

# Colorimetric Characterization of Digital Camera and Display

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## Abstract

Nowadays we come across wide range of digital cameras manufactured by different companies using different technologies and sensors to produce the best quality image possible. However, such differences in a digital camera could lead to unique RGB responses for the same scene. Moreover, the resulting RGB responses are not colorimetric as they don't have any direct correspondance to the XYZ color space. Therefore, it is essential to compute a transformation matrix that transforms device RGB to device independent color space such as CIE XYZ tristimulus values. In this paper, I train a third order polynomial regression on DC colorchart with 240 color samples to perform colorimetric characterization of a NIKON 5600 DSLR and display the output image on a calibrated and characterized Eizo display. My model yields an accuracy of average  $3.8 \Delta E$ . To further assess the performance of my colorimetric characterization model at reproducing accurate color of day-to-day objects, I performed a psychophysical experiment with 15 observers and found that for some cases my model leads in performance by a big margin.

**Keywords:** digital camera, colorimetric, DC color chart, calibration, characterization, polynomial regression, psychophysical experiment

## 1 Introduction

Digital cameras are used across various industries to capture and accurately reproduce color characteristics of a physical scene. However, different cameras generate different RGB responses for the same scene due to the difference in the sensitivity of the photodiodes used. Moreover, the RGB responses are not colorimetric i.e., there doesn't exist a linear transformation from device-dependent RGB to device independent tristimulus values because the spectral sensitivity of color sensor used in the digital camera do not correspond to the device independent XYZ based on standard CIE color matching function [Hong, Luo, and Rhodes \(2001\)](#). Therefore, we perform colorimetric characterization of digital cameras. Colorimetric characterization is a method to develop a mathematical model that could transform device-dependent RGB responses to device-independent color space for e.g. CIE XYZ tristimulus values such that different cameras with distinct RGB responses for the same scene result in similar tristimulus responses.

There are two major methods for color characterization namely, spectral sensitivity based and color target based [Hong et al. \(2001\)](#). In this project, I will use target based characterization. Target based characterization is a method that involves a reference target in my case a DC color chart which has 240 color samples. The RGB values of the samples are attained from the digital camera and tristimulus values are attained from a spectrophotometer. There are three major methods to obtain a transformation matrix namely; LUT based, polynomial model, and neural network [Chou, Luo, Changjun, Cheung, and Lee \(2013\)](#). For this coursework I am using a third order polynomial regression model in order to obtain a transformation matrix that accurately transforms device RGB values to device independent tristimulus values. I have used 3D LUT based profile for camera. It is also important to characterize an output device to view the image. Therefore, I also calibrate and characterize Eizo display. I perform matrix TRC based method to attain a profile for the display from the display RGB values and their corresponding XYZ values. Both camera profile and display profile are applied to the image and display respectively. They are connected through Profile Connection Space (PCS) such that the camera RGB values are transformed to device independent XYZ tristimulus values which are then converted to display RGB.

In section 2, I will review existing work in the field of colorimetric characterization of digital cameras. In section 3, I will discuss the steps involved in performing colorimetric characterization of an input device (digital camera) and an output device (commercial display). In section 4, I will discuss the setup of my psychophysical experiment. In section 5, I will discuss the results obtained. In section 6, I will conclude the findings and summarize my work.

## 2 Literature Review

Authors in [Hong et al. \(2001\)](#) have attempted to perform colorimetric characterization of a camera using target-based approach. They have used two different sets of reference target made out of different materials namely ANSI IT8 chart on Kodak Ektacolour Professional Paper with 264 color samples and Professional Color Communicator (PCC) using reactive dyes on cotton 40 samples of dyed cotton arranged with respect to lightness, hue, and chroma. They have used Agfa digital StudioCam which is a 12-bit digital camera. They manually adjusted the Lens' focus and aperture whereas, the rest of the settings were controlled by Agfa's FotoLook software. To get the RGB of the patches from the camera, they take average of 90% pixels excluding those on the boundaries. To attain the colorimetric data they have used spectrodensitometer which measures the spectral reflectance of each patch on the reference chart at the interval of 20nm. To compute the colorimetric data they have used 1931 CIE standard observer and D50 illuminant. Authors have employed the least square polynomial method to model the transformation from camera RGB to device independent color space i.e., XYZ. With the 3x11 polynomial model, authors were able to achieve a model with an average color difference ( $\Delta E$ ) of 1.

Authors in [Chou et al. \(2013\)](#) propose a computational way to determine the least number of color samples required to develop a target-based characterization model for a digital camera while also maintaining high model accuracy. To determine the most optimal number of samples required to train the model they propose a color selection method namely, Color Difference Iteration (CDI) and compare its performance with other existing methods such as Hardeberg and MAXMINC methods. Authors have used three different color charts to train their model namely, full Munsell atlas with 1562 color samples, Professional Color Communicator (PCC) with 1063 samples and GretagMacbeth ColorChecker DC Chart with 240 samples. They have used Nikon D80 to capture the samples. The experiment setup included camera placed at the top of the viewing booth where the CIE D65 illuminant was used to illuminate the color samples with a d/0 viewing geometry. Authors used the jpeg image generated by the camera instead of the raw image to get the RGB values resulting in no additional pre-processing steps and spectrophotometer was used to get the colorimetric data of the samples. Authors employ fourth order polynomial regression to fit the camera response (RGB) and colorimetric values (XYZ) for camera characterization. They found that increasing the order of the polynomial regression model increased the performance of the model on the training set but for the test set model's accuracy reached it's maximum accuracy at fourth order and it started decreasing as the order was increased greater than 4 due to overfitting of the model. Therefore, they concluded that fourth-order polynomial model provided the best performance with least number of samples when their color selection was method is used.

Authors in [He et al. \(2021\)](#) attempt to develop a novel camera-based color measurement model for human skin. There was no skin specific color chart so authors setup a digital imaging system which used Canon EOS 6D Mark II RGB DSLR to capture facial images of sixty subjects, from four different ethnic groups, under CIE D65 illumination. They also used SG ColorChart with 140 patches for training. To transform camera RGB to CIE XYZ values, authors tested three methods namely; linear transformation, polynomial regression upto third degree and root-polynomial regression upto two degrees. With this study, authors concluded that using their novel facial dataset outperformed the conventional color charts for accurate human skin color measurement. Moreover, out of six algorithms investigated in this study, 1st order polynomial regression gave the best results.

Authors in [Hong, Han, and Luo \(2000\)](#) compare the performance of colorimetric characterization model on high-end and low-end camera namely; Agfa StudioCam and Canon Powershot Pro 70 respectively. Authors have used IT8 color chart with 264 samples and to obtain XYZ values from camera RGB, they have used 2nd order least-square polynomial regression under D65 illuminant and CIE 1931 observer. Cathode-ray tube (CRT) display was used to analyze the accuracy of texture rendered by both the cameras. From the psychophysical experiment conducted, authors conclude that high-end camera outperformed low-end camera in terms of color matching and simulating texture.

Authors in [Bianco, Schettini, and Vanneschi \(2009\)](#) investigate the application of colorimetric characterization in the field of cultural heritage by digitizing their 3D models. The aim of this work is to develop a model that gives accurate color information to ensure preservation of ancient artefacts. They propose a novel target-based color characterization that uses empirical polynomial modeling. Their method also utilizes genetic algorithm (GA) as an optimization method to determine the optimal order of the polynomial model. Authors have used Minolta VIVID 900 non-contact 3D digitizer in this work. Macbeth ColorChecker CC with 24 samples and the Macbeth ColorChecker DC with 180 samples were used as the target chart and to obtain the colorimetric data (XYZ) spectrophotometer was used. From the experiment, authors found that as the order of the polynomial model increased the training error reduced but the model started to overfit on the test set.

### 3 Methodology

I am using NIKON 5600 DSLR camera with Nikon F mount lens Nikkor 35-80mm. I have set the camera to manual mode so that I can calibrate the camera as per my needs and once I have a transformation model I could use it to reproduce the results with the same camera settings. There are three major controlling parameters of camera namely; exposure time (shutter speed), aperture, and ISO. Where Exposure time determines how long the camera must collect light from sample, aperture controls the amount of light entering and ISO determines camera's sensitivity to light. Initially, I used the camera settings mentioned in the literature discussed in section 2. But it resulted in an overexposed image for my camera so I kept the ISO and aperture same as mentioned in [Chou et al. \(2013\)](#) and changed the exposure time to achieve a well exposed image. The final settings of my camera are mentioned in table 1. Once the camera has been calibrated I placed it on a tripod to maintain steadiness during experiment.

Specification	Image Size	Sensitivity	Focal length	F-number	Exposure time
Setting	6016x4016	ISO 400	48nm	F/6.3	1/60

Table 1: Camera settings

#### 3.1 Colorimetric Camera Characterization

To perform colorimetric camera characterization we have to develop a model that can map the input camera RGB values to device independent color space such as XYZ under a certain illuminant. To achieve this we need data that has RGB values along with its corresponding XYZs under an illuminant for the model to learn the relation. I have used GretagMacbeth DC ColorChecker which has 240 color patches. One can use a spectrophotometer such as EyeOne pro to get the tristimulus values of each patch. To get the device RGB, I placed the DC colorchecker under D50 illuminant which was simulated by JUST NORMLIGHT lighting booth which is an LED based viewing booth. I captured the image with my calibrated camera in a dark room. The resulting raw image is a 14-bit NEF file which is a Nikon specific file format for raw images. Figure 1 shows the pipeline of steps involved in colorimetric characterization of a raw image.

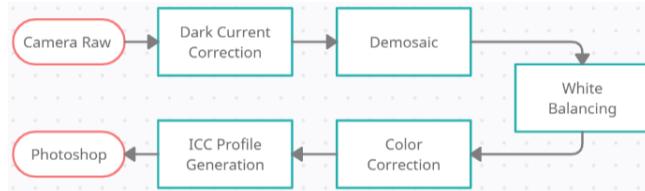


Figure 1: Flow diagram of camera characterization

To remove noise, I perform dark current correction on the raw image by subtracting the dark frame from it. Dark current refers to a small amount of current that flows through the photodiodes even in the absence of light [Camera noise and temperature tutorial \(n.d.\)](#) which leads to non-zero intensity even in the absence of light. Dark frame refers to an image captured in complete darkness with camera shutter closed and lens covered with lid which will give us the image noise. This is subtracted from the image. We can also obtain black level of an image from its metadata using Phil Harvey's Exiftool. Which is a command-line based open-source tool to read metadata of different formats including camera specific metadata formats [Exiftool \(2022\)](#). In the next step, I have performed demosaicing, also known as debayering, which reconstructs a color image from the raw image which contains incomplete color samples from the sensor overlaid with color filter array (CFA) [Demosaicing \(2022\)](#). In the next step, I have employed MATLAB's builtin function illumgray which is an implementation of gray world algorithm to achieve white balancing. While estimating the illuminant, Gray world algorithm assumes that the average R, G, and B values of the scene are equal which means that the scene is neutral gray [yan Huo, lin Chang, Wang, and xia Wei \(2006\)](#). Finally, I chromatically adapt the image to estimated illuminant.

An alternative method to read and process raw image is by using Dave Coffin's DCRAW which is said to result in better quality output [Coffin \(n.d.\)](#). It is an open-source command-line based application that can read raw files of various formats and convert them to a standard 16-bit TIFF format. Unlike JPEG, TIFF doesn't use any compression technique therefore, resulting in a better quality image without losing any important details in the image. Table 2 summaries all the commands I used along with their functions [Coffin \(2015\)](#). For the first command listed, I used the same raw image with no light captured earlier. Final dcraw command used: `dcraw -K darkness.pgm -w -T -6 -q 3 -o 5 <filename>.NEF`

Command	Function
dcraw -D -4 -j -t 0	This generates dark frame from a raw image with no light
-K darkframe.pgm	Subtracts the dark frame from the raw image
-q 3	Demosaic algorithm based on Adaptive Homogeneity-Directed (AHD) interpolation
-w	Perform white balancing
-o 0	Generates output image in camera raw color space
-T -6	outputs 16-bit TIFF file instead of PPM

Table 2: DCRAW commands

Once when the raw image was preprocessed, I opened it in Adobe Camera Raw to get the RGB values of DC colorchart patches. I supplied RGBs and XYZs to a third order polynomial regression model to estimate co-efficient matrix that could transform one color space to the other. For this I used charac3 defined in the color engineering toolbox. Then I used polyconvert3 to create a 3D Look Up Table (LUT). Finally, I encoded it to uint16 L\*a\*b\*. I pasted this encoded data inside the CLUT tag of the cube5.icc profile. I changed the curve tag to a straight line from 0 to 65535. I changed the PCS tag to Lab. I changed the grid point to 17 as I have 17 nodes in my 3DLUT. I changed the Mcurve tags to 1 and specified media white point tag as XYZ of D50 illuminant. I used the iccFromXml.exe application to convert the edited text file into an icc profile. To confirm if my profile was valid and didn't have any errors, I imported it to wxProfileDump.exe application and ran validation.

### 3.2 Display Characterization

For this project, I am using Eizo display as the output device. Before characterizing it, I will calibrate it using ColorNavigator 6 software. Table 3 shows the display settings manually entered for calibration. To verify it under Display preferences > color if it was using the correct profile.

Specification	Gamut	Brightness	White Point	Gamma
Setting	Adobe RGB	80 cd/m <sup>2</sup>	D50	2.2

Table 3: Display settings

To characterize a display, we will need XYZs and their corresponding display RGBs to train a model that could transform one color space to another. To achieve this, I used MeasureTool software that uses EyeOne pro to get the XYZs for the patches displayed on the screen. In output it gives a text file that contains XYZs along with the RGB values of 99 color patches displayed on the screen. To make the Y-value (luminance) of the white point equal to 100, I normalized XYZs by multiplying them to ratio of 100 by Y-value of white point. The sum of normalized XYZs of red, green, and blue patches came out to be approximately equal to that of white point which confirms that the device is additive. For the display I am doing MatrixTRC based profiling. So I used the red channel and luminance values of the gray ramp patches to find the gamma and TRC tag. I took the negative log of the normalized red channel and normalized luminance and fed it to LINEST function in excel which gave me a gamma of 2.13. Equation 1 can be used to find the TRC tag. Equation 2 represents the transformation of RGB to XYZ.

$$TRCtag = \text{gamma} * \left( 255 + \frac{255}{256} \right) \quad (1)$$

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.631681244 & 0.324344023 & 0.02781827 \\ 0.193148688 & 0.595116618 & 0.086977648 \\ 0.133503401 & 0.076044704 & 0.706146744 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2)$$

To create a MatrixTRC based display profile, I entered the transformation matrix shown in equation 2 inside the Colorant tag. Where each row represents XYZs of red, green, and blue colorants. Then I entered 546 computed from equation 1 under red, green, and blue TRC tag. I specified media white point as D50 illuminant and PCS tag as XYZ. I used the iccFromXml.exe application to convert the edited text file into an icc profile. To confirm if my profile was valid and didn't have any errors, I imported it to wxProfileDump.exe application and ran validation.

### 3.3 Visualization

To apply my icc profile for display, I opened ColorNavigator 6 software and loaded my profile manually. I confirm through display preferences > color that my profile was successfully applied to the display. Then I opened the processed camera raw image of DC color chart on photoshop and applied my camera LUT based profile from edit > assign profile. Figure 2 shows the resulting images where 2a represents the output image from DCRAW in camera raw color space, 2b represents the output image after applying my profile, and I had set the camera to give both raw and jpeg image so 2c represents the JPEG image in sRGB color space generated by camera.

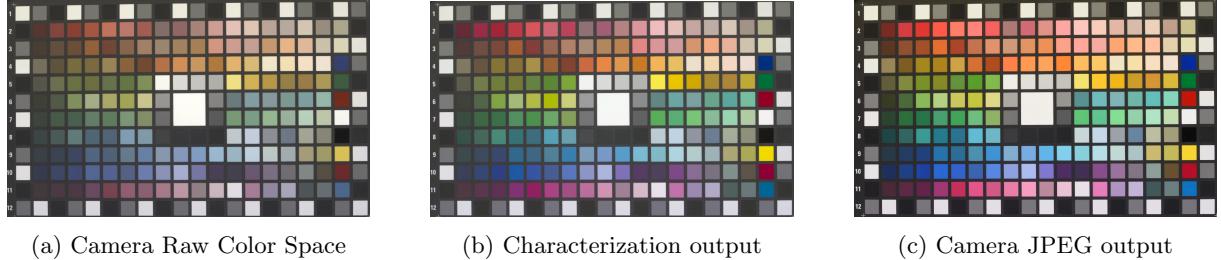


Figure 2: DC color chart output in different color space

## 4 Psychophysical Experiment

I conducted a psychophysical experiment to validate the performance of my characterization model at accurately reproducing colors of random day-to-day objects. I captured images of 10 objects under D50 illuminant while maintaining the same camera settings as mentioned in table 1 some of the samples are shown in figure 3. I invited 15 observers to rank the images on the scale of 1-3 where least rank means least accurate color representation and highest rank means most accurate color representation. The results are shared in section 5.

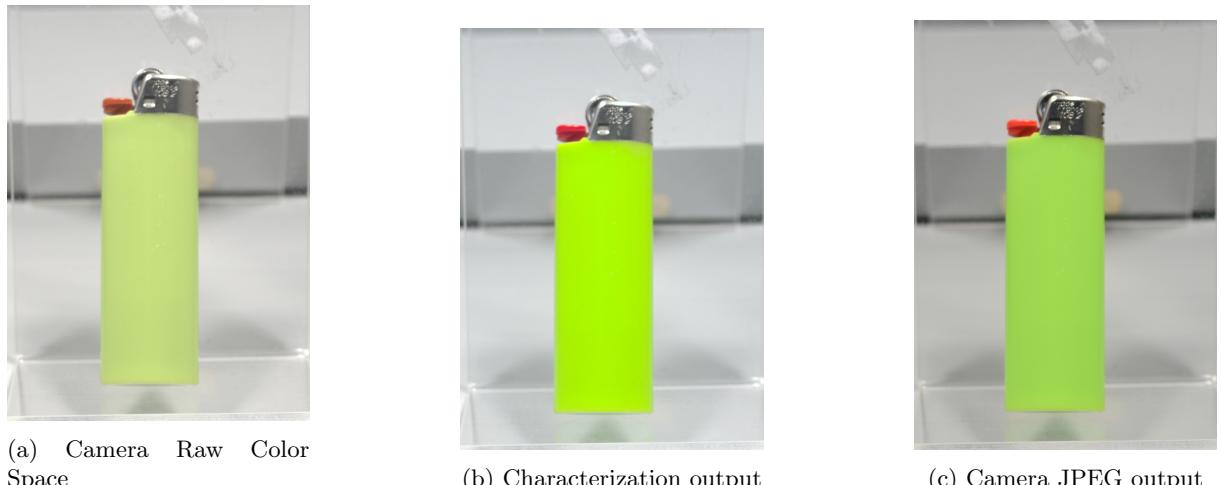


Figure 3: Sample objects for psychophysical experiment

## 5 Results

The third order polynomial regression gave an average color difference ( $\Delta E$ ) of 3.80. Figure 4 depicts the result of the Psychophysical experiment. We can deduce from the histogram that my characterization model does a reasonable job at reproducing accurate color of objects and in some cases my model leads by a big margin. Authors in [Hong et al. \(2001\)](#) point out that the transfer matrices are material dependent that is transformation matrix attained from color samples of a certain material will give best results at predicting color of samples made out of the same material. This could be a possible justification for the inconsistency in the performance of the model. Moreover, authors have also mentioned about the possibility of eye-camera metamerism which means that two different sets of RGB for two different scenes captured by the camera might appear similar to human eye.

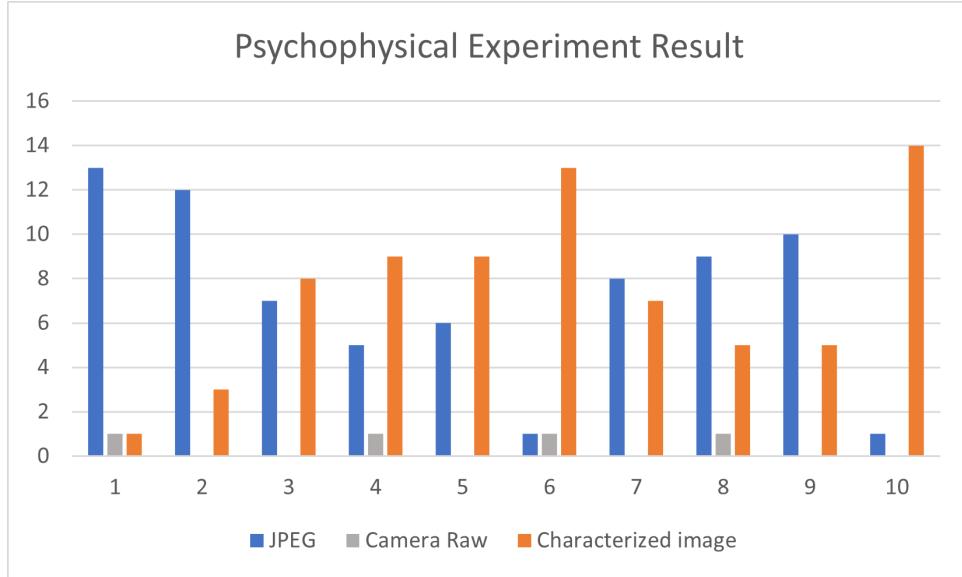


Figure 4: Histogram representation of Psychophysical Experiment

## 6 Conclusion

In this coursework, I attempt to calibrate and characterize input and output devices i.e., DSLR camera and display respectively. I have preprocessed the raw image by correcting its black level and performing demosaicing and white balancing. For the colorimetric characterization, I have used target-based approach whereas, to obtain the transformation matrix, I have used a third order polynomial regression which was trained on 240 color samples of DC colorchart. The regression model gives color accuracy ( $\Delta E$ ) of 3.8. The resulting co-efficients of the model were used to create a 3D LUT to generate icc profile for the camera. Similarly, for the display, I have used MeasureTool software to obtain the display RGB and their corresponding tristimulus values and used matrix TRC based method to create an icc profile. The profiles were applied to view color corrected DC chart on the calibrated display.

I have also performed a psychophysical experiment to verify the performance of my colorimetric characterization model at reproducing color accurately. The processed image generated by the camera was compared to my profiled image and the raw image. The results seem reasonable. Due to limited time I could not perform experiment to observe eye-camera metamerism as mentioned in [Hong et al. \(2001\)](#).

## References

- Bianco, S., Schettini, R., & Vanneschi, L. (2009). Empirical modeling for colorimetric characterization of digital cameras. In *2009 16th ieee international conference on image processing (icip)* (p. 3469-3472). DOI: 10.1109/ICIP.2009.5413828
- Camera noise and temperature tutorial.* (n.d.). Thorlabs, Inc. Retrieved from [https://www.thorlabs.com/newgroupage9.cfm?objectgroup\\_id=10773#:~:text=Dark%20Shot%20Noise%20\(%CF%83D,excited%20into%20the%20conduction%20band\).](https://www.thorlabs.com/newgroupage9.cfm?objectgroup_id=10773#:~:text=Dark%20Shot%20Noise%20(%CF%83D,excited%20into%20the%20conduction%20band).)
- Chou, Y.-F., Luo, M., Changjun, L., Cheung, V., & Lee, S.-L. (2013, 06). Methods for designing characterisation targets for digital cameras. *Coloration Technology*, 129. DOI: 10.1111/cote.12022
- Coffin, D. (n.d.). *Decoding raw digital photos in linux.* Retrieved from <https://www.dechifro.org/dcraw/>
- Coffin, D. (2015, Mar). *Dcraw.* Retrieved from <https://www.dechifro.org/dcraw/dcraw.1.html>
- Demosaicing.* (2022, Oct). Wikimedia Foundation. Retrieved from [https://en.wikipedia.org/wiki/Demosaic#:%~:text=A%20demosaicing%20\(also%20de%2Dmosaicing,CFA%20interpolation%20or%20color%20reconstruction.](https://en.wikipedia.org/wiki/Demosaic#:%~:text=A%20demosaicing%20(also%20de%2Dmosaicing,CFA%20interpolation%20or%20color%20reconstruction.)
- Exiftool.* (2022, Oct). Wikimedia Foundation. Retrieved from <https://en.wikipedia.org/wiki/ExifTool>
- He, R., Xiao, K., Pointer, M., Bressler, Y., Zhen, L., & Lu, Y. (2021, 01). A novel camera colour characterisation model for the colour measurement of human skin. *Electronic Imaging*, 2021, 222-1. DOI: 10.2352/ISSN.2470-1173.2021.16.COLOR-222
- Hong, G., Han, B., & Luo, M. (2000). Colorimetric characterisation of low-end digital camera and its application for on-screen texture visualisation. In *Proceedings 2000 international conference on image processing (cat. no.00ch37101)* (Vol. 1, p. 741-744 vol.1). DOI: 10.1109/ICIP.2000.901065
- Hong, G., Luo, M. R., & Rhodes, P. A. (2001). A study of digital camera colorimetric characterization based on polynomial modeling. *Color Research & Application: Endorsed by Inter-Society Color Council, The Colour Group (Great Britain), Canadian Society for Color, Color Science Association of Japan, Dutch Society for the Study of Color, The Swedish Colour Centre Foundation, Colour Society of Australia, Centre Français de la Couleur*, 26(1), 76-84.
- yan Huo, J., lin Chang, Y., Wang, J., & xia Wei, X. (2006). Robust automatic white balance algorithm using gray color points in images. *IEEE Transactions on Consumer Electronics*, 52(2), 541-546. DOI: 10.1109/TCE.2006.1649677