

Palette-Based RGB to Spectral Image Conversion, Compression, and Print Image Rendition Under Different Illuminants

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Abstract

A simple idea of RGB to spectral image conversion is proposed. A spectral reflectance with the closest colorimetric value to that of RGB pixel is picked up from the spectral color palette and embedded in each pixel of RGB image. SVD (Singular Value Decomposition) is applied to compress the high-resolution spectral image.

Spectral image data are rearranged to $(L \times L)$ pixels \times 36 spectra sub-block so that we can make use of strong correlations in both spatial and spectral. The spectral image could be very well reproduced from a small number of singular values by SVD. Although a transformed image has not the real world spectra but palette-based pseudo-spectra, the proposed method could be applied to estimate how much the huge spectral image data could be compressed, and to simulate the color appearances for a given set of ink and paper media under the different illuminants. The paper discusses the color reproducibility by SVD compression and introduces the estimated color appearances for inkjet prints under the different fluorescent lamps.

1. Introduction

A multi-spectral image carries the raw color information essential for estimating color under different illuminants.

A variety of multi-spectral image capture schemes¹⁻⁴ using a single-channel CCD camera with multi-band filters, electro-optic tunable filters, diffraction grating or prism have been proposed. It needs expensive and slow spectroscopic measurements to catch the spectral images with high spectral and high spatial resolutions. Since spectral information of natural objects is widely applied for remote sensing, printing, medical, or artistic imaging, alternative technologies for preserving the spectral data are much interested. Estimation of reflectance spectra from reduced low-dimensions has been attempted to approach this requirement.⁵⁻⁹ Karhunen-Loeve (K-L) transform or Principal Component Analysis (PCA) provided a mathematical solution to this problem. However, to guarantee the high precision restoration, these methods still

need multi-band sensors more than three channels. This paper proposes a simple but novel method to transform the conventional RGB tri-color images into spectral images with high spatial and spectral resolutions, where each RGB color pixel is replaced by the closest color chip in spectral pallets.⁸ A spectral color chip is composed of spectral reflectance or transmittance vectors in discrete 36 wavelengths measured by 10 nm steps in 380-730 nm. Although the transformed spectral image is not from the real world scene but carries the precise actual spectra just as painted by real pallets media such as ink and paper. Because the created spectral image is highly correlated both spatially and spectrally, it is compressed by employing Singular Value Decomposition (SVD). Finally the restored spectral image from compressed SVD data is used for the color appearance simulation on inkjet print with the same ink and paper set as spectral palette under the different illuminants.

2. Embedding Spectrum in RGB Pixel

Fig.1 shows the overview of proposed system. First, a RGB or XYZ tri-color image is transformed into $L^*a^*b^*$ image and also the look-up table with $L^*a^*b^*$ values corresponding to the spectral pallets data is generated. An each pixel in source image is replaced by the spectral chip with $L^*a^*b^*$ value closest to that of pixel. That is, the spectrum k is embedded in pixel i by looking-up the LUT pallets by choosing the chip $j=k$ to minimize the color difference between the $L^*a^*b^*$ values $LAB_{PIX(i)}$ of pixel i and $LAB_{SPECT(j)}$ of spectral chips $j=1,2,\dots,J$ as follows.

$$\Delta E_{ik}^* = \min_{j=1}^J \left\{ \Delta E_{ij}^* \right\} = \min_{j=1}^J \left\{ \left\| LAB_{PIX(i)} - LAB_{SPECT(j)} \right\| \right\} \quad (1)$$

For example, RGB image with $K \times L$ pixels is converted into the spectral image with $KL \times 36$ channels.

To create the high precision spectral images, sufficient number of spectral chips will be necessary, but it is difficult to measure the huge number of full color chips. So, the measured spectral pallets data are interpolated in practice.

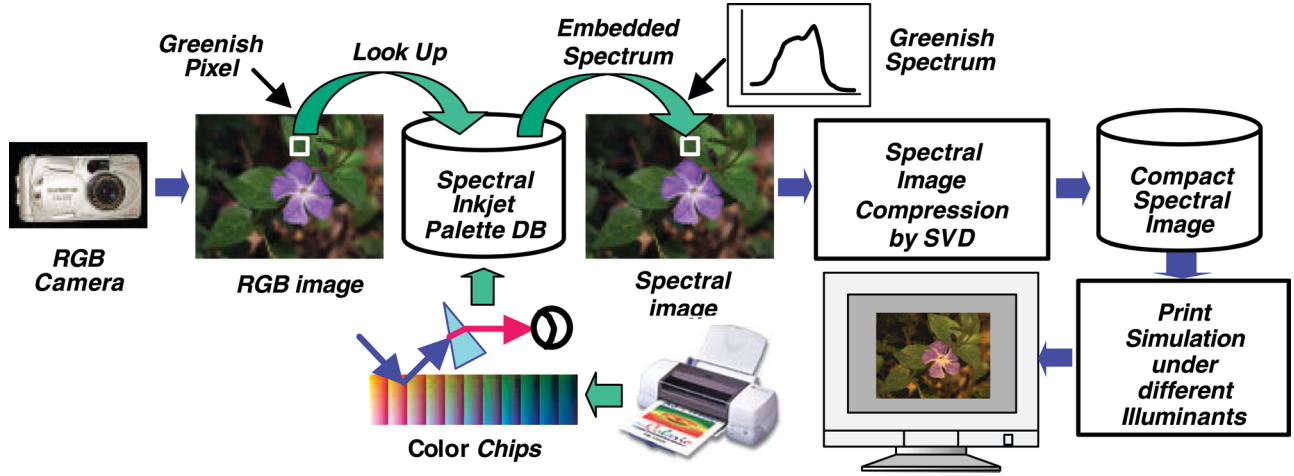


Figure 1. Overview of RGB to Spectral Image Conversion System using Spectral Palette

A test image in Fig.2 (a) with the color distribution in (b) was converted into spectral image (d), by looking up the inkjet spectral pallet in (c). The image (d) was created by directly looking up the closest spectrum from the 1331 basic inkjet spectral palette. The replaced color pixels obviously lack the gray levels because of insufficient number of spectral chips in palette.

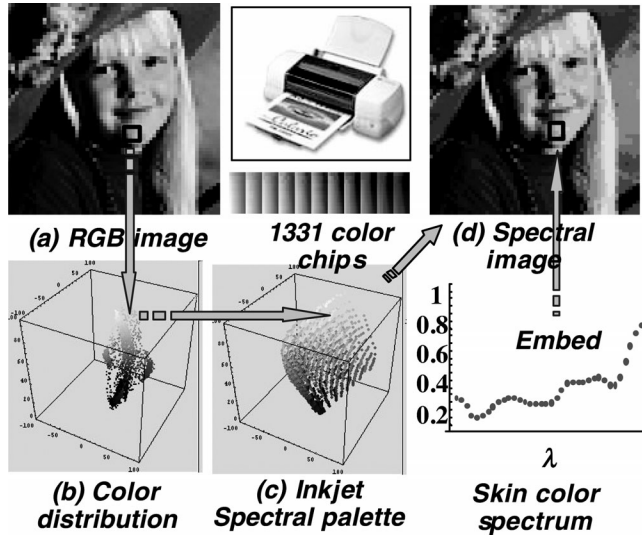


Figure 2. Spectral image conversion by inkjet palette

3 Interpolation of Spectral Color Pallet

A spectral color pallet was created by measuring the spectral reflectance for $N=11^3=1331$ CMY color chips printed by Epson PMC800 inkjet printer onto coated

Super-fine paper. Each color chip carries 36 spectra in 380~730 nm by 10 nm interval. The lack of spectral chips in pallet causes undesirable artifacts in tonal reproduction.

This problem is solved by increasing the printed number of chips or by spectral interpolation.

Figure 3 illustrates a basic idea of spectral interpolation. A linear spectral interpolation between i -th and $(i+1)$ -th spectral chips makes the new intermediate chip as follows.

Letting the multi-spectral vector of j -th chip be

$$C_j = [C_j(\lambda_1), C_j(\lambda_2), \dots, C_j(\lambda_{36})]^t \quad (2)$$

The intermediate spectrum $C_j(d)$ at distance ratio d from C_j and $(1-d)$ from C_{j+1} is calculated by

$$C_j(d) = (1-d)C_j + dC_{j+1} \quad (3)$$

If the spectral interval between C_j and C_{j+1} is divided by K (K is integer) discrete steps, the distance ratio d and new chip number jk at k -th position are given by

$$\begin{aligned} d &= (k-1)/K \\ jk &= K(j-1) + k \quad \text{for } k=1 \sim K \end{aligned} \quad (4)$$

Denoting the interpolated vector be C_{jk} for $C_j(d)$, each spectral element of new vector C_{jk} is calculated by

$$C_{jk} = [C_{jk}(\lambda_l)]^t ; l=1 \sim 36 \quad (5)$$

$$C_{jk}(\lambda_l) = \left(\frac{K-k+1}{K} \right) C_j(\lambda_l) + \left(\frac{k-1}{K} \right) C_{j+1}(\lambda_l)$$

Thus $j=1 \sim J$ colors chips are increased to J_{int} as follows.

$$J_{int} = K(J-1) + 1 \quad (6)$$

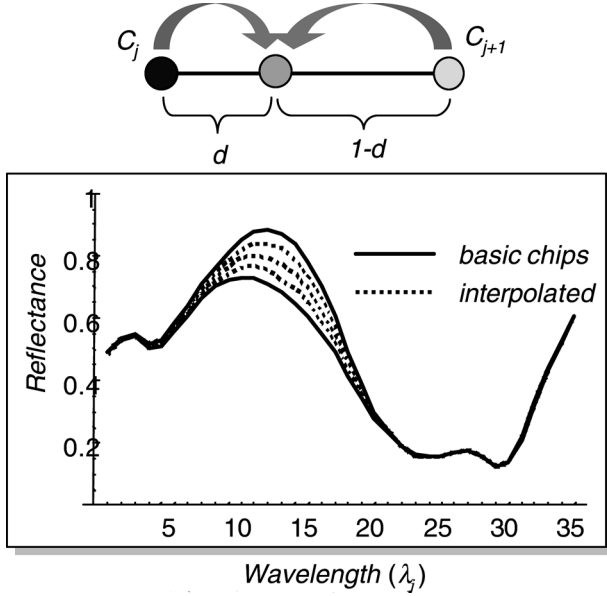
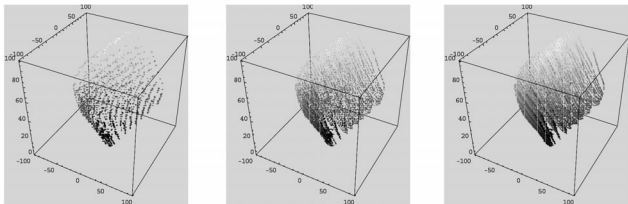


Figure 3. Spectral interpolation

Figure 4 shows an example of spectral images created by embedding the interpolated spectra in RGB image (a). Here (b), (c), and (d) show the converted images by $J=1331$ basic palette, $J_{int}=5331(K=4)$ and $J_{int}=10641(K=8)$ interpolated palettes. (e), (f), and (g) show the color distributions of the corresponding palettes in CIELAB space. The images shown in (c) and (d) are clearly improved in the gradation as compared with (b).



(a) Original (b) 1331 chips (c) 5321 chips (d) 10641 chips



(e) Basic palette (f) K=4 interpolation (g) K=8 interpolation

Figure 4. Gradation improvement by spectral interpolation

4. Spatial-Spectral Sub-Block Replacement

Because the converted spectral image has 12 times as much as data amount in comparison with the original, the data is to be compressed and stored. In order to make use of spatial and spectral correlations, the source image was divided into sub-blocks by $L \times L$ pixels and each sub-block was rearranged into matrix form of L^2 pixels \times 36 spectra as shown in Fig.5. The rearranged spectral block is correlated spatially and spectrally.

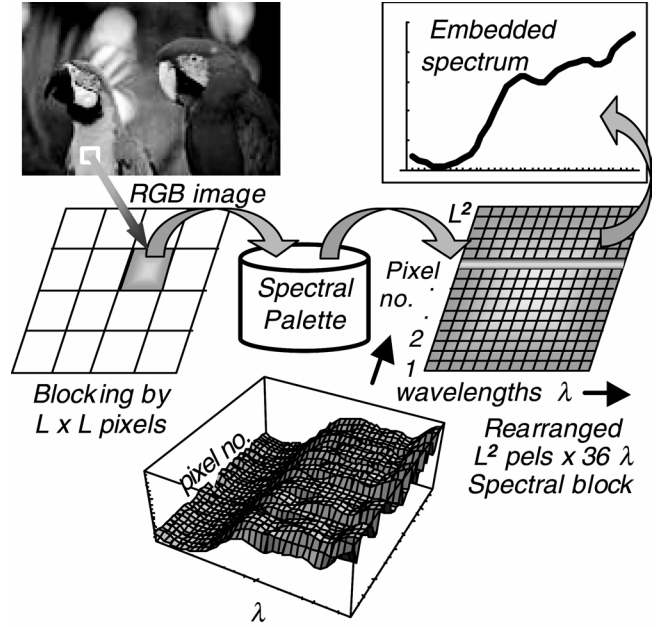


Figure 5. Blocking and rearrangement of spectral image data

5. Compression of Spectral Image by SVD

Since the rearranged spectral sub-block is highly correlated spatially and spectrally, it can be compressed by removing the redundancies. Here the data compression based on *SVD* (Singular Value Decomposition) has been introduced.

The matrix data in sub-block (m, n) is represented by

$$\mathbf{R}_{mn} = \begin{bmatrix} r_{ij} \end{bmatrix}_{mn} ; i = 1, 2, \dots, L^2, j = 1, 2, \dots, 36$$

$$; m = 1, 2, \dots, M, n = 1, 2, \dots, N \quad (7)$$

where, r_{ij} denotes a spectral reflectance of i -th pixel at j -th wavelength $\lambda = 380 + 10(j-1) \text{ nm}$. M and N are the block numbers in row and column of sub-blocks.

In case of $L=6$, \mathbf{R}_{mn} is represented by square matrix with 36 pixels \times 36 spectra. The local spectral image \mathbf{R}_{mn} in mn -th sub-block can be expressed by SVD as

$$\mathbf{R}_{mn} = \begin{bmatrix} r_{ij} \end{bmatrix}_{mn} = \mathbf{U}_{mn} \mathbf{A}_{mn} \mathbf{V}_{mn}^t \quad (8)$$

where, the columns of U_{mn} and V_{mn} are the eigenvectors of $R_{mn}R_{mn}^t$ and $R_{mn}^tR_{mn}$. U_{mn} and V_{mn} are $L^2 \times L^2$ and 36×36 square matrices, while A_{mn} is $L^2 \times 36$ rectangular matrix with the singular values for R_{mn} along its diagonal. Because U_{mn} and V_{mn} are orthogonal, when R_{mn} is a matrix with maximum rank $(R_{mn})=36$ for $L^2 > 36$, A_{mn} is given by

$$A_{mn} = U_{mn}^t R_{mn} V_{mn} = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & 0 & \dots & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \dots & 0 & \lambda_{36} \\ \hline & & & & 0 \end{bmatrix} \quad (9)$$

Here, a sub-block image R_{mn} is approximated by

$$\hat{R}_{mn} \equiv \hat{U}_{mn} \hat{A}_{mn} \hat{V}_{mn}^t \quad (10)$$

that is, the $L^2 \times 36$ matrix R_{mn} can be restored from the reduced number of S (< 36) singular values \hat{A}_{mn} and the eigen vectors of $L^2 \times S$ \hat{U}_{mn} and $S \times L^2$ \hat{V}_{mn} matrices.

$$\hat{A}_{mn} = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & 0 & \dots & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \dots & & \lambda_S \\ \hline & & & & 0 \end{bmatrix} \quad (11)$$

6. Experimental Results

6.1 Reconstruction from Compressed SVD Image

The spectral image was compressed by small number of SVD parameters and reconstructed. Figure 6 shows a spectral reflectance restored from only two singular values ($S=2$) and corresponding eigen vectors. The dotted plots show the reproduction as compared with the original solid line. The complex reflectance is almost well reconstructed in detail. Figure 7 shows the spectra in a purple petal of "daily flower" restored from the reduced number S of singular values. As well, most of the local spectral sub-blocks were very well reconstructed from just two singular values and two major eigenvectors of U_{mn} and V_{mn} . Fig.8 illustrates the color error vs. dimension of SVD for sub-block size $L=6, 8$, and 16 .

The rms color differences were $\Delta E^*_{94} \cong 5$ or less with $S=2\sim 3$ for $L=6$ or 8 and increased a little bit for $L=16$. In case of $L=16$ with $S=2$, the spectral image compression ratio by SVD reaches about $1/64$.

6.2 Print Simulation Under Different Illuminants

The proposed method enables to simulate the appearance of color prints under the various illuminants as

if printed with the same set of ink and paper used in palette without any expensive spectral camera.

Figure 9 shows an example of predicted print images under the illuminant D50, and three different fluorescent lamps for non-coated plain paper and photo-quality papers with Epson PM800C 6 color inkjet printer. The simulation clearly shows how the color appearance changes across the illuminants and photo-quality paper gives the brilliant colors much better than plain paper.

7. Conclusion

A basic idea for embedding the spectral pallet in RGB pixels been proposed. SVD representation was useful for the spectral image compression. We applied SVD for local sub-block image array in rearranged $36 \text{ pixels} \times 36 \text{ spectra}$, so that we could make use of strong correlations in both spatially and spectrally. This is the reason why the multi-spectral image could be restored from a very few singular values in accurate.

Although a created image has not the real world spectra but pallet-based pseudo-spectra, the proposed method will be applied, for instance, to estimate how much the huge spectral image data could be compressed, or to simulate the color appearances for different ink and paper media under the various illuminants. Since the number of spectral chips is not enough, spectral interpolation technique would help to embed them in full-color RGB image. The reliability in linear spectral interpolation for limited number of spectral chips made by color ink or other materials should be evaluated in future works.

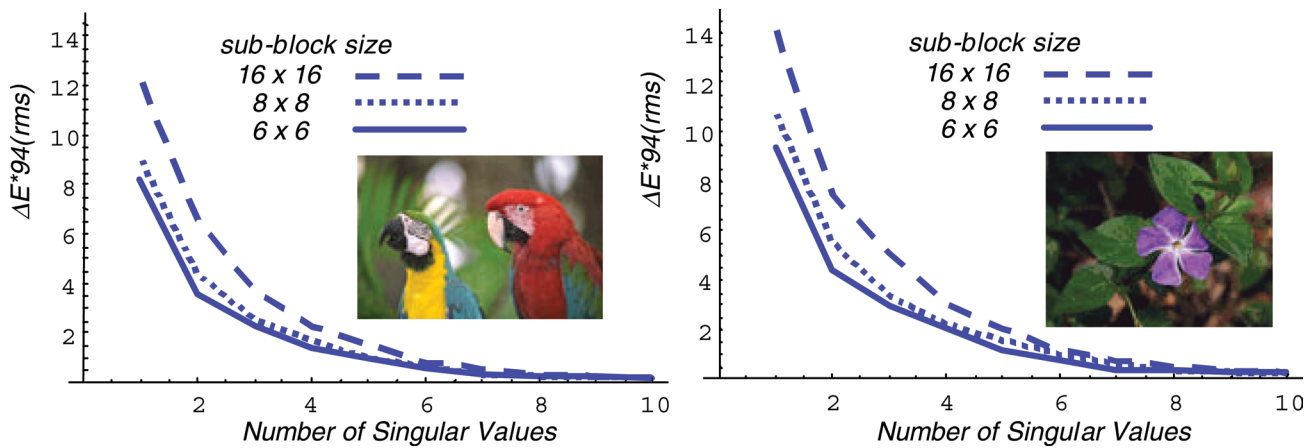
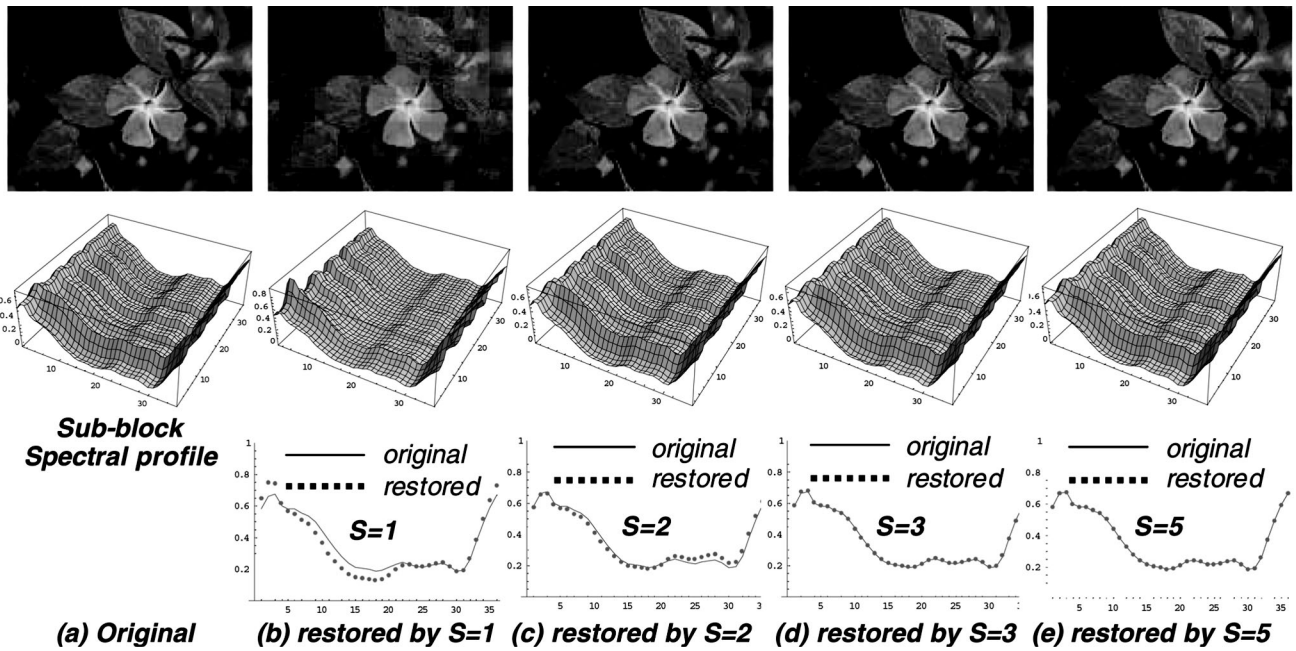
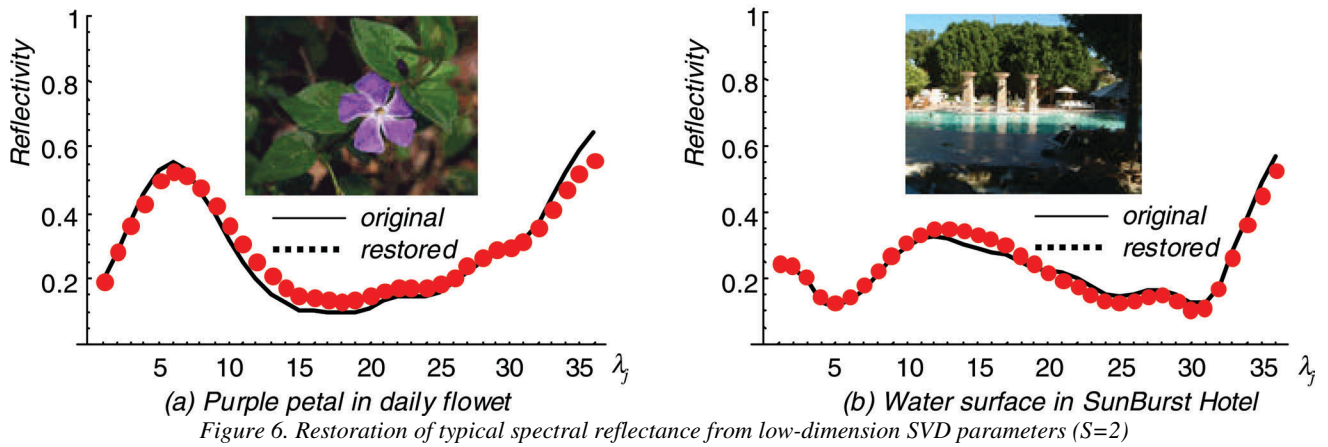
References

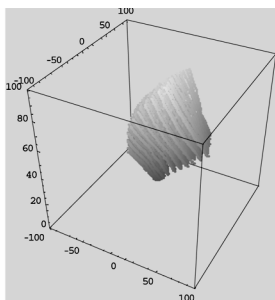
1. S. Tominaga: J. Opt.Soc. Am., A13, 2163 (1996)
2. B. Hill: Proc. SPIE, 3409, pp.2-13 (1998)
3. F. H. Imai and R. S. Berns: Proc. 6th CIC, 224 (1998)
4. Y. Miyake and T. Yokoyama: Proc. SPIE, 3648, 218 (1999)
5. S. Toyooka, et al: Proc. 2nd Intl. Symp., Multispectral Imaging, 59 (2000)
6. J. P. S. Pakkinen, et al: J. Opt. Soc. Am., A6, 318 (1989)
7. T. J. Jaaskelainen, et al : J. Opt. Soc. Am., A7, 725 (1990)
8. J. Tajima, Proc. 6th CIC, 86 (1998)
9. N. Tsumura, et al: J. Opt. Soc. Am., A16, 9, 2169 (1999)
10. H. Haneishi, et al: Applied Optics, 39, 35, 6621 (2000)
11. H. Kotera, Proc. MCS'01, 45 (2001)

Biography

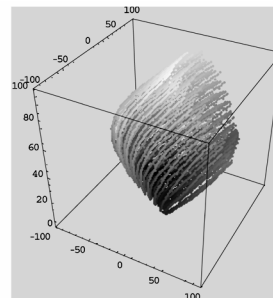
Hiroaki Kotera received his B.S degree from Nagoya Institute of Technology and Doctorate from University of Tokyo. He joined Matsushita Electric Industrial Co in 1963. Since 1973, he has been working in digital color image processing at Matsushita Research Institute Tokyo, Inc. In 1996, he moved to Chiba University. He is a professor at Dept of Information and Image Sciences. He received

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Spectral palette with plain paper



Spectral palette with photo paper

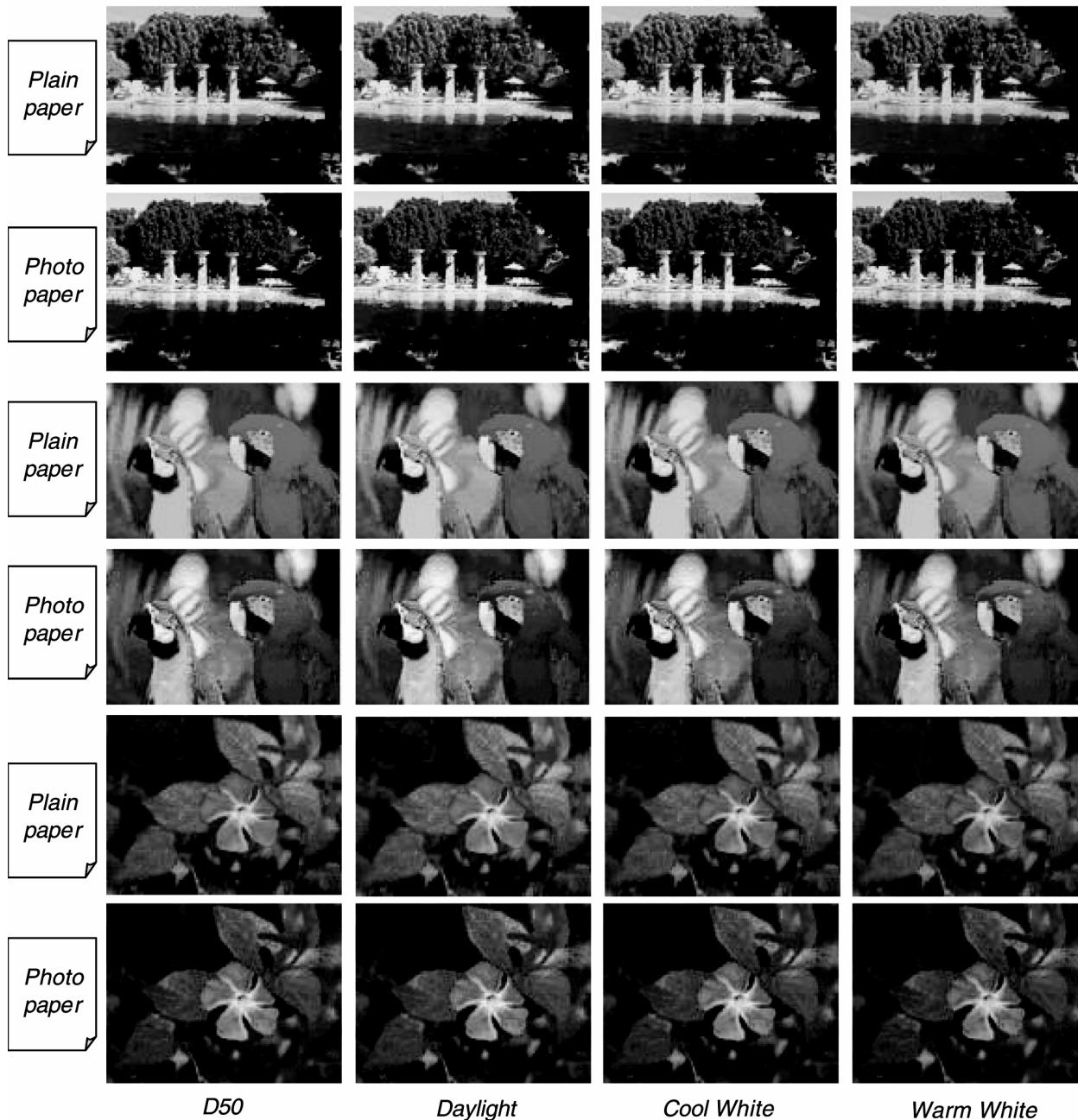


Figure 9. Color appearances in inkjet print under typical fluorescent lamps