# Characterization of Digital Camera Based on Spectral Estimation and Reconstruction.

Mei-Chun Lo [+], Ruey-Kuen Perng [‡] , and Xin-Yan Shen [+]
[+]Department of Information Management, Shih Hsin University, Taipei, Taiwan
[‡] Department of Computer Science and Information Engineering, Providence University, Taichung, Taiwan

## Abstract

*As polynomial regression is an effective methodology, statistic methods are traditionally used to characterize digital cameras; and hence establish the relationship between RGB and XYZ. From correlated research, high-order polynomial algorithms definitely give us the balance between the costs and computational times. However, from that way, it can only work at a fixed/tested light source which is already known. Consequently, when light source is changed, it is required to measure and rebuild another profile data. Also, such methods couldn't solve metamerism, caused due to the errors of XYZ calculation via camera's receptor inside, which is different from our human eyes. Therefore, it would be meaningful to characterize the digital camera, to have the ability to adapt the change of light sources. The valid method considered would be to estimate and reconstruct both spectrum of an object and a light source used. Then XYZ under any light source can be obtained accordingly. Basis vectors at appropriate amount, theoretically, can approximate reflectance/radiance spectra of objects. Also in practice, it gives satisfactorily acceptable results and reduces unnecessary calculations. Hence, via an SVD (Singular Value Decomposition) approach, an adaptive method of basis vectors was carried out in this study to estimate the spectral radiance of objects considered. A set of Gaussian-type spectral sensitivity functions of sensors, optimized by iteration using the Wiener, for camera simulated was used. Therefore in a known light condition using either of the Wiener and the PI, the spectral energy (radiance), which the camera sensor picks up with basis vectors, could be rebuilt. Consequently, the color profile of XYZ values could be obtained via the calculation of product of spectral radiance of objects, color matching function. Finally the relationship between RGB and XYZ for a digital camera tested in any light source could be established easily. Consequently, a universally performing camera characterization model could be derived.*

## Introduction

Colorimetrically in color applications, the color of an object in a scene depends both upon the spectral composition (i.e. spectral radiance) of the light that illuminates the object and the object's spectral reflectance. Tri-stimulus values CIEXYZ are used to recognize what the eyes see. The CIEXYZ is composed of light source spectral energy E(λ), object surface spectral reflection R(λ) and observer color matching functions ( $\bar{x}$ , $\bar{y}$ , and $\bar{z}$ ). Above relationship can be established by equation (1).

$$\begin{aligned} X &= \int_a^b E(\lambda)\bar{x}(\lambda)R(\lambda)d\lambda \\ Y &= \int_a^b E(\lambda)\bar{y}(\lambda)R(\lambda)d\lambda \\ Z &= \int_a^b E(\lambda)\bar{z}(\lambda)R(\lambda)d\lambda \end{aligned} \tag{1}$$

Using $p$ to substitute CIEXYZ, $r= E(\lambda)\ R(\lambda)$ for spectral energy of object surface, $W$ for color matching function, then a matrix form can be used to replace equation (1) and expressed as below (equation (2)).

$$p = W^T \cdot r \tag{2}$$

In a digital camera characterization, the tested camera's response, simulated human eyes, of actual color stimulus, could be determined by the transforming its device dependent space RGB to the device independent space CIEXYZ. Practically, a polynomial regression approach using the least squares method is used to characterize a digital camera in question; and usually a set of optimized coefficients for 3-by-3 matrix (denoted as M in this paper later) can be effectively performed the characterization. Consequently CIEXYZ can be defined by equation (3).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = [M] \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix}, [M] = \begin{bmatrix} r1 & g1 & b1 \\ r2 & g2 & b2 \\ r3 & g3 & b3 \end{bmatrix} \quad (3)$$

However matrix M from regression is workable at fixed illuminant. Every different light source has its own particular matrix M (Jetsu *et al.* 2006).

A spectral reconstruct method, based on basis vectors, was applied for the digital camera characterization in this study. The surface spectral radiance of an object under a specific illumination condition, measured by spectrophotometer ranged in 400-700nm at interval of 10nm, would produce 31 data-points. Therefore, for the ColorChecker considered with 24 color patches, it would consist of a 31x24 matrix of color signal data. This color signal matrix can be composed of both basis matrix and coefficients matrix, shown as equation (4).

$$\underset{\text{ColorChecker Color Signal}}{\begin{bmatrix} 31\times 24 \end{bmatrix}} = \underset{\text{Basis matrix; one column one basis}}{\begin{bmatrix} 31\times 3 \end{bmatrix}} \bullet \underset{\text{Coefficients matrix}}{\begin{bmatrix} 3\times 24 \end{bmatrix}} \quad (4)$$

In this paper, an SVD (Singular Value Decomposition) method was used to firstly analyze the surface reflection of a large numbers of objects surface; and to further find the entire spectral basis vectors which can approximate the spectral reflection/radiance of objects. Also the coefficients matrix can be obtained using methods of the Pseudo-Inverse(Valero *et al.* 2006) and the Wiener (Ge *et al.* 2005). Therefore the original spectral reflection (i.e. radiance) of objects considered could be rebuilt by multiplication of both basis vectors and specific coefficients obtained.

An ideal equi-energy illuminant E was used in this study to rebuild the spectral radiance of 1600 color patches in Munsell Book Glossy Database (Orava). The illuminant E, ideally having equal spectral power distribution (SPD), was hypothetical to provide a perfect modality to build a known database of spectral radiance by the multiplication of its SPD and the spectral reflectance of database of interest (e.g. Munsell Book Glossy Database). Consequently, a satisfactorily universal performing camera characterization model could be derived. Hence the model derived should have carried out effective characterization results under various viewing light sources or illuminants with different color temperatures.

Both a digital camera and the human eyes have different responses to the same spectral energy. Original output RGB values from camera's sensor are integral results of the spectral energy and camera sensor's response curve. A non-real camera using a triad of sensors with an optimal Gaussian type of spectral responses obtained by an iteration approach was chosen in this study to estimate original RGB values, and further to derive a universal camera characterization model. The choice of non-real camera sensors avoided the unnecessary inherent interference variables, produced by a real/physical camera considered, in the process of spectral estimation. As a consequence, using in a real commercial camera, those uncertainties would more-or-less have impacts on the predictions accuracy by using the model derived.

## Experimental and Methodology

Four steps of procedure were carried out in this study as shown in Figure 1. The first, by applying SVD, all the spectral basis vectors, used to reconstruct spectral radiances of objects under the E illumination condition was found. As mentioned earlier, 31 spectral basis vectors should be predicted. Then in second step, by carrying out an iteration approach, a set of optimal Spectral Sensitivity Functions of Sensors (SSFS) for a simulated three-primary digital still camera which was suggested by Sun and Chen (2005) was predicted. In the optimization process of simulated SSFS, the iteration approach was implemented using the Wiener (Ge *et al.* 2005) to the recovery of spectral radiance of objects (colors) tested.

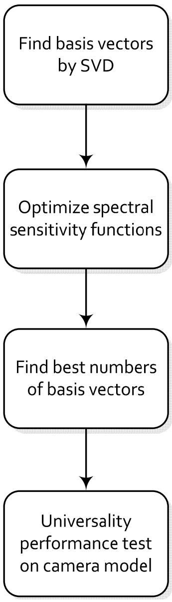


*Figure 1. Experimental procedure in the derivation of digital camera device characterization.*

Subsequently, in the 3rd step, the obtained optimal spectral sensitivity functions carried out a search of the optimally minimum number of basis vectors in that the spectral reconstruction results could be still satisfactorily obtained. Finally, the characterization models, derived via spectral reconstruction process using the optimized set/number of basis vectors, would be evaluated under different illumination conditions.

### Singular Value Decomposition (SVD)

The spectral radiance of each color considered can be reconstructed via the spectral-radiance basis vectors, estimated using *a priori SVD-based* spectral analysis of known existing databases of radiance color spectra under a known illuminant condition (here as mentioned, illuminant E was used).

Suppose a representative dataset of radiance color spectra with $m$ color samples are collected in the study. Every color in database is uniformly sampled at $n$-1 wavelength intervals. Then $R$, a $n$-by-$m$ matrix, can be derived using the SVD method and written as equation (5).

$$R = U \cdot S \cdot V^T \approx U_k C_k = (u^{(1)}, u^{(2)}, \cdots, u^{(k)}) C_k \qquad (5)$$

Here $U$ is a $n$-by-$n$ orthogonal matrix, $V$ is a m-by-m orthogonal matrix, and $S$ denotes a diagonal matrix. Both $U$ and $S$ can be expressed by equations (6) and (7) respectively.

$$U = (u^{(1)}, u^{(2)}, \cdots, u^{(n)}) \qquad (6)$$

$$S = diagonal(d_1, d_2, \cdots, d_n) \qquad (7)$$

Here $u^{(1)}, u^{(2)}, \cdots, u^{(n)}$ are basis vectors in question; $d_1, d_2, \cdots, d_n$ are singular values, singular values represent the weight of corresponding basis vectors in original database. A common convention is to order the singular values in non-increasing fashion. The former singular data would have the bigger values than the latter ones, and their corresponding basis vectors would have more weight. In this case, the diagonal matrix $S$ is uniquely determined by $R$.

An extensive analysis of color spectra of the full set of Munsell Book Glossy Database of 1600 color patches based on SVD was used in this study. As mentioned above, the purpose of this analysis was to look for the most efficient basis number, from the statistical point of view, for a given color set by using basic functions. In the beginning, five basis vectors, considered sufficiently representing the spectral accurately enough, were firstly selected after the analysis, and illustrated in Figure 2.

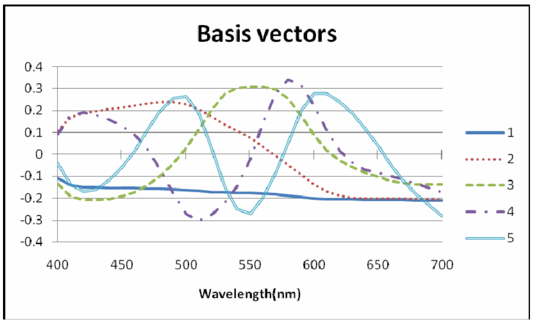


*Figure 2. First 5 basic vectors of Munsell Book Glossy.*

Moreover, the accuracy of representing the spectra, using every of the basis-vectors number ≤ 5, was evaluated. Accuracy performances were tested in terms of both singular value $d_k$ and character existence rate en(k) (Ge *et al.* 2005), and listed in Table 2. The results showed that three vectors are adequately enough to achieve 93% of the variance of spectra (i.e. spectral radiance), as shown in Table 1.

Table 1. First 5 values of $d_k$ and en(k)

| k | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| $d_k$ | 78.7 | 21.3 | 12.4 | 4.0 | 3.0 |
| en(k) | 69.4% | 83.4% | 92.9% | 94.9% | 96.3% |

**Pseudo-Inverse**

As described above, spectral radiance of objects (colors) can be composed of both basis vectors and coefficients. The explicit formula is:

$$r = u^{(1)}c_1 + u^{(2)}c_2 + \cdots + u^{(k)}c_k = U_k c \tag{8}$$

From equation (2), it could obtain the formula

$$p = W^T U_k c$$

And, the Pseudo-Inverse is just the inverse:

$$c = (W^T U_k)^+ p \tag{9}$$

If the channels of sensors used in this study were limited to three, so that $k = 3$. Then

$$c = (W^T U_3)^{-1} p$$

**Wiener**

Statistically based on Wiener method, the below formula could be obtained:

$$c_3 = (C_k C_k^T)(W^T U_k)^T (W^T U_k (C_k C_k^T)(W^T U_k)^T)^{-1} \tag{10}$$

$$c = c_3 p \tag{11}$$

Firstly the combination values $c_3$ could be computed via equation (10), then, multiply with camera's original output values, we have the coefficients *c*. Due to constant spectral sensitivity of sensor in changes light source (Romero *et al.* 2006) , coefficients *c* produced from Wiener is valid in any illuminant.

**Optimized Spectral Sensitivity Functions**

As mentioned earlier, following up the study from Sun and Chen (2005), the possibility of using sensors, with a Gaussian profile centered on the predetermined peaking wavelengths for RGB sensors responses in 581, 551, and 450 nm respectively, was studied here.

Every of the triad of Gaussian Sensor's spectral sensitivity functions are defined in equation (12). Here $P$ and $\sigma$ terms represent peaking wavelength and distribution-curve smoothness. Using an optimized factor $t$, the Gaussian function can be shaped into rectangle-like, and used to increase the color-rendering accuracy.

$$S(\lambda) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\frac{(P-\lambda)^2}{2S^2}\right)} \tag{12}$$

$$S(\lambda) = (1-t)S(\lambda) + t \cdot \begin{cases} 1; & P - \frac{\sigma}{2} \le \lambda \le P + \frac{\sigma}{2} \\ 0; & otherwise \end{cases} \tag{13}$$

Table 2. Parameters used to optimize spectral sensitivity functions of sensors.

| | R | G | B |
|---|---|---|---|
| Response | 0.56939 | 0.65399 | 1.00000 |
| P | 581 | 551 | 450 |
| σ | 40 | 38 | 25 |
| t | 0.0 | 0.05 | 0.12 |

Hence, the $P$, $\sigma$ , and t values suggested by Sun and Chen (2005), were adopted in the process of spectral reconstruction. Each of the PI and the Wiener approaches was used to optimize spectral reconstruction of Munsell Book Glossy 1600 color samples, tested under E illumination condition. Therefore, the optimized relative peaking responses, obtained for each of RGB sensors, were 0.57, 0.65, and 1.00 respectively. Those experimental data are listed in Table 2. The optimized spectral sensitivity functions are shown in Figure 3, and compared with CIE 1931 color matching functions.

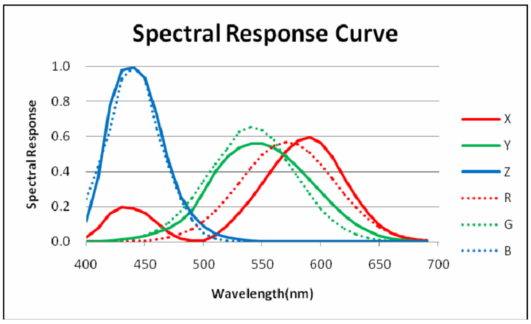


Figure 3. Compare CIE 1931 color matching functions with the optimized spectral sensitivity functions

## Results

### Experimental (1): Find the Best Minimum Number of Basis Vector

As mentioned earlier, the optimally adequate minimum number of basis vectors representing the spectra accurately enough, have been discussed widely in the literature, and also was one aim in this study. Therefore preliminarily under D50 illumination condition, using an iteration approach of either of the Wiener and the Pseudo-Inverse, the quality of the resulting estimated spectral radiance recovered in different amount of basis vectors were evaluated using SOCS Typical Data Set. Two error measures of RMSE (root of mean square error) and CIEDE2000 color difference (i.e. $\Delta E^*_{00}$) were proposed to evaluate the quality. The SOCS (Standard Object Colour Spectra Database for Colour Reproduction Evaluation) database (ISO 2003), provided by ISO (International Organization for Standardization) is a collection of about 50,000 reflectance or transmittance spectra with wavelength range from 400 to 700 nm at 10 nm intervals. As for SOCS Typical data Sets, “Typical sets” refers to sets of typical spectral reflectance in SOCS database. It is part of “Graphics” and “Face” which is out of proportion to whole SOCS database, and is suggested to be used as representative data of SOCS database for evaluating. The selection of “typical sets” can reference to ISO/TR 16066 technical report (ISO 2003).

For every reference sample in SOCS Typical database, Two measures considered were calculated with the reference color signal considered (in database) to the corresponding recovered color signal. RMSEs was computed between the recovered spectra and original reference ones in the 31-dimensional space; while $\Delta E^*_{00}$ was calculated between XYZ values of the recovered color signal and those of the original reference color signal in question.

*Table 3. Different numbers of basis-vectors performance*

| k | method | RMS | $\Delta E^*_{00}$ | |
|---|---|---|---|---|
| | | | Ave | Max |
| 3 | PI | 0.05690 | 0.415 | 2.859 |
| | Wiener | 0.05686 | 0.420 | 2.864 |
| 4 | Wiener | 0.05691 | 0.426 | 2.875 |
| 5 | Wiener | 0.05693 | 0.422 | 2.879 |

Table 3 shows RMSE, and $\Delta E^*_{00}$ values of both mean (i.e. Ave.) and maximum (i.e. Max). It can be seen that both PI and Wiener gave similar performances of spectra reconstruction. Also the use of three basis vectors leads sufficient recovery results which correspond to Chiao's findings (Chiao *et al.* 2000) it seems that, as a triad of sensors was hypothesized used in the simulated camera in this study, the use of more amount of basis vectors than 3 didn't increase the quality of spectral recovery. Still for more comprehensive comparisons between both iteration approaches of Wiener and PI, they would be separately applied in next the stage of derivation of camera characterization models which were based on basis-vectors algorithm described earlier.

**Experimental (2): Universality Performance Test on Camera Characterization Models**

Three spectral datasets were chosen to test the universality performance in terms of $\Delta E^*_{00}$, of various camera characterization models, derived under six illumination conditions based on different approaches.

*Table 4. Data set for Performance Test*

| Test Set | Database | Number of colors |
|---|---|---|
| 1 | Munsell Book Glossy | 1600 |
| 2 | SOCS | 53489 |
| 3 | SOCS Typical Sets | 235 |

Those spectral data sets, listed in Table 4, were: 1) Munsell Book Glossy, as used in the derivation of spectral recovery model; 2) whole set of SOCS; 3) SOCS Typical Sets. Six illumination conditions of interest, divided into two categories of “D65, D50, A” and “F2, F8 and F11” used as illuminants, were considered in the test. Totally, five types of models were developed here to characterize simulated camera. Those were derived separately using: a) 3-by-3 matrix of dependent regression model under every of six tested illuminants; b) 3-by-3 matrix of independent regression approach, only under D50; c) basis-vectors approach based on the Pseudo-Inverse method; and d) also basis-vectors approach, but implementing the Wiener technique.

*Table 5. Performance obtained under D65, D50, and A illumination conditions (a for dependent regression, b for independent regression, c for basis-vectors approach using the Pseudo-Inverse method, and d for basis-vectors approach using the Wiener method).*

| Set | | D65 | | D50 | | A | |
|---|---|---|---|---|---|---|---|
| | | **Ave** | **Max** | **Ave** | **Max** | **Ave** | **Max** |
| **1** | a | 0.306 | 1.120 | 0.255 | 1.208 | 0.238 | 1.554 |
| | b | 7.434 | 15.32 | 0.255 | 1.208 | 30.48 | 44.76 |
| | c | 0.283 | 1.160 | 0.226 | 1.318 | 0.812 | 3.016 |
| | d | 0.318 | 1.180 | 0.245 | 1.333 | 0.802 | 3.003 |
| **2** | a | 0.282 | 2.399 | 0.258 | 2.484 | 0.282 | 3.970 |
| | b | 6.325 | 24.53 | 0.258 | 2.484 | 28.86 | 45.28 |
| | c | 0.276 | 2.420 | 0.310 | 2.858 | 1.016 | 8.777 |
| | d | 0.298 | 2.453 | 0.319 | 2.864 | 1.007 | 8.772 |
| **3** | a | 0.329 | 1.818 | 0.318 | 2.485 | 0.381 | 3.972 |
| | b | 6.524 | 14.23 | 0.318 | 2.485 | 29.74 | 44.91 |
| | c | 0.344 | 2.000 | 0.415 | 2.859 | 1.160 | 7.588 |
| | d | 0.360 | 2.009 | 0.420 | 2.864 | 1.152 | 7.583 |

*Table 6. Performance obtained under F2, F8, and F11 illumination conditions (a for dependent regression , b for independent regression, c for spectral recovery approach using the Pseudo-Inverse method, and d for basis-vectors approach using the Wiener method).*

| Set | | F2 | | F8 | | F11 | |
|---|---|---|---|---|---|---|---|
| | | Ave | Max | Ave | Max | Ave | Max |
| 1 | a | 0.909 | 3.977 | 0.913 | 3.740 | 1.069 | 4.470 |
| | b | 23.06 | 31.00 | 20.01 | 22.05 | 38.78 | 46.20 |
| | c | 0.790 | 1.963 | 0.482 | 1.297 | 3.530 | 9.017 |
| | d | 0.790 | 1.963 | 0.482 | 1.297 | 3.530 | 9.017 |
| 2 | a | 1.128 | 6.689 | 1.059 | 5.898 | 1.275 | 7.920 |
| | b | 21.10 | 31.66 | 18.45 | 23.04 | 36.19 | 46.86 |
| | c | 0.877 | 3.598 | 0.524 | 3.363 | 3.299 | 14.64 |
| | d | 0.848 | 3.589 | 0.524 | 3.363 | 3.299 | 14.64 |
| 3 | a | 1.151 | 5.134 | 1.133 | 4.964 | 1.306 | 6.070 |
| | b | 22.13 | 31.08 | 19.49 | 22.38 | 37.50 | 46.71 |
| | c | 0.883 | 2.560 | 0.610 | 2.854 | 3.457 | 8.508 |
| | d | 0.883 | 2.560 | 0.610 | 2.854 | 3.457 | 8.508 |

The results obtained are summarized in Tables 5 and 6 for both illumination conditions of "D65, D50, A", and "F2, F8, F11" respectively. As expected, the independent regression model unacceptably performed the worst, and only gave satisfactory results under D50 which was used to derive 3-by-3 matrix. Again both Wiener and PI models gave similar predictions for all spectral data sets under every illumination condition considered. Additionally, there were no noticeable differences between the basis-vectors approaches of both Winner and PI and the dependent regression one, under all illumination conditions except A and F11, for every data set. Figures 4 and 5 depict the spectral power distributions of these two categories of illuminants. As shown, it was found that illuminant A has higher energy in longer wavelengths than that in lower ones; while F11 consists of apparent peaking effect of spectral power distribution curve. This resulted in that basis vectors, calculated using the Munsell Book Glossy under equi-energy illuminant E, couldn't reconstruct spectral radiances of those databases under both A and F11 as accurately as those under the other illumination conditions.

Figures 6 and 7 show comparisons between the real spectral radiance and the predicted one, of a test sample respectively under the F11 and A illuminating conditions.

It can be clearly seen that there were poor recovery in whole wavelength and only higher-wavelength segments respectively under illuminants F11 and A. However, in a strictly speaking, those prediction performances were still visually considered satisfactorily acceptable.

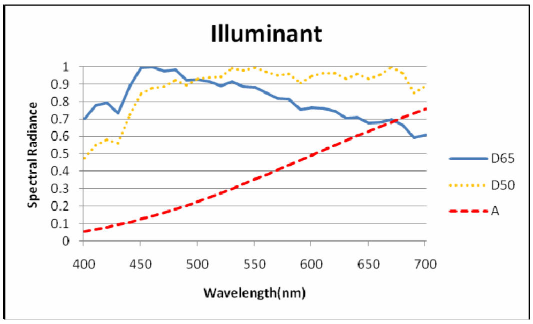


*Figure 4. Spectral power distributions of D65, D50, and A illuminants.*

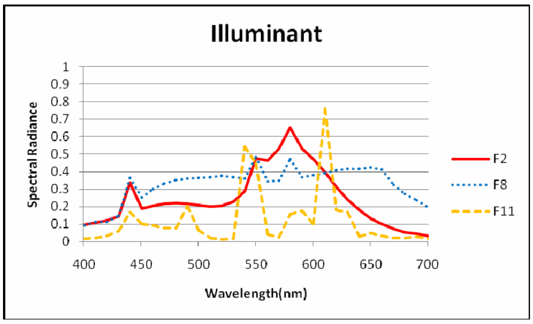


*Figure 5. Spectral power distributions of F2, F8 and F11 illuminants.*

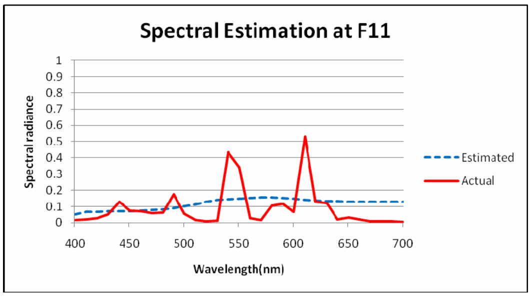


*Figure 6. Estimated and actual spectral radiances of a test color under illuminant F11*

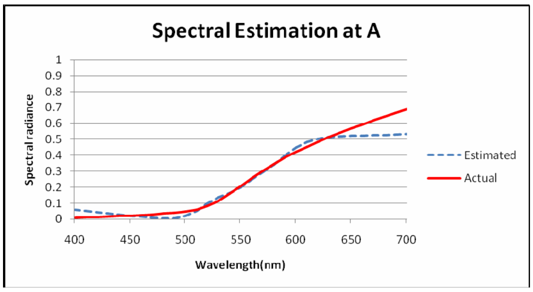


*Figure 7. Estimated and actual spectral radiances of a test color under illuminant A*

## Conclusions

Based on basis-vectors approach, via either of the Pseudo-Inverse or the Wiener approaches, the derived camera characterization models could achieve optimally highly universality performance if the illuminant is daylight and the three sensors that capture the image have Gaussian-type sensitivities. It indicates that color constancy can be satisfactorily fulfilled. However, the application of the invariant will depend upon the extent to which the real illuminants that resemble Daylight ones and the sensors of the camera, of more-or-less wide spectral sensitivity, can provide results that are not far removed from those that the ideal Gaussian type of triads of sensors gives.


## Acknowledgements

This research has mainly supported by the National Science Council of Taiwan for financial assistance.


## References


1. Chiao, C. C., Cronin T.W., and Cronin D., Color signals in natural scenes: characteristics of reflectance spectra and effects of natural illuminants. J Opt Soc Am A 2000(17), 218-224 (2000).
2. Ge, W., Chang-jun, L., Yun-long, Z., and Luo, M. R., Improvement in the estimation of reflectance functions generated using the basis vectors. Photographic Science and Photochemistry, 23(5), 340-350 (2005).
3. ISO, Graphic Technology ｜ Standard Object Colour Spectra Database for Colour Reproduction Evaluation (SOCS) (2003).
4. Jetsu, T., Heikkinen, V., Parkkinen, J., Hauta-Kasari, M., Martinkauppi, B., Lee, S. D., Color calibration of digital Camera using polynomial transformation, CGIV 2006, IS&T's Third European Conference on Color in Graphics, Imaging, and Vision, University of Leeds, UK, 163-166 (2006).
5. Orava, J. The Reflectance Spectra of 1600 Glossy Munsell Color Chips. (http://spectral.joensuu.fi/databases/download/munsell_spec_glossy_all.htm)
6. Romero, J., Hernández-Andrés, J., Nieves, J. L., and Valero, E. M., Spectral sensitivity of sensors for a color-Image descriptor invariant to changes in daylight conditions, Color Research and Application, 31(5), 391-398 (2006).
7. Sun, P. L., and Chen, C. C., Optimizing spectral sensitivity functions for a three-primary digital still camera, Color Association of Taiwan 2005 Conference, 71-80 (2005).
8. Valero, E. M., Nieves, J. L., Nascimento, S. M. C., Amano, K., and Foster, D. H., Spectral recovery from natural scenes with an RGB digital camera, CGIV 2006, IS&T's Third European Conference on Color in Graphics, Imaging, and Vision, University of Leeds, UK, 195-198 (2006).