An Evaluation of Multispectral Imaging Techniques for Camera Characterization

T.L.V. Cheung and S. Westland
Colour & Imaging Institute, University of Derby, Kingsway House East Kingsway, Derby, United Kingdom

Abstract

One approach to camera characterization is to attempt to recover the spectral properties of the surfaces in a scene and then compute the tristimulus values from these estimated reflectances. This paper addresses the question of whether such spectral-based characterization methods can outperform traditional characterization methods. In this paper we have evaluated three different techniques for camera characterization that employ multispectral methods. The Imai and Berns method and the Hardeberg method are based on the use of a linear model of reflectance with three basis functions whereas the Shi and Healey method allows the use of a higher dimensional linear model. The characterization performance (median ΔE) of the techniques using the full set training samples was found to be 3.69, 4.26 and 3.55 respectively for the Imai and Berns method, the Hardeberg method and the Shi and Healey method. In a previous study we found that polynomial and neural-network methods are able to perform characterization on the same data with a median ΔE of 2.02 and 2.01 respectively. We find no evidence, therefore, that multispectral imaging techniques provide any advantage over traditional characterization methods for a three-channel camera imaging under a single illuminant. Further work is required to evaluate multispectral techniques for multiple imaging under more than one light source and for cameras with more than three color channels.

Introduction

Traditional imaging systems such as digital *RGB* cameras capture device- and illuminant-dependent images. That is, the *RGB* values that the camera measures are specific to that camera (device). Several methods exist[1-4] that enable camera *RGB* data to be transformed into device-independent CIE *XYZ* data. However, this effectively converts the color camera into a spatial colorimeter and the *XYZ* values are still illuminant-dependent. This dependency can be a serious problem, especially since the spectral sensitivities of most commercial color cameras are not identical to (or a linear transform of) the human spectral sensitivities or the CIE color-matching functions. Thus two surfaces with differing spectral reflectance factors can result in identical *RGB* responses (and thus identical *XYZ* values when transformed) and yet may have different *XYZ* values to each other when measured using a spectrophotometer or colorimeter that utilizes the CIE color-matching functions. Recently, many researchers[5,6] have suggested multispectral imaging as a means of addressing this problem. In a multispectral imaging system, the responses of a number of color channels (usually more than three) are used to attempt to recover spectral information about surfaces that are imaged. If successful this would effectively convert the color camera into a spatial spectrophotometer and would ultimately enable the measurement of device- and illuminant-independent images. Such a system is possible with relatively few color channels because the spectral properties of most surfaces are relatively smooth functions of wavelength.[7] A possible device-characterization method is to try to recover the spectral properties of the surfaces in the scene and then compute the tristimulus values from these estimated reflectances.[8] This paper addresses the question of whether such spectral-based characterization methods can outperform traditional characterization methods. Three multispectral methods are evaluated.

Multispectral Imaging Techniques

The idea underpinning spectral-based device characterization is that once the spectral reflectance factors have been estimated the computation of tristimulus values is trivial. Therefore characterization based upon multispectral imaging is a two-stage process: firstly, the camera responses are used to estimate the reflectance values, and secondly, the tristimulus values are computed. In this section we describe three methods for multispectral imaging that are evaluated in this paper. These methods are discussed in terms of a trichromatic imaging system because the focus of this paper is the characterization of typical consumer imaging devices though they all can be extended for use with cameras with more than three channels.

The method developed by Hardeberg assumes that the reflectance spectra are adequately represented by a three-dimensional linear model and that the illuminant and camera sensor characteristics are known.[9] The camera response R for a channel is shown in Equation 1,

$$R = \sum E(\lambda)S(\lambda)P(\lambda), \quad (1)$$

where $E(\lambda)$ is the spectral power distribution of the illuminant, $S(\lambda)$ is the channel spectral sensitivity and $P(\lambda)$ is the surface spectral reflectance at each wavelength interval λ. The reflectance P in Equation 1 can be replaced with a weighted sum of basis functions derived from a linear model. If $V_i(\lambda)$ represents the first three basis functions ($i \in \{1, 2, 3\}$) from the linear model and w_i are the weights that represent a particular spectrum P, then we can write,

$$R \approx \sum_{\lambda} E(\lambda)S(\lambda)\left(\sum_{i} V_i(\lambda)w_i\right) \quad (2)$$

The known quantities can be grouped together to yield Equation 3,

$$T_i = \sum E(\lambda)S(\lambda)V_i(\lambda), \quad (3)$$

If Equation 2 is considered for all three camera channels it can be rewritten as a linear matrix equation, thus

$$\mathbf{R} = \mathbf{Tw} \quad (4)$$

where $\mathbf{R}$ is a 3×1 matrix of camera responses, $\mathbf{T}$ is a 3×3 matrix (see Equation 3), and $\mathbf{w}$ is a 3×1 matrix of weights. Equation 4 can be solved for $\mathbf{w}$ thus,

$$\mathbf{w} = \mathbf{T}^{-1}\mathbf{R}, \quad (5)$$

where $\mathbf{T}^{-1}$ represents the inverse of the matrix $\mathbf{T}$. We note that Finlayson refers to $\mathbf{T}$ as the lighting matrix.[8]

The Hardeberg method requires that the camera spectral sensitivities and the spectral power distribution of the illuminant are known so that, with a knowledge of the basis functions, the lighting matrix may be defined. However, the method proposed by Imai and Berns does not require the spectral properties of the channels and illumination to be known but rather assumes a linear relationship between the camera responses and the weights that represent reflectance spectra in a linear model.[10] Consider a set of characterization target with m known spectral reflectances that are represented in a linear model by $\mathbf{w}$ (so that $\mathbf{w}$ is a $3 \times m$ matrix) and the corresponding camera responses $\mathbf{R}$ (a $3 \times m$ matrix). Imai and Berns simply write that $\mathbf{R}$ and $\mathbf{w}$ are related thus,

$$\mathbf{R} = \mathbf{Tw}, \quad (6)$$

where $\mathbf{T}$ is a 3×3 matrix that can be determined empirically via a least-squares fit. Specifically, we can compute $\mathbf{T}$ using

$$\mathbf{T} = \mathbf{wR}^{-1}. \quad (7)$$

Shi and Healey examined a higher-dimensional linear model for characterizing a three-channel color scanner to generate device-independent values from scanner responses.[11] Since spectral reflectance functions typically require a linear model with more than three degrees of freedom for accurate representation, an approach to characterization that allows incorporation of high-dimensional models is worth exploring. Consider a set of characterization target with known spectral reflectances $\mathbf{P}$ and known camera responses $\mathbf{R}$. A minimization process is carried out to find the $\mathbf{P}$ that is most similar in Euclidean distance to a training spectral reflectance vector for a given $\mathbf{R}$. For a given training spectral reflectance vector $\mathbf{P_i}$, the element $\mathbf{P}^*$ that minimizes $\|\mathbf{P}^* - \mathbf{P_i}\|$ is the solution of a linear least-squares problem and is given by:

$$\mathbf{P}^* = \mathbf{V_1}(\mathbf{w_1}^*)^\mathbf{T} + \mathbf{V_2}(\mathbf{SV_2})^{-1}[\mathbf{R} - \mathbf{SV_1}(\mathbf{w_1}^*)^\mathbf{T}] \quad (8)$$

In this equation, $\mathbf{V_1}$ and $\mathbf{V_2}$ denote the fourth to n and the first three basis functions respectively and $\mathbf{w_1}$ is the set of weights for the fourth to n basis functions for $\mathbf{P_i}$. The effective spectral sensitivity channels of the camera is represented by $\mathbf{S}$.

Experimental

An Agfa digital StudioCam camera, a three-chip CCD device with 8-bit resolution for each channel and 4500×3648 pixel spatial resolution, was used in this study. During the experiment the automatic white-balance setting was disabled. Two imaging targets, the Macbeth ColorChecker DC chart and the Macbeth ColorChecker chart, were used for characterization. The spectral reflectance factors of the patches on the two charts were measured using a Macbeth ColorEye 7000A reflectance spectrophotometer. The imaging system consisted of two gas-filled tungsten lamps arranged approximately in a 0/45 illumination/viewing geometry. A Minolta CS1000 spectroradiometer was used for the measurement of illuminant spectral power distribution.

Linearization and Spatial Correction

The linearization and spatial-correction method described below are based upon a method described by Sun and Fairchild.[12] The camera *RGB* responses were measured for a series of Munsell grey chips (N6/ to N9/ at intervals of 0.5 value), an NCS uniform white paper, and the dark condition (with the camera lens cap in place) to allow a gamma correction for the camera. This converted the raw camera responses to values that were linearly related to the camera input[4]. During the experiment, the camera and lighting positions were fixed, and the *RGB* values of the Munsell grey chips were measured with each chip in turn in the centre of the camera's field of view. Each patch generated an image region of about 40×60 pixels but the values of a central sub-region (11×11 pixels) were averaged to generate the mean *RGB* values for that patch. For each camera channel, the camera responses for each grey patch were plotted against the mean reflectance of each patch and the relationship was fitted using a second-order polynomial. A polynomial relationship was established for each channel and then all subsequent camera responses were linearized using these relationships before further processing. Thus, for the green channel,

$$G' = a_G + b_G G + c_G G^2 \qquad (9)$$

where G is the raw camera response and G' is the linearized response for the green channel.

Spatial correction was also performed to minimize the effect of any spatial non-uniformity of the intensity of the illumination or of the sensitivity of the camera CCD. For example, for the green channel, Equation 10 was used to convert the linearized channel response G' to the spatially corrected value G_S at each pixel position, thus

$$G_S = \frac{(G_W - G_B)\times(G' - G_B)}{(G_W - G_B)} \qquad (10)$$

where G_W and G_B are the mean linearized channel values for the uniform white and black (dark) samples respectively. Similar equations were used to obtain the spatially corrected values for the red and blue channels.

Training/Testing Protocol

A total of 192 patches in the Macbeth ColorChecker DC chart and the 24 patches of the Macbeth ColorChecker chart were used as training and testing sets respectively. These two characterization stimuli were used for memorization and generalization tests. Memorization represents the ability of a system to back-predict the training data that were used to determine the system. Generalization represents the ability of a system to predict testing data that were not used to develop the system and this is a more critical test of the characterization models. Smaller training sets were derived by randomly sub-sampling the 192 patches to generate training sets containing 160, 130, 100, 70 and 40 samples.

Implementation of Algorithms

CIE tristimulus values were computed for the patches using the 1964 CIE observer data and the illuminant data measured for the light source. Color errors between measured and estimated samples of each training size are presented in CIELAB color difference (ΔE^*_{ab}) values. When a sub-set of less than 192 training samples was used the sub-set was randomly selected five times and the mean error score computed. All computations were performed in MATLAB programming environment. The camera spectral sensitivities were estimated[13] using quadratic programming method[14] and are illustrated in Figure 1.

The method for computing the basis functions for a set of reflectance spectra employs singular value decomposition and is provided as a single command SVDS in MATLAB. The basis functions used were derived based upon the Macbeth ColorChecker DC samples in the training set and are shown in Figure 2.

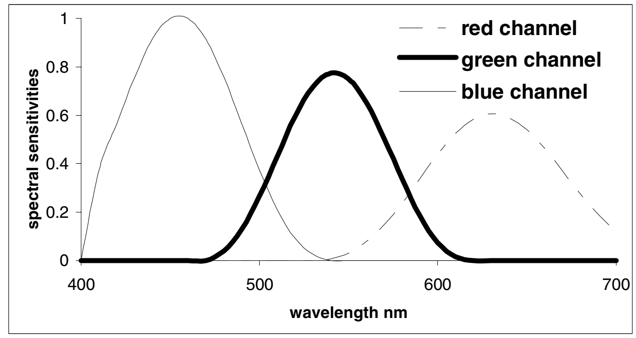

Figure 1. Estimated camera spectral sensitivities

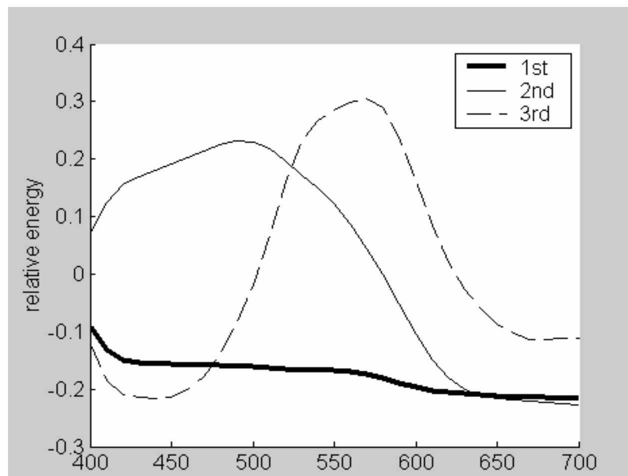

Figure 2. First 3 basis functions of the 192 Macbeth DC ColorChecker training samples

Results

Figure 3 shows an example of reflectance recovery performance based on Imai and Berns method using one of the Macbeth ColorChecker surfaces. In general, most of the estimated reflectances are quite similar to the original ones but where errors occur they tend to be at the far ends of the spectrum. Figures 4 and 5 illustrate the characterization errors (median and maximum CIELAB errors respectively) for the Imai and Berns method. The median errors are almost independent of the size of the training set. However, as the training set size increases, the maximum training error increases and the maximum testing error decreases. In particular, as the number of training samples becomes large, the generalization or testing performances of the model returns smaller maximum errors.

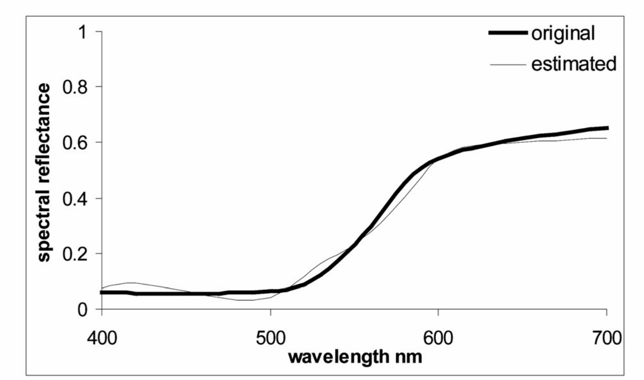

Figure 3. Example of spectral reflectance recovery of a Macbeth ColorChecker sample (orange) using the Imai and Berns method

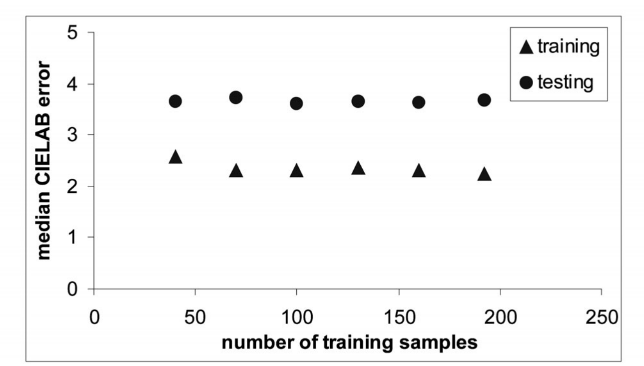

Figure 4. Effect of training size on characterization performance (median error) using Imai and Berns method.

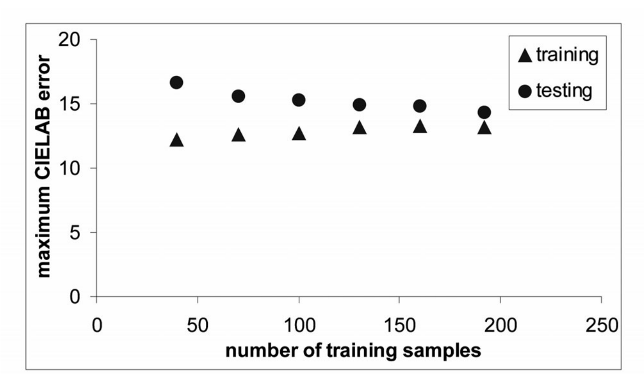

Figure 5. Effect of training size on characterization performance (maximum error) using Imai and Berns method.

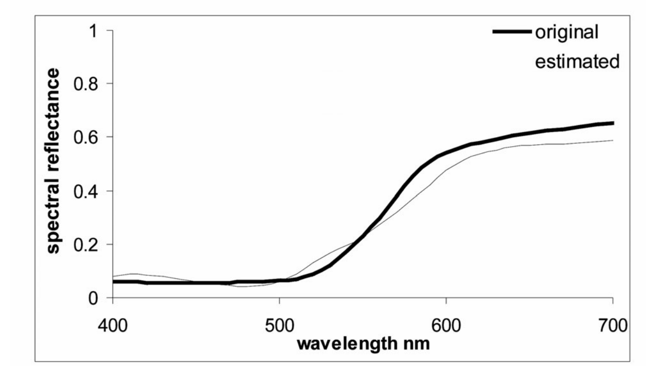

Figure 6. Example of spectral reflectance recovery of a Macbeth ColorChecker sample (orange) using the Hardeberg method

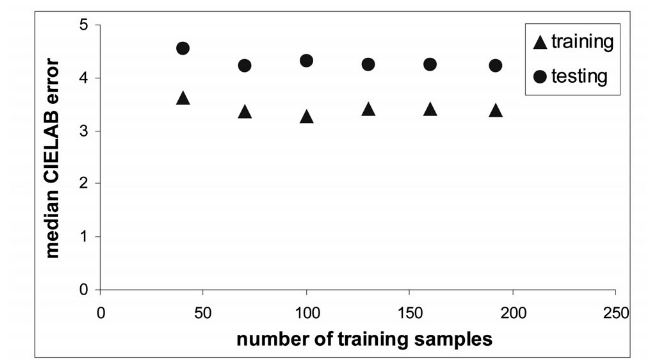

Figure 7. Effect of training size on characterization performance (median error) using Hardeberg method.

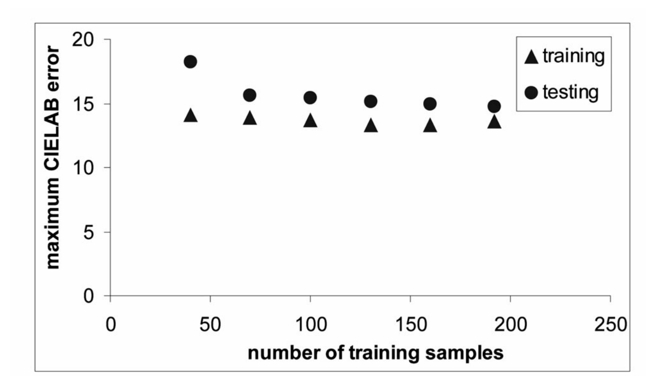

Figure 8. Effect of training size on characterization performance (maximum error) using Hardeberg method

Figure 6 illustrates the reflectance recovery performance using estimates of camera sensitivities (Hardeberg method) of the same Macbeth ColorChecker surfaces as used for Figure 3. Figures 7 and 8 show performance for this method and are analogous to Figures 4 and 5. Figure 7 shows that both generalization and memorization errors are very stable until the training set size falls to about 40 samples. The maximum test error given in Figure 8 illustrates that the model leads to poorer memorization performance than generalization when the training set size increased from 70 samples.

The results of reflectance recovery using the Hardeberg method are generally similar to those using the Imai and Berns method. The errors tend to be a little smaller for the Imai and Berns method, however, and one possible reason for this is that the estimates of the camera spectral sensitivities may be noisy.

Figures 9 and 10 show the median and maximum color differences using the higher-dimensional model (Shi and Healey method). Performance using this method is generally better than that obtained with the Hardeberg or Imai and Berns method. Note that the training and testing errors are reported for different numbers of basis functions in the linear model of reflectance. The linear model was always obtained using the full set of 192 training samples.

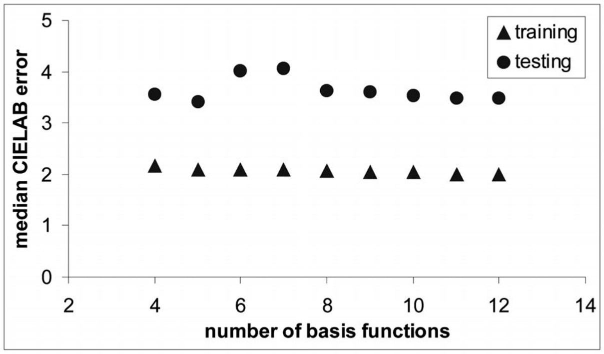

Figure 9. Effect of number of basis functions on characterization performance (median error) using the Shi and Healey method.

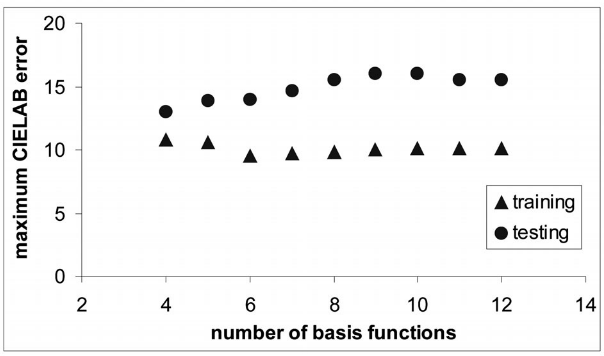

Figure 10. Effect of number of basis functions on characterization performance (maximum error) using the Shi and Healey method

One likely reason why the Shi and Healey method performs the best is that the other two methods are based upon a linear model of reflectance with only three dimensions and there is much evidence that such a model is inadequate to represent the spectra of typical surfaces.[7]

Discussion

In this paper we have evaluated three different techniques for camera characterization that employ multispectral methods. The Imai and Berns method and the Hardeberg method are based on the use of three basis functions when used with a trichromatic imaging system. The generalization performance (median ΔE) of the techniques using the full set training samples was found to be 3.69, 4.22 and 3.55 respectively for the Imai and Berns method, the Hardeberg method and the Shi and Healey methods (with four basis functions). In a previous study we found that polynomial and neural-network methods are able to perform characterization on the same data with a median ΔE of 2.02 and 2.01 respectively.[15] We find no evidence, therefore, that multispectral imaging techniques provide any advantage over traditional characterization methods for a three-channel camera imaging under a single illuminant. Further work is required to evaluate multispectral techniques for multiple imaging under more than one light source and for camera with more than three color channels.

References

1. Horn BKP (1984), Exact reproduction of colored images, *Computer vision, graphics and image processing*, **26**, 135-167.
2. Martinez K, Cupitt J and Saunders D (1993), High resolution colorimetric imaging of paintings, *Proceedings of SPIE*, **1901**, 25-36.
3. Tominaga S (1999), Colour coordinate conversion via neural networks, in *Colour Imaging, Vision and Technology*, edited by LW MacDonald and MR Luo, John Wiley.
4. Cheung TLV, Westland S, Connah DR and Ripamonti C (2003), Characterization of colour cameras using neural networks and polynomial transforms, *Journal of Coloration Technology* (in press).
5. Sugiura H, Kuno T, Watanabe N, Matoba N, Hayashi J and Miyake Y (1999), Development of highly accurate multispectral cameras, *International Symposium on Multispectral Imaging and Colour Reproduction for Digital Archives*, Chiba University (Japan), 73-80.
6. Berns RS and Shyu MJ (1995), Colorimetric characterization of a desktop drum scanner using a spectral model, *Journal of Electronic Imaging*, **4** (4), 360-372.
7. Maloney LT (1986), Evaluation of linear models of surface spectral reflectance with small numbers of parameters, *Journal of the Optical Society of America A*, **3** (10), 1673-1683.
8. Finlayson GD and Morovic PM (1999), Metamer constrained colour correction, *Proceedings of the 7th Color Imaging Science Conference*, Scottsdale (USA), 26-31.
9. Hardeberg JY (1999), Acquisition and reproduction of colour images: colorimetric and multispectral approaches, *PhD thesis*, Ecole Nationale Superieure des Telecommunications, France.
10. Imai FH and Berns RS (1999), Spectral estimation using trichromatic digital cameras, *International Symposium on Multispectral Imaging and Colour Reproduction for Digital Archives*, Chiba University (Japan), 42-47.
11. Shi M and Healey G (2002), Using reflectance models for color scanner calibration, *Journal of the Optical Society of America A*, **19** (4), 645-656.
12. Sun Q and Fairchild MD (2001), Statistical characterization of spectral reflectances in human portraiture, *Proceedings of the 9th Color Imaging Conference*, Scottsdale (USA), 73-79.
13. Finlayson GD, Hordley SD and Hubel PM (1998), Recovering device sensitivities with quadratic programming, *Proceedings of the 6th Color Imaging Science Conference*, Scottsdale (USA), 90-95.
14. Chen Q (2001), Estimation of digital camera's spectral sensitivity, *MSc Dissertation*, University of Derby (UK).

15. Cheung TLV and Westland S (2002), Colour camera characterisation using artificial neural networks, *Proceedings of the 10th Color Imaging Conference*, Scottsdale (USA), 117-120.

Biography

Vien Cheung graduated from The Hong Kong Polytechnic University with a BSc degree in Textile Chemistry. She then obtained an MSc in Colour Imaging at the Colour & Imaging Institute at University of Derby. She is currently a postgraduate student at the Colour & Imaging Institute working on methods for device characterization and multispectral imaging with Dr. Stephen Westland.