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White point preserving color correction based on root polynomial model

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Abstract

The RGB values of images acquired by digital cameras are all device related, that is, the same image is different on different devices. That is, they are not colorimetric. The approximate linear conversion between RGB value and XYZ value of the camera can be obtained by the least square (LS) method. The error caused by mapping function is relatively large. For digital camera response value, ρi has expansibility. The RGB value of camera response is expanded by polynomial (PCC), and then the conversion coefficient is obtained by least square fitting method. In the same way, the root polynomial (RPCC) can also be used to increase the number of terms of higher degree to the camera response value, so that the first-order linear mapping can be converted into higher-order nonlinear mapping, and the conversion accuracy can be improved. Due to the importance of preserving white points in color restoration, we propose a new method, which is based on the root polynomial expansion of RGB value of camera response, and introduces white point preserving mechanism, namely white point preserving root polynomial color correction (WPP-RPCC). Compared with linear correction (LCC), polynomial (PCC) and root polynomial (RPCC), this method provides better color correction in terms of square error. Under exposure and multi sample tests, white point preservation is introduced for root polynomials of different orders, and white point zero error mapping constraint is added. It is generally proved that WPP-RPCC is superior to other existing methods.

Keywords

White point preserving color correction, root polynomial model.

1. Introduction

With the development of science and technology and the improvement of people's living standard, digital cameras are ubiquitous, which has gradually become a necessity of life. After decades of rapid development, digital cameras with billions of pixels are no longer a dream. While pursuing high definition of image, the color performance of image is also gradually being paid attention to. The image resolution ability of the early digital camera itself is limited, so that the image taken can not be overlapped because of the insufficient resolution, which means that the details of the image can not be accurately recorded. In short, it is impossible to accurately analyze the image taken. At present, these problems have been gradually overcome with the improvement of the resolution ability of image sensing elements in digital cameras.

After the resolution of image clarity of digital camera, different types of digital camera equipment have different photometric and chroma characteristics. The spectral sensitivity function of color sensor in digital camera can not correspond with the three stimulus values based on CIE color matching function independent of the device. [1] Therefore, there will always be some distortion when color is transmitted, that is, different devices will have different display effects when displaying the same image. How to achieve the consistency of color reproduction among different devices is a common problem to be solved [2] in order to

realize the true reproduction of color, color management should be implemented for the transmission and reproduction process of each equipment. In the color management of digital cameras, RGB space of camera is converted into equipment independent color space such as CIEXYZ or CIELAB color space, which is used as a bridge to achieve the consistency of image color collection and reproduction. At present, the color expression of digital cameras has become the focus of consumers[3]. This long-term neglected problem has become the target of urgent improvement by the corresponding experts and digital camera manufacturers.

The research on color characterization is a field of international concern. There are many related professional research institutions, professional associations, standardization organizations and academic exchanges, and many important research results have been achieved. At present, there are two methods to study color characterization[4]: 1. the method based on spectral sensitivity. The method needs to use special instruments to measure the spectral sensitivity of camera, and then find out the relationship between spectral sensitivity and CIE chromaticity matching function. Many experts have done a lot of work in this regard. But because this method needs to use monochromator and other professional equipment, the instrument is expensive and strict to the physical characteristics of the object, the measurement speed is slow and the operation is complex, and the high requirements of the measuring environment led to the error of the results. 2. target color method. This method only needs light box, digital camera and spectrophotometer to take photos to obtain RGB information of image under specific light source of standard light box, calculate the three-stimulus value of sample by spectrophotometer, and construct conversion equation by RGB information and CIEXYZ information of image code camera response value The operation, the instrument is cheap and can also achieve certain accuracy. This method is often used in the color correction of digital cameras, scanners, displays, printers and other image input and output devices. The common methods are polynomial regression, neural network and the three-dimensional table method with large computation. Because the neural network method is complex [5][6], and it needs a long training time, the 3D lookup table method needs to measure a large number of samples to establish the lookup table, and it is difficult to get regular nodes in RGB color space by simple method, which makes interpolation algorithm more complex, so in real-world applications, it is rarely used neural network and search table method to carry out chromaticity of digital cameras Characteristic. At present, polynomial and root polynomial are widely used in digital camera chromatic characterization. The color sensors in the corresponding input equipment such as scanner, color digital camera are not color comparison, that is, RGB value in the device is not linear transformation with CIEXYZ value independent of the device. In general, it is assumed that RGB value is approximately linear related to XYZ value, and then the transformation determines the corresponding coefficient by linear regression of least square method. Although the least square method can reduce the square error of residual error to the greatest extent, it does not indicate which color will be well mapped and which color mapping effect is worse. For example, for one calibration set, one white reflection may be mapped accurately, but for another calibration set, a high chroma error occurs. But because of the importance of preserving white dots and grayscale in color reproduction [7], Finlayson and drew developed the WPPLS program. WPPLS, as the name implies, determines that the mapping is based on the best least square transformation to convert RGB to XYZ and constrains it to the error free white and gray [8].

By definition, WPPLS method may not be as good as the minimum square regression for using a set of calibration reflections for residual square error. But the residual square error is just a pure digital concept. It is not exactly the same as the precise visual error[9].

In this paper, we focus on the digital camera, and propose a method of conversion of the algorithm of the white point preserving root polynomial optimization. The method is divided into two steps: firstly, the corresponding root polynomial is extended to the RGB value of the

camera response of the trained sample, and the corresponding extended matrix is obtained, and then the corresponding white point is mapped with zero error. The white point preserving root polynomial method is used to optimize the conversion matrix to minimize the color conversion error in a given training set and finally realize the white mapping constraint.

In the second section, we mainly introduce the main color conversion methods of color characterization, such as least square method, polynomial regression model and root polynomial model. In the third section, the method and algorithm process of the white point preserving root polynomial are introduced. In the fourth section, the simulation process of experiment is mainly reported. The fourth section mainly discusses the experimental results. The last section concludes.

2. Camera color characterization

In this section, we consider how to map RGB values of input devices to XYZ tristimulation values. Specifically, although the method shown is also suitable for other input devices and other color conversion, we focus on digital cameras.

2.1. Colors and images form models

The structure of digital camera is similar to the visual system of human eye. Its imaging principle is mainly divided into the following steps: the light emitted by the light source is irradiated on the target, and through the absorption and reflection of the object, a part of the reflected light enters the optical system, and then filters through the filter, and finally reaches the CCD (charge combined device) of the camera.

The basic model ρ_i= [r g b] for the camera response of a three channel color digital camera can be described as:

$$\rho = \int_{\omega} E(\lambda)S(\lambda)R(\lambda)\mathrm{d}\lambda + \mathrm{n} \qquad (1)$$

We use a n × 1 vector to represent the reflectivity R (λ) of the surface of the object, where n is the number of samples within the visible spectrum. The wavelength used in this paper is 400-700nm, and the interval is 10nm. The spectral energy distribution function E (λ) of scene light source of digital camera and spectral sensitivity function s (λ) of sensor of digital camera can be expressed by n × 1 vector and N × 3 matrix s (λ) = [r g b], respectively. N is the noise of three channels of digital camera. Generally speaking, the digital camera can get raw raw raw data through the above methods. Under normal circumstances, the raw data needs to be processed accordingly, including white balance, gammer correction and other corresponding processing. The following image processing steps are different according to the manufacturers. These processing steps are generally non-linear. Such processing usually reduces the accuracy of the chromaticity characteristics of digital cameras. The nonlinear can be expressed by the photoelectric conversion function F. Equation (1) can then become:

$$\rho = F\left(\int_{\omega} E(\lambda)S(\lambda)R(\lambda)\mathrm{d}\lambda + \mathrm{n}\right) \qquad (2)$$

Among them, the f model is a three channel nonlinear function of digital camera.

2.2. 2.2 polynomial regression model

Polynomial regression model is a known model structure, which transforms RGB information of digital camera response value with CIEXYZ color space information independent of device to determine unknown parameters in parameter model. At present, many researchers have explained the method of chromaticity characterization of polynomial regression with least square fitting. At the same time, the research shows that the polynomial model has higher accuracy than the linear regression model.

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If the RGB camera response signal value of one color sample in the color card is represented by a 1 ×3 vector r = [R G B], then the corresponding XYZ tristimulus value can be represented by H = [x y z]. Assuming that there are n color samples in the reference color card, the RGB response signal values of N color samples are represented by a 3 × n matrix R, and the corresponding tristimulus value XYZ can be represented by a 3 ×N H matrix. In this case, formula 3 shows that the RGB camera signal value is converted to CIEXYZ by using the polynomial model,

$$H = MR \tag{3}$$

Where, M is an unknown 3 × n conversion matrix, and a good transfer matrix M can accurately predict the CIEXYZ value corresponding to the color card, so that the color difference between the predicted value and the measured value is the smallest. Usually, the least square method is introduced to directly calculate the prediction error in the CIEXYZ space.

$$E = \|H - MR\|_2^2 \tag{4}$$

The minimum e value can be obtained by least square regression fitting method. Then the solution of M corresponding to the least square method is:

$$M = (R^T R)^{-1} R^T H \tag{5}$$

Where R^T is the transpose of R matrix and R^{-1} is the inverse of R matrix. The order of R depends on the number of terms in the polynomial model. In order to improve the accuracy of color space conversion, the nonlinear transformation between RGB and CIEXYZ is realized by adding high-order terms or cross terms of channels to R. Generally, the camera response value can be expanded arbitrarily. The commonly used polynomials in this paper are as follows:

1. $\rho_{1,3} = (r, g, b)$
2. $\rho_{2,9} = (\mathrm{r, g, b, rg, rb, gb, r^2, g^2, b^2})$
3. $\rho_{3,19} = (\mathrm{r, g, b, rg, rb, gb, r^2, g^2, b^2, rg^2, r^2g, rb^2, r^2b, gb^2, g^2b, r3, g3, b3, rgb})$
3. $\rho_{4,34} = (\mathrm{r, g, b, rg, rb, gb, r^2, g^2, b^2, rg^2, r^2g, rb^2, r^2b, gb^2, g^2b, r3, g3, b3, rgb,}$
   $\mathrm{rg^3, r^2g^2, r^3g, rb^3, r^2b^2, r^3b, g^3b, g^2b^2, g^3b, r^2gb, rg^2b, rgb^2, r^4, g^4, b^4})$

In this paper, four polynomials with different extensions are studied. The lower corner of vector ρ represents the order and number of terms of the extension. The number of terms of the four polynomials are 3, 9, 19 and 34 respectively. By using polynomial regression transformation with different number of terms, the influence of polynomial number on the accuracy of color characterization model is studied. The advantage of polynomial model is that the algorithm is simple and easy to understand, the operation speed is fast, and the sample selection is flexible, but it is not universal and can not meet the accuracy requirements.

2.3. Root polynomial regression model

The root polynomial model is very similar to the polynomial regression model [10], and the transformation equation between the RGB value polynomial of the source color space and the CIEXYZ chromaticity coordinate value of the target color space related to the device is also established to realize the transformation of the color space. Suppose the number of training samples is n, and the RGB value of the sample color block is the row vector of the input matrix, then the 1×3 vector X_i of the corresponding color space XYZ value is the row vector of the output matrix H, where M is the coefficient matrix to be solved.

This experiment focuses on the following root polynomials:

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$$\bar{\rho}_{1,3} = (r, g, b)$$

$$\bar{\rho}_{2.,6} = (\mathrm{r}, g, b, \sqrt{rg}, \sqrt{gb}, \sqrt{rb})$$

$$\bar{\rho}_{3,13} = (\mathrm{r}, g, b, \sqrt{rg}, \sqrt{gb}, \sqrt{rb}, \sqrt[3]{rg^2}, \sqrt[3]{gb^2}, \sqrt[3]{rb^2}, \sqrt[3]{gr^2}, \sqrt[3]{bg^2}, \sqrt[3]{br^2}, \sqrt[3]{rgb})$$

$$\bar{\rho}_{4,22} = (\mathrm{r}, g, b, \sqrt{rg}, \sqrt{gb}, \sqrt{rb}, \sqrt[3]{rg^2}, \sqrt[3]{gb^2}, \sqrt[3]{rb^2}, \sqrt[3]{gr^2}, \sqrt[3]{bg^2}, \sqrt[3]{br^2}, \sqrt[3]{rgb}, \sqrt[4]{r^3g}, \sqrt[4]{r^3b}, \sqrt[4]{g^3r}, \sqrt[4]{g^3b}, \sqrt[4]{b^3r}, \sqrt[4]{b^3g}, \sqrt[4]{r^2gb}, \sqrt[4]{g^2rb}, \sqrt[4]{b^2rg},)$$

3. Using white point preserving root polynomial to transform color space

In this section, we mainly describe the color correction method of white point preserving root polynomial in detail. Compared with white point preserving color correction and root polynomial model, this method has a certain improvement effect. Inspired by finalayson and Hurlbert's use of root polynomial color correction, we extend the root polynomial for RGB value of camera response of color card. Compared with linear correction (LCC), the root polynomial extension can significantly reduce the size of color difference. Compared with polynomial model (PCC), the ability to reduce color difference is also improved. At the same time, it can also reduce the color difference when the exposure is changed It has a certain stability. Due to the importance of keeping white points and gray levels in color restoration. We extend the RGB response of the camera by the root polynomial, and then introduce the white point keeping mechanism into the color correction. In this way, when the exposure is changed and noise is introduced, the residual square is minimized, and the visual error is also smaller.

4. Simulation experiment

In order to test the performance of our white point preserving root polynomial, this paper selects Sony A6300 and Nikon D610 camera two types of RGB digital cameras which are commonly used in the market as the research object, these two kinds of digital cameras in the same environment for image acquisition, processing, etc. are slightly different, but the impact on the experimental results is not big, which also proves the wide applicability of the white point preserving root polynomial (WPP-RPCC) algorithm proposed in this paper. The first data set includes 140 reflectance samples of X-Rite SG color chart, the second is 170 samples of DuPont color chart, the third is the third 1995 surfaces cooled at the Simon Fraser University, and the fourth is the 24 color standard color chart (color checker CC). For these three data color cards, we conducted simulation experiments, in which we mainly integrated sensor sensitivity and color matching function under D65 light source, and generated corresponding digital camera response set (RGB value) and tristimulus value (XYZ). The spectrum of 31 spectral channels is calculated, that is, sampling every 10 nm between 400-700 nm. Next, the corresponding simulation experiments are carried out for different color characterization methods. The comparison methods are different orders of PCC model (M = 1 is linear color correction), white preserving color correction (WPPLS), white preserving polynomial color correction (WPP-PCC) and white preserving root polynomial color correction (WPP-RPCC). After applying these transformations to RGB data, the corresponding XYZ values are generated. Then it is converted to CIELAB space to calculate the residuals. Experiments are carried out to test the proposed algorithm from different angles.

In Table Ⅰ, we use the Munsell color card set as the training set, the Mcc, Dupont, and SG color card sets as the test sets, and use SONY and Nikon camera sensors for testing. From the table, we can see that the various methods are in As the order increases, the color difference generally

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decreases. Whether using a SONY camera or a Nikon camera, when the PCC model order is 4, a very large error occurs. When MCC is used as the training sample, WPP-RPCC is significantly better than WPPLS and PCC, and the performance of RPCC is slightly better than WPP-RPCC. However, the residual square error is only a purely numerical concept, and is not completely consistent with the precise visual error. When using the SG test set, WPP-RPCC is better than PCC and RPCC of the same order when the order is 4.

Table Ⅰ The average value, minimum value, maximum value and median value of CIELAB space color difference are given by the colorimetric characterization results of Sony and Nikon cameras

Dataset	MCC				Dupont				SG			
SONY												
Model type	avg	max	min	med	avg	max	min	med	avg	max	min	med
PCC	1.24	5.02	0.19	0.83	1.67	7.17	0.09	0.87	0.96	5.13	0.07	0.68
PCC,2	1.08	4.66	0.25	0.79	1.46	6.21	0.11	0.87	0.80	4.77	0.06	0.33
PCC,3	0.83	3.64	0.21	0.56	1.05	4.36	0.13	0.66	0.68	3.60	0.06	0.38
PCC,4	8.59	27.86	0.94	7.36	15.37	61.74	0.62	13.10	9.87	39.17	0.65	6.85
RPCC,2	1.04	5.87	0.14	0.69	2.12	11.22	0.04	0.76	0.86	5.81	0.14	0.63
RPCC,3	0.78	2.11	0.13	0.51	4.61	41.77	0.10	0.82	0.76	5.53	0.08	0.56
RPCC,4	0.79	2.36	0.08	0.56	6.48	45.79	0.11	1.13	0.70	3.70	0.06	0.49
WPPLS	1.25	4.93	0.15	1.06	1.75	7.14	0.05	0.99	0.97	5.03	0.15	0.97
WPP-PCC,2	1.08	4.66	0.21	0.77	1.47	6.21	0.09	0.84	0.81	4.78	0.10	0.48
WPP-PCC,3	0.84	3.66	0.23	0.56	1.06	4.35	0.15	0.66	0.69	3.62	0.07	0.42
WPP-PCC,4	0.73	2.84	0.16	0.58	1.06	3.49	0.08	0.74	0.67	3.23	0.11	0.43
WPP-RPCC,2	1.21	6.76	0.26	0.84	3.27	18.93	0.08	0.74	0.92	6.69	0.11	0.45
WPP-RPCC,3	0.85	2.76	0.25	0.54	6.84	57.98	0.14	0.80	0.84	6.07	0.05	0.46
WPP-RPCC,4	0.78	2.92	0.11	0.43	9.94	94.54	0.15	1.22	0.71	3.16	0.07	0.46
Dataset	MCC				Dupont				SG			
NIkon												
Model type	avg	max	min	med	avg	max	min	med	avg	max	min	med
PCC	2.77	7.98	0.29	2.02	5.82	24.00	0.17	2.75	2.51	19.93	0.04	0.88
PCC,2	2.15	6.05	0.05	1.65	3.87	23.06	0.05	2.55	1.87	18.4	0.09	0.92
PCC,3	5.65	16.9	0.33	3.42	11.13	32.98	0.09	9.95	4.17	17.91	0.28	2.06
PCC,4	8.62	28.47	1.01	6.69	16.32	129.28	0.69	14.71	11.04	76.57	0.97	7.53
RPCC,2	1.76	5.72	0.19	0.96	5.21	29.38	0.07	1.57	1.73	15.29	0.08	0.55

RPCC,3	1.66	5.73	0.08	1.19	18.07	152.99	0.07	1.70	1.52	10.57	0.01	0.53
RPCC,4	1.57	6.14	0.08	1.15	13.50	111.57	0.10	2.75	1.51	8.26	0.08	0.67
WPPLS	2.71	8.07	0.35	2.16	5.95	25.38	0.08	2.86	2.49	20.5	0.13	3.36
WPP-PCC,2	2.16	6.09	0.11	1.81	3.95	25.70	0.02	2.41	1.93	19.37	0.05	0.94
WPP-PCC,3	1.51	5.77	0.06	1.23	3.47	17.02	0.07	1.95	1.39	12.12	0.05	0.71
WPP-PCC,4	1.23	6.08	0.12	0.94	2.54	16.28	0.09	1.81	1.42	8.93	0.05	0.89
WPP-RPCC,2	1.73	5.55	0.18	1.14	4.52	24.71	0.09	1.47	1.67	14.35	0.09	0.74
WPP-RPCC,3	1.92	5.80	0.12	1.34	21.54	186.40	0.08	1.63	1.66	11.39	0.10	0.75
WPP-RPCC,4	1.86	8.74	0.14	0.88	14.81	93.34	0.07	2.57	1.57	10.02	0.06	0.87

Next, we use the MCC test set, and use SONY and NIKON cameras to test under different exposure conditions. In this article, we also simulate the scene by multiplying the camera response value RGB and the corresponding XYZ value by the coefficients 1/2 and 2 Increase and decrease of radiation. Use the RGB value and XYZ value after different exposure processing to test the color correction obtained by the following different algorithms. We use the MCC as the test sample from Table 2 and change the exposure conditions. The performance of PCC is worse than that under no exposure conditions. The RPCC model remains relatively stable under the change of exposure conditions. After introducing the white point retention mechanism, the stability of WPP-PCC, especially when the order is 4, is better than that of the PCC model. When the order of WPP-RPCC is 4, the exposure condition is multiplied by 2, and the effect at this time is better than the no-exposure condition.

Table Ⅱ Simulation results of synthetic MCC dataset under different exposure conditions under SONG and NIKON cameras

Dataset	MCC				MCC divided by 2				MCC multiplied by 2			
SONY												
Model type	avg	max	min	med	avg	max	min	med	avg	max	min	med
PCC	1.24	5.02	0.19	0.83	1.24	5.02	0.19	0.83	1.24	5.02	0.19	0.83
PCC,2	1.08	4.66	0.25	0.79	1.16	4.19	0.22	0.91	1.58	5.68	0.15	1.57
PCC,3	0.83	3.64	0.21	0.56	0.95	2.92	0.35	0.79	2.35	8.89	0.16	1.66
PCC,4	8.59	27.86	0.94	7.36	20.5	33.7	0.92	23.22	188.3	1206.6	1.49	19.88
RPCC,2	1.04	5.87	0.14	0.69	1.04	5.87	0.14	0.69	1.04	5.87	0.14	0.69
RPCC,3	0.78	2.11	0.13	0.51	0.74	2.11	0.13	0.51	0.75	2.11	0.13	0.51
RPCC,4	0.79	2.36	0.08	0.56	1.02	2.76	0.27	0.78	0.74	2.21	0.08	0.51
WPPLS	1.25	4.93	0.15	1.06	1.25	4.93	0.15	1.06	1.25	4.93	0.15	1.06
WPP-PCC,2	1.08	4.66	0.21	0.77	1.15	4.21	0.21	0.91	1.61	5.67	0.16	1.55
WPP-PCC,3	0.84	3.66	0.23	0.56	0.95	2.91	0.31	0.76	2.33	8.88	0.15	1.58

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WPP-PCC,4	0.73	2.84	0.16	0.58	0.84	1.77	0.34	0.76	5.62	25.22	0.10	1.21
WPP-RPCC,2	1.21	6.76	0.26	0.84	1.21	6.76	0.26	0.84	1.21	6.76	0.26	0.84
WPP-RPCC,3	0.85	2.76	0.25	0.54	0.85	2.76	0.25	0.54	0.85	2.76	0.25	0.54
WPP-RPCC,4	0.78	2.92	0.11	0.43	1.12	3.57	0.84	0.92	0.75	2.69	0.09	0.42
NIKON												
Model type	avg	max	min	med	avg	max	min	med	avg	max	min	med
PCC	2.77	7.98	0.29	2.02	2.77	7.98	0.29	2.02	2.77	7.98	0.29	2.02
PCC,2	2.15	6.05	0.05	1.65	2.9	7.65	0.03	2.33	4.33	14.18	0.14	4.04
PCC,3	5.65	16.9	0.33	3.42	13.36	29.64	0.71	13.86	21.41	177.93	0.24	6.63
PCC,4	8.62	28.47	1.01	6.69	19.78	33.24	1.4	20.98	390.5	3484.4	1.23	28.56
RPCC,2	1.76	5.72	0.19	0.96	1.76	5.72	0.19	0.96	1.76	5.72	0.19	0.96
RPCC,3	1.66	5.73	0.08	1.19	1.66	5.73	0.08	1.19	1.66	5.73	0.08	1.19
RPCC,4	1.57	6.14	0.08	1.15	1.71	6.38	0.07	1.08	1.55	6.02	0.07	1.15
WPPLS	2.71	8.07	0.35	2.16	2.71	8.07	0.35	2.16	2.71	8.07	0.35	2.16
WPP-PCC,2	2.16	6.09	0.11	1.81	2.78	7.85	0.12	2.30	4.37	13.48	0.03	3.63
WPP-PCC,3	1.51	5.77	0.06	1.23	2.46	7.49	0.18	2.10	7.09	55.88	0.02	2.74
WPP-PCC,4	1.23	6.08	0.12	0.94	2.25	7.52	0.21	1.96	55.42	598.78	0.04	4.62
WPP-RPCC,2	1.73	5.55	0.18	1.14	1.73	5.55	0.18	1.14	1.73	5.55	0.18	1.14
WPP-RPCC,3	1.92	5.80	0.12	1.34	1.92	5.80	0.12	1.34	1.92	5.80	0.12	1.34
WPP-RPCC,4	1.86	8.74	0.14	0.88	2.10	9.28	0.03	1.36	1.82	8.47	0.05	1.06

Next, we introduce the influence of noise, which is composed of independent signal and non independent signal. There are three kinds of noise in the process of camera imaging: shot noise, dark noise and readout noise. The shot noise and dark noise satisfy Poisson distribution, which is related to the signal; the readout noise is Gaussian distribution, which is independent of the signal. In this paper, we set the value of noise signal as follows[11], we set std(standard deviation,) to 0.05, through the signal value processing, using a variety of algorithms for chroma characterization. On the basis of no exposure and exposure conditions increased by 1/2 and 2 times respectively, the influence of adding noise on MCC and SFU test sets is as follows: through table 3, after adding noise, the color difference in Table 3 is obviously larger than that in Table 2. The color difference of sfmcc is smaller than that of SFU. The effect of RPCC on noise is reduced when the exposure is increased.

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Table Ⅲ. Test results for MCC and SFU test sets with noise added when using SONG camera

Dataset	MCC（noise）				MCC div by 2（noise）				MCC mul t by 2(noise)			
Model type	avg	max	min	med	avg	max	min	med	avg	max	min	med
PCC	1.27	5.21	0.21	0.91	1.25	4.96	0.25	0.80	1.31	5.51	0.25	0.91
PCC,2	1.06	4.90	0.04	0.74	1.19	4.28	0.13	0.88	1.70	5.74	0.12	1.53
PCC,3	0.98	3.44	0.11	0.81	1.08	2.97	0.31	0.63	2.38	7.83	0.16	1.65
PCC,4	8.65	27.70	0.82	7.91	20.5	33.55	1.21	23.4	186.	1187	1.52	19.4
RPCC,2	1.12	6.16	0.16	0.81	1.15	5.63	0.08	0.87	1.06	5.92	0.10	0.68
RPCC,3	0.82	2.34	0.21	0.66	0.83	2.03	0.21	0.77	0.81	1.88	0.10	0.64
RPCC,4	0.84	2.29	0.08	0.74	1.05	2.89	0.14	0.87	0.76	2.18	0.05	0.73
WPPLS	1.34	5.00	0.19	1.04	1.30	5.34	0.16	1.02	1.29	4.63	0.12	0.82
WPP-PCC,2	1.16	4.74	0.11	0.99	1.22	4.12	0.22	1.04	1.75	5.69	0.23	1.59
WPP-PCC,3	0.91	3.67	0.17	0.64	1.00	2.89	0.24	0.76	2.39	8.42	0.11	1.77
WPP-PCC,4	0.90	2.99	0.33	0.80	0.83	1.83	0.3	0.63	5.59	24.14	0.13	1.31
WPP-RPCC,2	1.28	6.68	0.16	1.06	1.40	7.14	0.33	1.11	1.36	7.64	0.25	1.05
WPP-RPCC,3	0.95	2.61	0.07	0.77	0.88	2.78	0.06	0.66	1.02	3.12	0.13	0.75
WPP-RPCC,4	0.98	5.37	0.11	0.49	1.27	4.41	0.17	1.00	0.98	2.59	0.18	0.81
Dataset	SFU（noise）				SFU div by 2（noise）				SFU mult by 2（noise）			
Model type	avg	max	min	med	avg	max	min	med	avg	max	min	med
PCC	1.11	11.32	0.05	0.77	1.15	11.16	0.04	0.83	1.08	11.85	0.03	0.74
PCC,2	1.01	10.25	0.02	0.72	1.14	10.98	0.03	0.87	1.21	8.51	0.01	0.86
PCC,3	0.94	8.15	0.02	0.69	1.14	9.61	0.04	0.92	1.76	60.79	0.05	1.00
PCC,4	9.67	91.53	0.38	8.14	18.03	64.69	1.11	18.17	154.9	13293	0.29	9.63
RPCC,2	1.01	11.35	0.04	0.68	1.06	11.74	0.01	0.75	0.98	11.4	0.02	0.63
RPCC,3	1.16	38.22	0.04	0.65	1.21	40.69	0.03	0.70	1.13	41.43	0.04	0.59
RPCC,4	1.27	49.42	0.02	0.61	1.54	52.36	0.03	0.81	1.27	52.78	0.02	0.56
WPPLS	1.17	11.00	0.06	0.85	1.24	12.80	0.04	0.90	1.11	11.86	0.03	0.76
WPP-PCC,2	0.99	10.04	0.02	0.71	1.13	11.21	0.05	0.89	1.23	8.44	0.02	0.93
WPP-PCC,3	0.95	8.45	0.02	0.69	1.15	9.72	0.06	0.91	1.76	64.97	0.04	1.02
WPP-PCC,4	0.91	12.65	0.01	0.58	1.17	9.22	0.03	0.90	3.62	166.87	0.03	1.03
WPP-RPCC,2	1.14	17.74	0.03	0.76	1.16	17.54	0.03	0.80	1.05	16.18	0.07	0.68

WPP-RPCC,3	1.22	45.39	0.03	0.65	1.33	47.22	0.03	0.73	1.28	52.47	0.03	0.67
WPP-RPCC,4	1.56	121.17	0.03	0.67	2.08	103.7	0.04	0.99	1.59	72.27	0.03	0.60

On the other hand, we also test the proposed wpp-rpcc for SFU test set under different light sources, namely D65 light source and F11 light source [10]. From table 4 and table 5, it can be seen that the color difference of wpp-rpcc with order 2 is better than that of wpp-rpcc with order 3 and 4. At the same time, when the light source is F11, the chromatic aberration with noise and different exposure conditions is much smaller than that with a light source.

Table Ⅳ color difference results of SFU data set under A light source

Datatest	SFU			SFU (noise)			SFU div by 2(noise)			SFU mult by 2 (noise)		
IlluminantA（Std=0.05）												
model type	avg	max	med	avg	max	med	avg	max	med	avg	max	med
PCC	0.97	9.63	0.56	1.07	9.27	0.72	1.15	9.56	0.81	1.03	9.43	0.65
PCC,2	0.92	8.06	0.55	1.03	8.65	0.71	1.14	8.24	0.86	1.16	11.7	0.74
PCC,3	3.96	32.8	2.31	3.99	32.9	2.33	6.93	50.3	4.46	11.8	58.6	3.09
PCC,4	12.21	339	8.48	12.3	348	8.48	18.9	66.15	18.7	181	251	9.816
RPCC,2	0.92	10.6	0.54	1.02	11.5	0.67	1.10	12.8	0.78	0.98	11.1	0.61
RPCC,3	1.10	48.9	0.44	1.24	48.1	0.62	1.28	1.92	0.76	1.14	44.3	0.54
RPCC,4	1.10	63.9	0.42	1.25	74.6	0.60	1.44	64.8	0.79	1.15	54.8	0.52
WPPLS	1.01	9.55	0.59	1.11	10.02	0.72	1.16	9.60	0.85	1.16	9.47	0.76
WPP-PCC,2	0.92	8.09	0.56	1.01	8.23	0.69	1.13	7.85	0.89	1.19	8.78	0.92
WPP-PCC,3	0.86	6.38	0.50	0.95	6.21	0.65	1.16	6.64	0.91	1.76	32.4	1.01
WPP-PCC,4	0.83	5.58	0.44	0.95	6.04	0.63	1.14	5.36	0.88	0.95	6.04	0.63
WPP-RPCC,2	1.04	16.8	0.60	1.16	18	0.76	1.16	15.8	0.79	1.16	18.2	0.76
WPP-RPCC,3	1.24	62.1	0.49	1.19	44.2	0.64	1.24	45.5	0.75	1.19	44.1	0.64
WPP-RPCC,4	1.76	297	0.46	1.51	238	0.61	1.84	261	0.82	1.51	238	0.61

Table Ⅴ color difference results of SFU data set under F11 light source

Datatest	SFU			SFU (noise)			SFU div by 2(noise)			SFU mult by 2 (noise)		
IlluminantF11 （Std=0.05）												
model type	avg	max	med	avg	max	med	avg	max	med	avg	max	med
PCC	0.64	6.95	0.39	1.15	7.22	0.97	1.14	6.70	0.97	1.15	8.46	0.99
PCC,2	0.57	5.78	0.38	1.11	6.51	0.95	1.12	6.88	0.95	1.26	15.4	1.04
PCC,3	0.54	5.06	0.36	1.09	5.31	0.93	1.09	5.87	0.95	1.84	30.1	1.21
PCC,4	3.59	30.1	1.82	3.82	29.87	2.1	7.58	48.19	4.99	217.9	7623	2.65
RPCC,2	0.64	10.7	0.37	1.16	12.57	0.98	1.14	9.38	0.94	1.21	14.6	0.97
RPCC,3	0.65	15.9	0.31	1.19	17.2	0.95	1.18	19.9	0.94	1.30	34.8	0.95

RPCC,4	0.72	23.2	0.30	1.39	81.35	0.91	1.41	48.96	0.98	1.42	49.1	0.94
WPPLS	0.67	6.75	0.42	1.34	6.65	1.20	1.42	7.19	1.28	1.34	7.77	1.20
WPP-PCC,2	0.57	5.72	0.38	1.15	6.28	0.99	1.15	5.96	0.99	1.46	23.6	1.18
WPP-PCC,3	0.54	5.09	0.36	1.11	5.14	0.98	1.16	5.90	1.02	1.72	29.7	1.19
WPP-PCC,4	0.51	5.32	0.34	1.14	7.25	0.97	1.15	6.31	0.98	2.89	115	1.29
WPP-RPCC,2	0.69	14.3	0.38	1.15	5.97	1.01	1.15	6.59	0.97	1.35	14.6	1.08
WPP-RPCC,3	0.69	20.8	0.32	1.15	11.27	0.93	1.30	31.4	0.98	1.43	38.1	0.99
WPP-RPCC,4	0.68	25.1	0.31	1.34	35.30	0.95	1.29	26.38	0.98	1.47	91.9	0.92

5. Conclusion

In this study, we obtain various color cards from two different digital cameras to study the accuracy of WPP RPCC based on the polynomial (PCC), root polynomial (RPCC) and white point keeping constraint mechanism under different exposure conditions, noise and camera characterization model under a and F11 light sources. Among them, the polynomial model (PCC) makes the first-order linear mapping transform into the higher-order nonlinear mapping, thus improving the accuracy. But it doesn't mean that the higher the order is, the better the correction effect is. Sometimes, with the increase of order, the regression accuracy has not been improved. The relative effect of RPCC model is relatively small under exposure condition. The regression accuracy is better than that of PCC. After introducing the constraint of white point retention mechanism, the white mapping of zero error map can be kept while optimizing global error. Although the white point preserving root polynomial (WPP RPCC) is slightly worse than RPCC in terms of square error, the square error is not related to visual error. Under different conditions, the white point preserving root polynomial (wpp-rpcc) has better stability when the order is 2.

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