCSG) and 24 ColorChecker RC (abbreviated in CCRC) were imaged. 14 gray colors located in the center of CCSG were used for linearization. CCRC as training samples and testing samples were verified for accuracy of spectral reconstruction.

The spectral reflectance factors of the patches on the two charts were measured using an GretagMacbeth Spectrolino spectrophotometer. During the experiment the camera and lighting positions were fixed, and the RGB values of the CCSG achromatic samples and CCDC were measured with each in the center of the camera's field of view. Each patch generated an image region of about 20x20 pixels, but the values of a central subregion (12x12 pixels) were averaged to generate the mean RGB values for that patch.

A. Spectral-sensitivities-based technique

1. The raw digital responses were computed for 14 CCDC gray samples under the actual light source that was used to illuminate the samples during imaging and the spectral sensitivities of the camera, and normalized in the range 0–1 based on the largest reflectance luminance.

2. The actual camera responses of 14 CCDC gray samples were measured and normalized in the range 0–1 based on (255, 255, 255).

3. For each camera channel, a n-order polynomial or γ power law function was used to fit the relationship between the actual camera responses and the raw digital responses for the achromatic patches, then function Γ was built.

4. Apply the estimates of function Γ to the measured camera responses for the CCDC samples to yield the linearized RGB values for those values.

5. Perform spectral reconstruction for CCDC samples based on PCA.

B. Luminance- based technique

1. The luminance reflectance factors Y were computed for 14 CCDC gray samples under the actual light source that was used to illuminate the samples during imaging, and normalized in the range 0–1 based on the largest reflectance luminance.

2. The actual camera responses of 14 CCDC gray samples were measured and normalized in the range 0–1 based on (255, 255, 255).

3. For each camera channel, a n-order polynomial or γ power law function was used to fit the relationship between the actual camera responses and the luminance reflectance factors for the achromatic patches, then function Γ was built.

4. Apply the estimates of function Γ to the measured camera responses for the CCDC samples to yield the linearized RGB values for those values.

5. Perform spectral reconstruction for CCDC samples.

C. Radiation intensity- based technique

1.The radiation intensity I were computed for 14 CCDC gray samples under the actual light source that was used to illuminate the samples during imaging, and normalized in the range 0–1 based on the largest radiation intensity.

2. The actual camera responses of 14 CCDC gray samples were measured and normalized in the range 0–1 based on (255, 255, 255).

3. For each camera channel, a n-order polynomial or γ power law function was used to fit the relationship between the actual camera responses and the radiation intensity for the achromatic patches, then function Γ was built.

4. Apply the estimates of function Γ to the measured camera responses for the CCDC samples to yield the linearized RGB values for those values.

5. Perform spectral reconstruction for CCDC samples based on PCA.

Thus for each technique we attempt to obtain linearized camera responses and then use PCA to reconstruct the spectral reflective factor. All computations were performed using MATLAB, RMS errors and CIELAB ΔE^*_{ab} were taken into account to test the performance of spectrum and color differences between original and reconstructed spectra.

VII. Results and Discussion

First, we analyzed the linearity of Nikon D700. Figure 2 shows compare between non-linearity and linearization based on radiation intensity. The three plots on the left-hand side of Figure 2 show the normalized R (upper plot), G (middle plot), and B (lower plot) values for the gray samples plotted against the respective normalized measured radiation intensity. The solid line in each panel shows the polynomial fit to the data. it is evident that the linearity of Nikon D700 is low. However, these polynomial functions were used to subsequently convert all actual camera responses to linearized camera responses before further processing. The three plots on the right-hand side of Figure 2 show the normalized linearized R (upper plot), G (middle plot), and B (lower plot) values for the achromatic samples plotted against the normalized measured radiation intensity for those samples.

Table 1 shows the values of the exponent that were estimated using each of the three linearization techniques. We found the exponents of each channel are similar for three linearizations, which means power law functions are similar, and there are similar relationship between different raw digital camera responses and actual digital camera responses. Just as table 2 and table 3 shows spectral reconstruction performance for CCDC samples based on linearization by three various techniques. Because the PCA spectral reconstruction method is not perfect, color differences will still be obtained even if the input/output nonlinearity is estimated perfectly. After linearized, spectral reconstruction performance either spectral RMS or CIELAB ΔE are better than non linearity. Generally, spectral-sensitivities-based linearization and radiation intensity- based linearization are quite similar in spectral and chromatic accuracy, which are better than performance of luminance- based linearization.

Table 4, table 5, table 6 and table 7 are different with table 2 and table 3 in function fit. Table 4 and table 5 use 3rd polynomial fit, table 6 and table 7 use 5th polynomial fit. It's obvious that the level of polynomial fit is higher; the accuracy of linearization function is higher. The accuracy of linearization techniques using a power law function is between 3rd and 5th polynomial fit, higher than 3rd, lower than 5th.But a power law form of the nonlinearity is simpler than polynomial fit, it only needs estimate an exponent comparing with mutli-coefficients of polynomial fit. There are same conclusions that spectral-sensitivities-based linearization and radiation intensity-based linearization are better than Luminance-based linearization. This means building linearization by radiation intensity instead of raw digital camera response is feasible, because in most conditions we don't know spectral sensitivities of camera.

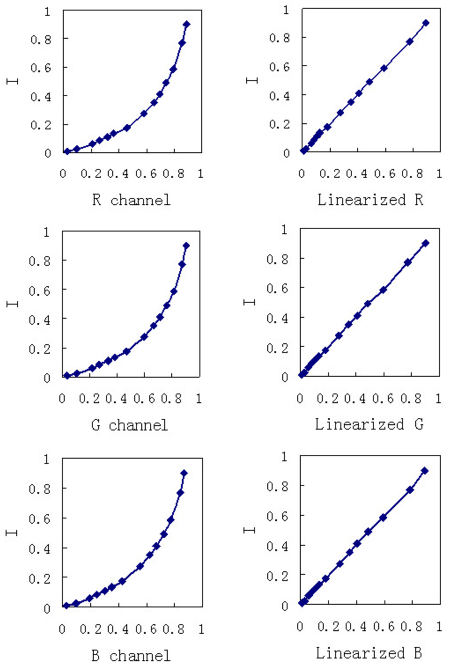

Figure 2. Radiation intensity I of 14 achromatic patches plotted against the spatially averaged camera channel RGB responses (blocks) for each patch and fifth-order polynomial fit (solid lines) (left column) and the linearized camera responses (blocks) converted from the polynomial fit (right column).The circles in the right-column graphs should lie along the straight line if the linearization process is perfect. All data are shown normalized in the range 0–1.

From the analysis above we can see that the linearity of the common commercial digital camera is poor, the accuracy of the spectra reconstruction has been improved greatly after linear calibration. The reconstruction method based on PCA is to simulate the whole system as a linear system.

TABLE I.
Estimation of the Exponent Using Each of the Three Different Linearization Techniques

Linearization method	Estimate of exponent		
	Red channel	Green channel	Blue channel
Spectral-sensitivityies-based	2.193	2.321	1.962
Luminance-based	2.176	2.429	1.97
Radiation intensity-based	2.187	2.34	1.98

TABLE II.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT LINEARIZATION TECHNIQUES USING A POWER LAW FUNCTION IN COLOR DIFFERECE

Linearization method	Maximum ΔE	Minimum ΔE	Media ΔE
Non linearity	29.47	5.74	12.5
Spectral-sensitivityies-based	16.9	1.76	6.70
Luminance-based	17.43	2.23	6.93
Radiation intensity-based	17.01	1.74	6.72

TABLE III.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT LINEARIZATION TECHNIQUES USING A POWER LAW FUNCTION IN RMSE

Linearization method	Maximum RMSE	Minimum RMSE	Media RMSE
Non linearity	0.3196	0.0223	0.0803
Spectral-sensitivityies-based	0.1280	0.0175	0.0515
Luminance-based	0.1267	0.0181	0.0514
Radiation intensity-based	0.1272	0.0176	0.0514

TABLE IV.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH THREE DIFFERENT LINEARIZATION TECHNIQUES USING 3RD POLYNOMIAL FIT IN COLOR DIFFERECE

Linearization method	Maximum ΔE	Minimum ΔE	Media ΔE
Non linearity	29.47	5.74	12.5
Spectral-sensitivityies-based	19.07	1.3	7.29
Luminance-based	19.04	1.52	7.31
Radiation intensity-based	18.89	1.54	7.22

TABLE V.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH THREE DIFFERENT LINEARIZATION TECHNIQUES USING 3RD POLYNOMIAL FIT IN RMSE

Linearization method	Maximum RMSE	Minimum RMSE	Media RMSE
Non linearity	0.3196	0.0223	0.0803
Spectral-sensitivityies-based	0.1601	0.0049	0.0509
Luminance-based	0.1611	0.0051	0.0511
Radiation intensity-based	0.1604	0.0050	0.0509

TABLE VI.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT LINEARIZATION TECHNIQUES USING 5TH POLYNOMIAL FIT IN COLOR DIFFERECE

Linearization method	Maximum ΔE	Minimum ΔE	Media ΔE
Non linearity	29.47	5.74	12.5
Spectral-sensitivityies-based	17.98	1.34	5.96
Luminance-based	17.86	1.23	5.96
Radiation intensity-based	17.82	1.21	5.90

The following experiment is to perform spectral reconstruction using polynomial regression based on a trichromatic camera system. Fist we use the non-linearized digital camera responses and the polynomial regression to reconstruct spectra.

TABLE VII.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT LINEARIZATION TECHNIQUES USING 5TH POLYNOMIAL FIT IN RMSE

Linearization method	Maximum RMSE	Minimum RMSE	Media RMSE
Non linearity	0.3196	0.0223	0.0803
Spectral-sensitivityies-based	0.1726	0.0077	0.0521
Luminance-based	0.1730	0.0075	0.0520
Radiation intensity-based	0.1716	0.0076	0.0518

From table 8 and table 9 we can see that with the number of polynomial terms increase, the reconstruction error in terms of color difference and RMSE will decrease, especially when the number is increased from 6 to 8, the trend is the most obvious: the average ΔE decreases from 11.7 to 4.84, the average RMSE decreases from 0.0537 to 0.0396, which indicates that the joins of rgb term and constant term will improve the model's accuracy.

TABLE VIII.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT TERMS OF POLYNOMIAL REGRESSION MODEL IN COLOR DIFFERECE (DIGITAL CAMERA RESPONSES ARE NON-LINEARIZED)

Polynomial Numbers	Maximum ΔE	Minimum ΔE	Media ΔE
3	29.47	5.74	12.51
6	30.63	3.38	11.7
8	10.8	1.08	4.84
11	10.1	1.1	3.74

TABLE IX.
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT TERMS OF POLYNOMIAL REGRESSION MODEL IN RMSE (DIGITAL CAMERA RESPONSES ARE NON-LINEARIZED)

Polynomial Numbers	Maximum RMSE	Minimum RMSE	Media RMSE
3	0.3196	0.0223	0.0803
6	0.1262	0.0164	0.0537
8	0.0717	0.0095	0.0396
11	0.063	0.0105	0.0306

TABLE X. .
COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT TERMS OF POLYNOMIAL REGRESSION MODEL IN RMSE (DIGITAL CAMERA RESPONSES ARE LINEARIZED)

Polynomial Numbers	Maximum ΔE	Minimum ΔE	Media ΔE
3	17.82	1.21	5.9
6	12.23	0.65	3.83
9	10.8	0.23	3.81
11	9.42	0.14	2.88

TABLE XI. COMPARISON OF SPECTRAL RECONSTRUCTION PERFORMANCE WITH DIFFERENT TERMS OF POLYNOMIAL REGRESSION MODEL IN RMSE (DIGITAL CAMERA RESPONSES ARE LINEARIZED)

Polynomial Number	Maximum RMSE	Minimum RMSE	Media RMSE
3	0.1716	0.0076	0.0518
6	0.1568	0.0063	0.0376
9	0.0697	0.0108	0.0371
11	0.0863	0.0113	0.0332

We also tested that increasing the number of cross terms or square terms will also contribute to the improvement of the model, and their contribution are basically same, that is to say the only use of cross terms or square terms will not greatly affect the accuracy of the reconstruction when the total number of polynomial terms is same. When the number is 11, the model includes constant term, cross terms, square terms and RGB term which considers various impact factors, the 11-term is practically an exact fit. From table 8 and table 9 we can see that when there is no any pre-process on the digital responses, the reconstruction using polynomial regression model already provide higher accuracy than using linear model on pro-processed digital camera responses. This indicate that the linearity of Nikon D700 digital camera is relatively poor, and on the other hand, it shows that the proper chosen of polynomial regression model is suitable for non-linear imaging system, and its reconstruction performance is better than other linear system model method.

Simultaneously, we use radiation intensity-based linearization put forward in this article to calibrate actual digital camera responses, and then reconstruct spectra by polynomial regression method. Table 10 and table 11 show the result of comparison in color difference and RMSE. We can easily see linearized data can improve greatly accuracy of polynomial regression model, when the number of polynomial terms is 3, color difference and RMSE of reconstructed spectra are higher than linear model based on PCA. When the number is 6, whose performance is basically same with 11-term polynomial regression model whose data is non-linearized. The result shows polynomial regression method is very suitable for non-linearization imaging system although, if we can process actual digital responses by linearization method firstly, the accuracy of model can be improved greatly, the number of terms and complexity of polynomial regression model can be reduced greatly.

VI. CONCLUSIONS

This study investigates techniques for accounting for the nonlinearity of the input-output response of a digital camera system. Three various linearizations are carried out for a Nikon D700 camera and the Macbeth ColorChecker RC achromatic samples. A new radiation intensity-based linearization technique is put forward and the performance of spectral reconstruction is tested using the ColorChecker DC samples. The results show the accuracy of intensity-based linearization technique is similar with spectral sensitivities-based technique, but better than luminance-based technique. In our experiment, the test of linearization technique is only for three imaging channel, so spectral reconstruction and chromatic accuracy is lower than multi-spectral imaging system. if using a conventional trichromatic digital camera combined with either absorption filters or multi-illumination, the spectral reconstruction results will improve highly accuracy.

The results of experiments show also the linearity of the common commercial digital camera is poor; many algorithms put forward are only suitable for linear imaging system. The polynomial regression technique has been applied for color camera, scanner, and printer characterizations and calibrations, it's suitable for nonlinear imaging system, so we can expand this method from colorimetry to spectra. In general, the accuracy improves as the number of terms in the equation increase. Simultaneously, if actual digital camera responses were linearized firstly, the accuracy of model can be improved greatly; the number of terms and complexity of polynomial regression model can be reduced greatly.

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REFERENCES

[1] Miguel A. López-álvarez; Javier Hernández-Andrés; Javier Romero; F. J. Olmo; A. Cazorla and L. Alados-Arboledas, "Using a trichromatic CCD camera for spectral skylight estimation, Applied Optics", vol. 47, no. 34, pp. H31-H38, 2008.

[2] Chen Yiyi, Xu Haisong, Zhang Xiaodou, M.Ronnier Luo, "Study of Spectral Reconstruction Based on Digital Camera", ACTA OPTICA SINICA, vol. 29,no. 5), pp.1417-1419, 2009.

[3] Martin Rump, Arno Zinke, Reinhard Klein, "Practical spectral characterization of trichromatic cameras", ACM Transactions on Graphics, vol. 30, no. 6, 2011.

[4] Seyed Hossein Amirshahi, Seyed Ali Amirhahi, "Adaptive non-negative bases for reconstruction of spectral data from colorimetric information", Optical Review, vol. 17, no. 6, pp. 562-569, 2010.

[5] R.Z.Morawski, A.Miekina, "Improving Absorbance Spectrum Reconstruction via Spectral Data Decomposition and Pseudo-Baseline Optimization", IEEE Transactions on Instrumentation and Measurement, vol. 58, no. 3, pp.691-697, 2009.

[6] Jukka Antikainen; Mikael von und zu Fraunberg; Joni Orava; Juha E. Jaaskelainen and Markku Hauta-Kasari, "Spectral imaging of neurosurgical target tissues through operation microscope", Optical Review, vol. 18, no. 6), pp.458-461, 2011.

[7] Cui Chi, Hyunjin Yoo, Moshe Ben-Ezra, "Multi-Spectral Imaging by Optimized Wide Band Illumination", International Journal of Computer Vision, vol. 86, no. 2-3, pp.140-151, 2010.

[8] F. H. Imai, S Quan, M. R. Rosen, and R. S. Berns, "Digital camera filter design for colorimetric and spectral accuracy", in Proceedings of the 3rd International Conference on Multispectral Color Science (Joensuu, Finland), pp. 23–26, 2001.

[9] Guowei Hong, M. Ronnier Luo and Peter A. Rhodes, "A Study of Digital Camera Colorimetric Characterisation Based on Polynomial Modelling", Color Research & Application, vol. 26, no. 1, pp. 76-84, 2001.

[10] V.Cheung, S.Westland, C.J.Li, J.Hardeberg, D.Connah, "Characterization of trichromatic color cameras by usring a new multispectral imaging technique", J. Opt. Soc. Am. A, vol. 22, no. 7, 2005.

[11] Di Yuan Tzeng, Roy S. Berns, "A Review of Principal Component Analysis and Its Applications to Color

Technology”, Color research and application, pp. 84-98, 2004.
[12] Oh-Seol Kwon, Holly E. Gerhard, and Laurence T. Maloney, “Surface Reflectance Models Based on Characteristic Functions”, CGIV 2010--Fifth European Conference on Colour in Graphics, Imaging, and MCS/10 Vision 12th International Symposium on Multispectral Colour Science, pp. 560-565, 2010.
[13] Paviotti, Anna; Forsyth, David; Cortelazzo, “Guido, Lightness Recovery for Pictorial Surfaces”, International Journal of Computer Vision, vol. 94, no. 1, pp. 54-77, 2011.
[14] Johnson RA, Wichern DW. “Applied multivariate statistical analysis”, 5th edtion. New Jersey: Prentice Hall, 2002
[15] Jolliffe IT. “Principal component analysis”, 2nd ed. Springer series instatistics. New York: Springer-Verlag, 2002.
[16] Di-Yuan Tzeng, Roy S. Berns, “A Review of Principal Component Analysis and Its Applications to Color Technology”, Color Research and Application, vol. 30, pp. 84-98, 2005
[17] Di-Yuan Tzeng, Roy S. Berns, “Spectral-Based Ink Selection for Multiple-Ink Printing I.Colorant Estimation of Original Objects”, Proceedings.6th IS&T/SID Color Imaging Conference, pp. 106-111, 1998.
[18] Yang.L. and Hersch.R. D., “Kubelka-Munk Model for Imperfectly Diffuse Light, The Journal of Imaging Science and Technology”, vol. 52, no. 3), pp.1-7, 2008.
[19] V. Cheung, S. Westland, and M. G. A. Thomson, “Accurate estimation of the non-linearity of input-output response for color cameras”, Color Res. Appl. 29, pp.406-412, 2004.
[20] Kobus Barnard, Brian Funt, “Camera characterization for color research, “http: //www.CS.Berkeley.EDU/~kobus /research/publications/camera_characterization/index.html, 2001.
[21] G.W.Hong, M.R.Luo, P.A.Rhodes, “Study of digital camera colorimetric charaeterization based on polynomial modeling”, Color Research and Applieation, vol. 26, no. l: pp. 76-54, 2001.
[22] Henry R.Kang, “Computational Color Technology, SPIE-The International Society for Optical Engineering, 2005.
[23] Dupont D, “Study of the reconstruction of reflectance functions based on tristimulus values: Comparison of methods of optimization”, Color Research and Application, vol. 27, pp. 88-99, 2002.

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