Article:

Chou, YF, Luo, MR, Li, C et al. (2 more authors) (2013) Methods for designing characterisation targets for digital cameras. Coloration Technology, 129 (3). 203 - 213. ISSN 1472-3581

https://doi.org/10.1111/cote.12022

Methods for Designing Characterisation Targets for Digital Cameras

Yi-Fan Chou,[1,2*] M Ronnier Luo,[1] Changjun Li,[3] Vien Cheung,[1] and San-Liang Lee[2]

[1]*School of Design, University of Leeds, Leeds, UK*

[2]*Department of Electronic Engineering, National Taiwan University of Science and Technology, 43, Sec.4 ,Keelung Road., Taipei ,Taiwan, 106, R.O.C. Taipei, Taiwan*

[3]*School of Electronics and Information Engineering, Liaoning University of Science and Technology, Anshan, China, 114051*

[*]*Corresponding author: M9602302@mail.ntust.edu.tw*

Characterisation targets usually include a set of physical coloured samples. A characterisation model can be derived between the colorimetric values (tristimulus values) and camera responses (RGB values) taken from an imaging device such as a digital camera capturing the colours in the target. The performance of such model is highly dependent upon the number of colours and the colour region in the characterisation target. An ideal characterisation target should provide accurate model prediction without requiring too many samples. In this paper, a computational method is presented for colour selections to train a camera characterisation model based on a fourth-order polynomial model including 35 terms. Comparing with the available methods the newly developed method performed the best. Furthermore, this method was applied to propose generic targets in terms of colorimetric values. These targets should work reasonably well for a wide range of materials.

Keywords: colorimetry, camera response, characterisation target, characterisation model

Introduction

With the rapid development of digital technologies, the images obtained from digital cameras have been used for colour communication in the global supply chain. Specifying colours based on digital cameras have become popular in imaging area since its application is not limited by the form and size of the object measured comparing with traditional colour measuring instruments such as spectrophotometers. A characterisation model is frequently used to perform this task via a transformation between two colour spaces, e.g. for a digital camera, the output RGB values is transformed to CIE colorimetric values, such as XYZ or CIELAB [1]. The model is developed based on the two sets of data (colorimetric values and camera responses) from a characterisation target. Therefore, it is essential to include right colours in the characterisation target which can be used for deriving a reliable camera model.

Generally, when more colours are included in the target, the model can predict with better accuracy. However, a large number of colours requires more colour measurement efforts (time-consuming) and increases the cost for production. Characterisation target is also useful for industries that are involved with painting, coating or dying surface manufacturers where only one material is used. For example, paint manufacturers are only concerned with the colour quality on paint samples. In this case, accurate colour measurement for paint sample is important and a target chart consisted of paint samples will allow good characterisation performance. The aim of this research is to development generic methods to select a minimum number of colours necessary to construct a characterisation target, for which the characterisation model developed from the target can have high efficiency and achieve high model accuracy.

Camera Characterisation Model

The characterisation model is defined as a mathematical model based on a set of equations. Most of the characterisation models are constructed by first measuring the camera responses and colorimetric values of a characterisation target which has the same material to be characterised, say paint, and then by determining the mathematical model in order to transform colours between the two sets of the data [2]. There are three main approaches for digital camera characterisation: look-up table (LUT), neural network and polynomial models. The LUT method requires a lot of samples to reduce the interpolation errors [1]. Cheung *et al.* [3] compared neural network and polynomial transforms, and the results showed that the techniques were capable of producing almost identical results when properly used. The neural networks can be difficult and time-consuming to train. Therefore, in this study, the polynomial regression was chosen as the camera characterisation model. This polynomial regression consists of a series of coefficients determined by regression from a set of samples including camera responses (RGB) and colorimetric values (XYZ) [4]. The generic formula of the polynomial model is given in Eq. (1):

$$\begin{aligned} X_k &= \sum_{0 \le j_1+j_2+j_3 \le n} m_{X,j_1,j_2,j_3} R_k^{\,j_1} G_k^{\,j_2} B_k^{\,j_3} \\ Y_k &= \sum_{0 \le j_1+j_2+j_3 \le n} m_{Y,j_1,j_2,j_3} R_k^{\,j_1} G_k^{\,j_2} B_k^{\,j_3} \qquad k = 1,2,3,\ldots,K \qquad \text{Eq. (1)} \\ Z_k &= \sum_{0 \le j_1+j_2+j_3 \le n} m_{Z,j_1,j_2,j_3} R_k^{\,j_1} G_k^{\,j_2} B_k^{\,j_3} \end{aligned}$$

where X_k, Y_k and Z_k are the CIE tristimulus values of the k^{th} sample, R_k, G_k and B_k are camera signals of the k^{th} sample, K is the number of samples in the characterisation target; n is the order of the polynomial and j_1 , j_2 , j_3 are nonnegative integer indices; m_{X,j_1,j_2,j_3} ,

m_{Y,j_1,j_2,j_3}, m_{Z,j_1,j_2,j_3} are the model coefficients to be determined. Eq. (1) can be expressed in matrix form as given in Eq. (2).

$$g_k = Mf_k \qquad \text{Eq. (2)}$$

where f_k is the k^{th} camera response vector formed by given RGB vector; g_k is the k^{th} tristimulus values vector obtained by physical measurement using a spectrophotometer; M is the mapping matrix to transform f_k to the vector g_k of tristimulus values. The least squares method [5] can be used for determining the matrix M based on the known camera response vector f_k and the corresponding measured tristimulus values g_k from the training set. Letting

$$G = [g_1, g_2, ..., g_K], \text{ and } F = [f_1, f_2, ..., f_K] \qquad \text{Eq. (3)}$$

results in a matrix equation:

$$G = MF \qquad \text{Eq. (4)}$$

where M is 3 by N matrix, and F is N by K matrix and G is 3 by K matrix; N is depended on the order n, for instance, when $n = 4$, N is 35.

In the above matrix equation, the matrices G and F are known and M is unknown. Note that the linear system of equation G=MF may have no solution if K>N, or may have many solutions if K<N. In fact when K=N, it may have a unique solution, or no solution or many solutions depending on the conditions of the matrix G and F. In general, the least squares solution is required, which is modelled as:

$$\text{Minimise: } \| MF - G \|_2 \qquad \text{Eq. (5)}$$

Here $\| q \|_2$ is the 2-norm of the q vector [5]. The above solution can be written by

$$M = GF^{+} \qquad \text{Eq. (6)}$$

where F^{+} is the pseudo or generalised inverse of the matrix F. when K=N and problem (Eq.(5)) has a unique solution, F^{+} becomes the normal inverse F^{-1} of the matrix F. If the problem (Eq.(5)) has many solutions, the above solution is the minimum norm solution.

It is noted the size of the column vector f_k is determined by the order n of the polynomial according to Eq. (1). The order of the polynomial model used for camera characterisation affects the performance. This was first determined. The models with different orders were trained by the colours in the full Munsell atlas (1562 colours) and tested by the full GretagMacbeth ColorChecker® DC (MCDC) chart (170 colours). The details of the datasets will be introduced later.

Figure 1: Effect of the complexity of polynomial models on training and testing performance.

Figure 1 shows the training and testing performances with the increase of the complexity of polynomial models. The black bars indicate the model trained and tested by the Munsell samples. The grey bars indicate the model trained by the Munsell samples and tested by the MCDC samples. It can be seen that the accuracy of training performance increased with the complexity of the model. For testing performance, the best performance was obtained with a fourth-order polynomial model. In general, as the complexity of the model increases the training performance increases consistently whereas the testing performance will reach a maximum and subsequently decrease as the model over-fits the training data. In this work, it is found a fourth-order polynomial model provided a satisfactory performance with both training and test datasets. Li *et al.* [6] also found that the polynomial performed the best using camera data with a fourth-order polynomial model. Eq. (7) shows the model resulting the camera response vector f_k with a 35 by 1 vector:

$$\begin{aligned} f_k = [&R_k, G_k, B_k, R_kG_k, G_kB_k, R_kB_k, R_k^2, G_k^2, B_k^2, R_kG_kB_k, R_k^2G_k, R_k^2B_k, \\ &G_k^2R_k, G_k^2B_k, B_k^2R_k, B_k^2G_k, R_k^3, B_k^3, G_k^3, R_k^3G_k, R_k^3B_k, G_k^3R_k, G_k^3B_k, B_k^3R_k, \\ &B_k^3G_k, R_k^2G_kB_k, R_kG_k^2B_k, R_kG_kB_k^2, R_k^2G_k^2, R_k^2B_k^2, G_k^2B_k^2, R_k^4, G_k^4, B_k^4, 1]^t \end{aligned} \qquad \text{Eq. (7)}$$

where t is the transpose of the vector.

Colour Selections for the Training Target

It is suggested that the number of samples and their colour distribution have a large impact on model accuracy [7]. The efficiency of the characterisation process can be improved by reducing the number of samples in the training dataset. The existing methods [8; 9; 10] used to select the samples are introduced in this section. Finally, a new method will be proposed.

Hardeberg Method

Hardeberg and co-workers [10; 11] proposed a method to select a set of reflectance samples from Munsell patches [12] for the estimation of camera spectral sensitivity. They claimed that the chosen spectra in reflectance space were as different as possible from each other. The first sample r_{s1} selected is the spectral reflectance function with maximum root mean square value as defined in Eq. (8):

$$\| r_{s_1} \| \geq \| r_k \| \text{ for } k = 1...K, \text{ where } \| r \| = \sqrt{\tfrac{1}{n} \sum_{i-1}^{n} x_i^2} \qquad \text{Eq. (8)}$$

where K is the number of samples in the full set and n is the number of elements in a measured reflectance vector r. The second sample r_{s2} is obtained by minimising the condition number of the matrix $[r_{s1}\ r_{s2}]$; i.e. to select the ratio of the largest to the smallest non-zero singular value. The equation is expressed in Eq. (9).

$$\frac{w_{max}\left(\left[r_{s_1} r_{s_2}\right]\right)}{w_{min}\left(\left[r_{s_1} r_{s_2}\right]\right)} \leq \frac{w_{max}\left(\left[r_{s_1} r_k\right]\right)}{w_{min}\left(\left[r_{s_1} r_k\right]\right)} \quad \text{for } k = 1...K, k \neq \mathrm{s}_1 \qquad \text{Eq. (9)}$$

where w_{max} and w_{min} represent the maximum and minimum non-zero singular values of the matrix $[r_{s1}\ r_{s2}]$ respectively. The i^{th} sample could be selected in the similar way:

$$\frac{w_{\max}\left(\left[r_{s_1} r_{s_2} ... r_{s_i}\right]\right)}{w_{\min}\left(\left[r_{s_1} r_{s_2} ... r_{s_i}\right]\right)} \leq \frac{w_{max}\left(\left[r_{s_1} r_{s_2} ... r_{s_{i-1}} r_k\right]\right)}{w_{min}\left(\left[r_{s_1} r_{s_2} ... r_{s_{i-1}} r_k\right]\right)} \quad \text{for } k = 1...K, k \notin \{s_1, s_2, ..., s_{i-1}\} \qquad \text{Eq. (10)}$$

MAXMINC Method

By choosing the samples which are as different to each other as possible, Cheung and Westland [8] developed another method to select colours using 1269 Munsell samples [12] for camera characterisation. In their method, named MAXMINC, the colorimetric values (C) were used to define colours closest to its neighbours (MIN) in sets of predetermined sets based on the maximal difference (MAX).

The first sample selected was the sample having the largest variance of spectral reflectance suggested by Cheung and Westland [8] They compared the model performance with the first samples to have maximum and minimum spectral variance. In general, the former performed better. The use of the sample with the greatest variance in spectral reflectance as the first sample (likely to be a highly chromatic colour) would result in the larger colour difference for the subsequently colours selected. Hence, the sample with greatest variance was used as the first sample in the present study. Supposing that there were K samples in the pool and m samples had been selected, the $(m+1)^{th}$ sample is desired to be selected from the remaining K-m samples in the pool without replacement. For the MAXMINC method, the $(m+1)^{th}$ sample whose nearest neighbour was as far as possible is determined according to the maximum value of S_j shown in Eq. (11).

$$S_j = \min_{k=1}^{m} \left[\Delta E_{j,k} \right] \qquad \text{Eq. (11)}$$

where $\Delta E_{j,k}$ is the Euclidean distance between the j^{th} samples ($j \in \{1, 2, ..., K - m\}$) in the database and the k^{th} sample ($k \in \{1, 2, ..., m\}$) which was already selected. In implementing the method in this study, the Euclidean distances were calculated from the colour differences in CIELAB space as the original work.

The Colour Difference Iteration (CDI) Method

A new method named Colour Difference Iteration (CDI) is derived here to achieve high colour accuracy in terms of colour differences. During the selection process, a <u>source dataset</u> including XYZ and RGB are first provided. The number of samples in the source dataset and the <u>training dataset</u>, which are the samples selected from the source dataset are known.

Figure 2 shows the workflow for sample selection. K is the number of samples in the source dataset. The value m is predefined as the number of samples to be selected from the source dataset. In step 1, m equals to zero. Since there are K samples, each sample is a candidate. Each of the K samples is first used to train a characterisation model. Thus, K models are obtained. Each model is then applied to predict the colour accuracy of the full source dataset in terms of CIEDE2000 colour difference (ΔE_{00}) [13] under D65/10 condition. From each prediction, the model performance is obtained in terms of mean colour difference. For example, S_2 is selected and is denoted P_1 in Figure 2, because ΔE_2 is the smallest.

Figure 2: A schematic diagram showing the CDI method selecting characterisation samples.

Next step is the selection of the second sample which should provide the best combination with P_1 according to the performance. In order to avoid selecting P_1 twice, the previously selected sample P_1 is removed from the source dataset and m equals to one. Once again, each remaining sample from the source dataset combined with the already selected sample P_1 in turns are used for training the model. It results in K-1 models. Again, each model is used to predict the full source dataset. From the predictions, the sample combined with already selected sample P_1 with the smallest colour difference will be selected. The same process will be repeated until it reaches the desired number of samples. Therefore, the new method named as colour difference iteration (CDI) method. The CDI method is simple and easy to implement. It was found from many tests that the first sample (P_1) chosen was the lightest neutral colour in the source dataset with a ΔE_{00} about 15. This suggests that the lightest neutral colour should be included in the source dataset. Otherwise, the characterisation model's performance could be deteriorated.

Note that the model coefficients in Eq. (1) derived using one or few samples cannot be uniquely determined. When using an individual sample to determine matrix M in Eq. (2), there are many matrices M satisfying Eq. (2). Constraint must be added since the unknown model parameters are used as multipliers. It is better if these parameters are not too large in magnitude in order to reduce noise propagation and to prevent local oscillation in prediction. Therefore, the minimum norm of the unknowns is considered as a constraint [4]. The norm here used is the square root of the sum of squared unknowns. In the proposed method, the pseudo or generalized inverse is defined in Eq. (6). Hence, regardless of the number of samples used, the matrix *M* with minimum norm is obtained, resulting in a unique solution in each case. One may argue that this may not be the best solution. Although the method may not be proven to be optimal it allows satisfactory performance based on the fourth-order polynomial model and the collected data according to the testing result which will be presented in the following sections.

Data Collections

Three sets of samples were used: the Munsell book of Color having 1562 glossy paint chips [14; 15], the Professional Colour Communicator (PCC) consisting of 1063 textile samples [16] and a GretagMacbeth ColorChecker® DC (MCDC) including 240 colour patches. A Nikon D80 digital camera was used for imaging the samples. On the other hand, an X-Rite CE7000A spectrophotometer was used to measure all the test samples using the small aperture, specular inclusion and UV exclusion conditions.

Munsell Book of Color

The Glossy version® of the Munsell Book of Color [14; 15] includes 1562 paint chips. Each chip is specified by three Munsell attributes (Munsell Hue, Munsell Value and Munsell Chroma). There are 40 hue pages in the Munsell Book of Color. The lightness of a colour is expressed by the Munsell Value (V) ranged between 0 and 10 at 1-unit interval. The Munsell Chroma (C) represents the degree of chromatic content from zero (achromatic colours) to an open end.

Professional Colour Communicator (PCC)

The Professional Colour Communicator (PCC) [16] includes 40 loose-leaf pages of small cuttings of dyed cotton arranged according to changing lightness, hue and chroma based on the CMC(2:1) colour space [17]. There are totally 1063 textile-based samples in the system. The samples with constant hue angle are given in a page. These samples in each page are arranged according to the lightness (column) and chroma (row). In the PCC, each adjacent page has a 9-degree interval in hue angle, and there are 5-unit and 10-unit intervals for chroma and lightness respectively between each adjacent pair of samples.

GretagMacbeth ColorChecker® DC (MCDC)

The GretagMacbeth ColorChecker® DC target has 237 patches in a 12 cm by 20 cm grid including 167 matte colours, 10 glossy colours, 60 colours of the repeated three neutral colours (a black, a gray and a white patches) surrounding the border of the chart. The 10 glossy samples in the MCDC set which may give serious reflection problems in some lighting situations were excluded. Also, the 60 repeated 3 neural colours were discarded in the study. A large matte white patch at the chart centre occupying 4 patches positions was considered as 4 colours. Hence, 170 samples in total were used for this set.

Nikon D80 Digital Camera

In this project, a digital single lens reflex camera, Nikon D80 [18], was used for capturing images of all the samples mentioned in the last section to obtain camera RGB values. The digital camera was situated on the top of a cabinet illuminated by a CIE D65 simulator from each of the sides as shown in Figure 3. The illumination and viewing geometry can be considered as d/0, and the camera conditions are given in Table 1. Samples were placed on the base at the bottom of the cabinet. The images of samples were captured by the digital camera and the captured images were saved the captured images as jpeg files. The RGB values of samples were directly taken from the jpeg file. Therefore, the results could not be improved by additional steps such as channel balancing and linearisation.

Figure 3: Structure of the digital camera system

Table 1: Camera Setting

GretagMacbeth® COLOR-EYE® 7000A Spectrophotometer

The colorimetric CIE XYZ values were calculated from the reflectance measured by a GretagMacbeth® COLOR-EYE® 7000A Spectrophotometer [19]. The measuring conditions were small aperture, specular inclusion and UV exclusion conditions. The reflectance functions were measured between 400nm and 700nm at 10nm interval.

In total, three source datasets were accumulated. Each dataset contained camera responses and corresponding CIE tristimulus values. The three colour selection methods introduced above were compared using the data collected. The mean CIEDE2000 colour difference value was used to measure the model performance.

Comparison among Colour Selection Methods

The MCDC chart (170 samples) was first taken as the source dataset. Hardeberg, MAXMINC and CDI methods were used for selecting a subset of samples for developing models. The comparison was conducted based on the polynomial model. The models developed were tested using the full MCDC source data. For each method, the samples were reordered according to the sequence for the samples selected, i.e. the order in which samples were selected matched their importance to the model. The same procedure was also applied to the Munsell set and the PCC source dataset.

Table 2 lists the results for each method with the number of the samples (24, 60, 90, 120 and 170) used to develop the characterisation model. These numbers were arbitrarily chosen for easy arrangement in a chart. For the MCDC data, it can be seen that when 24 samples were chosen, the Hardeberg method had an average accuracy of 8.4 ΔE_{00}, the MAXMINC method 2.6 ΔE_{00}, and the CDI method 2.0 ΔE_{00}; while the ΔE_{00} values for the worst sample for each of the Hardeberg, MAXMINC and the CDI methods were 32.8, 11.8 and 7.9 ΔE_{00} units respectively. The results indicated that the CDI method performed the best among all the methods tested for all the subset of training samples.

Table 2 also shows the results for the Munsell and PCC sets. The CDI method was again the best in terms of the mean and maximum measures and the MAXMINC method performed better than the Hardeberg method. The results were quite consistent and showed the CDI method outperformed the other two methods. It was encouraging that the sample set with 60 samples for the CDI method gave better results than the sample set with 170 samples for the Hardeberg or the MAXMINC method. However, it should be noted that the Hardeberg method was proposed for spectral sensitivity estimation which is a different task than polynomial colorimetric characterisation. All the results were based on the polynomial model and the data collection from a Nikon D80 camera. Further work will consider testing with a wider range of models and using another camera.

Table 2: Testing the Hardeberg, MAXMINC and CDI methods developed using the subsets from the three source datasets in terms of mean ΔE_{00} colour differences and maximum values (in parentheses).

Figure 4 shows the plot of the Munsell samples selected using a) the Hardeberg, b) the MAXMINC and c) the CDI methods plotted in CIELAB a^*b^* and $L^*C^*_{ab}$ diagrams. Similarly, Figure 5 is analogous to Figure 4 except it is for the PCC samples. In each subplot of Figures 4 and 5, the largest dots represents 24-sample set, followed by the smaller ones of 60, 90, 120 and 170 the smallest dots. Note that the larger the dot, the more important the colour region. In addition, the colour gamut for each source dataset was also plotted in Figures 4 and 5. This was used to compare the colours selected and actual gamut of the source data.

Figure 4: Colour distribution of the Munsell samples selected by (a) Hardeberg (b) MAXMINC and (c) CDI methods plotted in (1) a^*b^* and (2) $L^*C^*_{ab}$ planes.

Figure 5: Colour distribution of the PCC samples selected by (a) Hardeberg (b) MAXMINC and (c) CDI methods plotted in (1) a^*b^* and (2) $L^*C^*_{ab}$ planes.

Figures 4(b) and 5(b) show that the MAXMINC method selected the samples covering the largest colour area and uniformly distributed in the colour space. The best method (CDI) in Figures 4(c) and 5(c) show that some regions are more important than others, e.g. the orange and yellow-green colours seem to be less important than the other colour regions. Also, darker colours are more important than lighter colours.

In the above test, the training dataset was a subset of the source dataset having the same material. Another test was conducted using the three datasets to predict each other in order to reveal the impact due to different materials. Therefore, the subsets with 170 samples in Table 2 selected from the MCDC, Munsell and PCC source datasets using the Hardeberg, MAXIMINC and CDI methods were employed as training datasets to develop the polynomial model to predict each of the three full source datasets. Since the full set of MCDC was used to test the three methods, only one set of the results is listed in Table 3. There was no difference between colour selection methods for MCDC. Table 3 summarises the test results in terms of mean and maximum ΔE_{00} values. The results in column 2 represent that the performance of the characterisation model trained using the 170 MCDC set tested based on three source datasets. The same method was used for the other two datasets. It was expected that the model performed the best for the data used as both training and testing data. For example, when the model trained using the MCDC set gave the most accurate prediction to the full MCDC dataset, i.e. with a mean of 1.2 ΔE_{00} units comparing with 1.7 and 3.2 for the Munsell and PCC sets respectively. Similar results can be found that the model trained using the subset of the PCC data selected by the CDI method gave a colour difference of 1.2, 2.8 and 3.4 ΔE_{00} units for the PCC, MCDC and Munsell datasets respectively. The above results clearly show that the performance of the camera characterisation model is material dependent. It also indicates that the MCDC chart was a well-designed characterisation target as it always performed the second best; while the best was always based on a target developed using the same material as the testing set. The textile sample set (PCC) seems to be the most material dependent, i.e. to give the poorest performance using this target to predict the Munsell or MCDC datasets. Comparing the three colour selection methods, the CDI outperformed the other two methods tested. For instance, the Munsell samples selected either by Hardeberg or MAXMINC gave higher prediction errors for all the three testing sets than that selected by the CDI method. The CDI method gave quite satisfactory predictions, i.e. 1.8, 1.2 and 4.2 ΔE_{00} units for the MCDC, Munsell and PCC sets respectively.

Table 3: Testing models derived using the 170 samples selected from the MCDC, Munsell and PCC samples in terms of mean and maximum (in parentheses) ΔE_{00}.

Colour Selection Guideline for Characterising Digital Cameras

In order to investigate the impact of different colour regions on the accuracy of the characterisation models, the F statistical test was used to investigate which regions have significant impact on the accuracy. For investigating a specific colour region such as L^* less than 30, the colours with lightness less than 30 were removed from the full set of 170 samples selected by the CDI method (referred to as CDI full set). The remaining colours were grouped to form a subset, i.e. it includes all colours lighter than L^* of 30. Then, the subset was compared with the CDI full set to see the effect on the model accuracy. A F-factor was used to determine which colour region had a significant impact on the characterisation model developed. The colour differences between the predicted and measured colour are denoted as $\Delta E_1, \Delta E_2 \ldots \Delta E_N$ where N is the number of the samples. Then, the F factor is defined in Eq. (12).

$$1 \leq \text{F factor} = \frac{V_1}{V_2}, \textit{where}\, V_1 > V_2 \qquad \text{Eq. (12)}$$

The V_1 and V_2 are defined as Eq. (13).

$$V_1 = \frac{1}{N_1}\sum_{i=1}^{N}\left(\Delta E_i^1 - \mu^1\right)^2, where\ \mu^1 = mean([\Delta E_1^1\ \Delta E_2^1 \ldots \Delta E_{N_1}^1])$$

$$V_2 = \frac{1}{N_2}\sum_{i=1}^{N}\left(\Delta E_i^2 - \mu^2\right)^2, where\ \mu^2 = mean([\Delta E_1^2\ \Delta E_2^2 \ldots \Delta E_{N_2}^2]) \quad \text{Eq. (13)}$$

where V_1 and V_2 represent the models' performance for the subset and CDI full set respectively; N_1 and N_2 represent the number of samples in the subset and CDI full set respectively. The investigated colour regions are listed in Table 4. Different subsets represent the colour regions tested. Each subset included the CDI full set (i.e. 170 samples in Table 2) excluding the following five regions: a) L* regions divided at 10 L^* unit interval; b) hue regions divided at 36° h_{ab} interval; c) the neutral colour region ($C_{ab}^* < 10$); d) the 2 most saturated colours in the above hue regions (see b)), and e) dark colours. The dark colour region was defined as L^* values less than 40 for the Munsell database because there was only one sample with L^* values less than 30 from the CDI (Munsell) full set. However, for the PCC samples there are too many with L^* values less than 40, therefore, the dark colour was defined as L^* values less than 30 for the CDI (PCC) full set.

Table 4: Investigation of the importance of colour regions for camera characterisation.

The results in Table 4 show that most of the F factors (values in bold) are larger than the F critical value. In other words, most of the colour regions had a significant impact on camera characterisation. When darker or more saturated colours were removed from the selected Munsell or PCC set, the F factors were the largest, i.e. for the Munsell set, the F factor of 60.083 for the region excluding lightness less than 40 was much larger than those of the other regions. This implies that the two most important regions should be always included in designing a characterisation target.

Development of Generic Characterisation Targets based on Colorimetric Values

The CDI method proposed earlier was developed to build a customized target for a particular material. This section intends to construct generic characterisation targets suitable for all different materials. A set of colorimetric values will be proposed and can be reproduced for all materials. The aim here is to develop characterisation targets giving accurate prediction to colours presented on different substrates with fewer samples. The target will be represented by a set of colorimetric values which are selected based on the CDI method as described in the previous section.

Approach 1: Averaged-CDI (ACDI)

In this approach, target colours were derived based on the top 50 samples selected from the Munsell dataset and the PCC dataset using the CDI method. In total, 100 samples were used. By removing colours in the too crowded areas, i.e. with ΔE^*_{ab} of 20 apart, the CIELAB values were averaged to form a representative set including 72 samples. Thus, the approach was named as "Averaged-CDI" (ACDI). The 72 physical samples are proposed to be produced in particular application.

In order to evaluate the performance of the new target, the closest colours from the Munsell and PCC datasets were chosen in turns. These samples were used to develop two characterisation models. The training performances i.e. tested by their own full dataset are given in Table 5.

Table 5: Performance of 72 selected colours to different sets in terms of mean and maximum (in parentheses) ΔE_{00} values.

The results show the mean ΔE_{00} values of 1.6 and 1.8 with maximum of 12.6 and 20.2 for the Munsell and PCC datasets respectively. These colours are plotted in Figures 6 a) and b) for a^*b^* and $L^*C^*_{ab}$ planes respectively.

(a) (b)

Figure 6: Colour distribution of the 72 samples for the new target.

Approach 2: Grid-CDI (GCDI)

Another approach called 'Grid-CDI' (GCDI) Method was developed based on the concept of the uniform distribution. By applying the CDI method again, 170 colours were selected from each of the Munsell and the PCC. In total, 340 samples were accumulated. These colours were presented in CIELAB space in terms of grid. Many grids were established ranged from -60 to 60 for a^* and b^* scales and from 25 to 85 for L^* scale. This approach includes three stages:-

Step 1: Consider the CIELAB space as a cube which is divided into sub-cubes with equal interval such as 20 or 30 units in a^* or b^* direction. The L^* interval was set at 10 units between 25 and 85. Figure 7 illustrates the process of dividing the cube into sub-cubes and the filled circles in the right diagram are colour centres.

Figure 7: Divide a space as cube into sub-cubes with equal intervals.

Step 2: Count the number of colours selected in each cube (with a sum of 340) and sort the sub-cubes in descending order, i.e. the more samples in a sub-cube, the more important is that colour region. The sub-cubes containing no colour were discarded. In Figure 8, the filled circles refer to the samples in each sub-cube and hollow circle is the centroid of the sub-cube.

Figure 8: Sorting sub-cubes in descending order.

Step 3: Store the centroid of each sub-cube to form the colorimetric target.

Using the above GCDI method, 92 colours in terms of CIELAB values were found at a 20-unit interval for a^* and b^* scales, and 64 target colours at a 30-unit interval. To test the target performance, the closest colours were selected from each of the Munsell and PCC datasets. The selected 24, 60 and full set were used to train the model and then the models were again tested to predict the full Munsell and PCC datasets. The results are given in Table 6.

Table 6: Performance of the GCDI method in terms of mean and maximum (in parentheses) ΔE_{00}.

It can be seen in Table 6 that by applying all available centres, i.e. 92 and 64 samples corresponding to the 20- and 30-interval respectively, both intervals covered the whole colour gamut and the 20-unit interval which contained more samples provided the best result as expected. For predicting the Munsell and PCC datasets, the model developed from 92 samples at 20-unit interval gave a performance of 1.6 ΔE_{00} units.

The colours from the GCDI method are uniformly distributed as shown in Figure 9, where the points are the target colorimetric values (centroid in a cube) with a 20-unit interval and the boundaries of the Munsell, PCC data sets are also plotted. When the points were located outside the gamut, the sample having the smallest colour difference from the point in the gamut boundary was selected. Again, the points are plotted in different sizes to distinguish their priority.

Figure 9: Colour distributions in CIE a*b* (left) and CIE L*C* (right) planes.

Comparing the two approaches from Tables 5 and 6, The ACDI method including 72 colours can achieve 1.6 and 1.8 ΔE_{00} units for predicting the Munsell and PCC respectively. The GCDI method including 92 samples can achieve 1.5 and 1.6 ΔE_{00} units for predicting the Munsell and PCC datasets respectively. It explicitly shows that the GCDI method provides more accurate prediction and includes reasonable number of samples (92 or 64). Hence, it is proposed to be used as a generic method.

Conclusions

A robust method for developing a target from a particular dataset for characterising digital cameras was proposed. The method based on the fourth-order polynomial model outperformed the existing methods by a large margin in terms of higher colour accuracy or reduced number of samples. It was found that with the same number of samples the newly developed CDI method always outperform the Hardeberg and MAXMINC methods.

The results also showed that it is recommended to use the same material to build the characterisation chart. This is to avoid the metameric effect due to the colorants used in different materials.

Two Methods – Averaged-CDI and Grid-CDI – to generate generic targets were also proposed. The results showed that good performances can also be achieved using either a target including 72 colours obtained by the ACDI method or targets including 92 or 64 colours obtained by the GCDI method.

References

[1] T Johnson, Displays, ***16*** *(1996) 183-191.*

[2] P Green, Overview of characterization methods (Chichester: Wiley, 2002).

[3] V Cheung, S Westland, D Connah and C Ripamonti, Color Technol, ***120*** *(2004) 19-25.*

[4] GW Hong, MR Luo and PA Rhodes, Color Res Appl, ***26*** *(2001) 76-84.*

[5] GH Golub and CFV Loan, Matrix Computations (Baltimore: Johns Hopkins University Press, 1983).

[6] CJ Li, G Cui and MR Luo, Proceedings of International Colour Association (2003) 166-170.

[7] HR Kang, Color technology for electronic imaging devices (Bellingham, Wash., USA: SPIE Optical Engineering Press, 1997).

[8] V Cheung and S Westland, J Imaging Sci Techn, ***50*** *(2006) 481-488.*

[9] TLV Cheung and S Westland, The Second European Conference on Colour Graphics, Imaging and Vision (2004) 116-119.

[10] JY Hardeberg, H Brettel and F Schmitt, Electronic Imaging: Processing, Printing, and Publishing in Color (1998) 100-109.

[11] JY Hardeberg, Acquisition and reproduction of color images: Colorimetric and multispectral approaches (Paris, France: Ecole Nationale Superieure des Telecommunications, 1999).

[12] JPS Parkkinen, J Hallikainen and T Jaaskelainen, J Opt Soc Am A, ***6*** *(1989) 318-322.*

[13] MR Luo, G Cui and B Rigg, Color Res Appl, ***26*** *(2001) 340-350.*

[14] D Nickerson, J Opt Soc Am, ***30*** *(1940) 575-586.*

[15] RG Kuehni, Color Res Appl, ***27*** *(2002) 20-27.*

[16] J Park and K Park, Journal of the Society of Dyers and Colourists, ***111*** *(1995) 56-57.*

[17] FJJ Clarke, R McDonald and B Rigg, Journal of the Society of Dyers and Colourists, ***100*** *(1984) 128-132.*

[18] Nikon, The Nikon guide to digital photography with the D80 digital camera (Tokyo: Japan, 2006).

[19] X-Rite, Color-Eye 7000A specification (2007).