Spectral-based Imaging Techniques and the Image Quality Challenge

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Abstract

One of the greatest challenges in color imaging reproduction is to match the appearance of a scene and a reproduction of its captured image, and at the same time assess and improve its overall image quality. This paper reviews many of the aspects that are relevant to the quality of color reproduction describing research performed on spectral color imaging from scene to printing, high-dynamic range imaging and displaying, color image matching quality assessment and color image appearance modeling.

Introduction

In the past, traditional color reproduction techniques in arts and crafts have been relying on techniques based on experience. In the pre-scientific color studies, philosophers just speculated on the nature of color. Color organization and representation started being systematized only during the 15th century. Color science began with the establishment of a correspondence between color and its physical stimuli in the 17th century. In the 19th century, the advance of sciences such as physics and chemistry contributed for the development of color science discipline. CIE (Commission Internationale de l'Eclairage) specified colorimetry in 1931 giving a physical relationship between measured stimulus and color science through a color response based on a standard observer.[1] The increasing speed of computing equipment and imaging devices such as digital cameras, electronic displays and printers, allowed the development of techniques for color imaging. This advent of electronic imaging in the last decades of the last century, supplanting film in popularity, was accompanied with a need to perform color management in a more systematic way. Then, color management systems based on colorimetry have been developed and incorporated as profiles in software interfacing and intermediating imaging devices.[2,3]

Colorimetric-based imaging can achieve pleasant reproduction under controlled environment but it fails when a critical color-matching application is required, such as textile color control, medical imaging or artwork reproduction. In particular, in the area of multimedia where we can access color images through the worldwide network of computers, the WYSIWYG (what you see is what you get) fidelity in the reproduction of color has become very important. Moreover, the traditional cross-media reproduction systems does not consider the ground truth of the original scene.

Multi-channel visible spectrum imaging (MVSI), also known as spectral imaging, multi-spectral imaging, multispectral imaging or spectral color imaging, offers an imaging paradigm that increases color accuracy at the expense of higher system bandwidth demands and increasing system complexity and cost.[4-10] Spectral color imaging performs a finer sampling in the wavelength domain and its techniques allow estimation of the spectral reflectance properties of the scene and therefore it can minimize the effects of metamerism.[2] Spectral color imaging helps to match the color appearance of original scene with reproduced images. Color science further developed with the advances in the study of physiology and psychophysics in the second half of the 20th century.[11,12]

Spectral color imaging can transcend the limitation in color accuracy of current trichromatic imaging systems providing wavelength resolution. However, a more complete concept of image quality has to include other relevant factors such as SNR (Signal-Noise ratio), spatial resolution, as well as, and intensity resolution and range. The increase in spatial resolution is currently going on actively as exemplified by the "megapixel war" of consumer camera manufacturers. However, light intensity resolution and range has just started been tackled by consumer camera manufacturers. The light intensity resolution and range is domain of high-dynamic range imaging.[13] Current commercial imaging devices are limited in the dynamic range of light intensity it can capture. As a consequence, when capturing scenes containing simultaneously deep shadows and highlights, the imaging device are not able to capture the whole range of intensities resulting in loss of detail in the shadows and/or bright areas of images. Moreover, the lack of light intensity resolution can lead to undesired quantization artifacts.

Spectral color imaging and high-dynamic range imaging can help to increase the fidelity of color reproduction but in order to match color image appearance in cross-media and cross-environmental conditions it is also necessary to consider how our vision system adapts to viewing conditions. This lead to a whole new field in color science dedicated to color appearance modeling.[12] Although CIE colorimetry is based on human vision, it cannot predict the appearance of color images in day-to-day conditions because it is based on adapted eyes in pre-defined laboratory conditions, unlike the environment where most colors are seen. The specification and prediction of color appearance should also consider the influence of environmental factors in the sensation of color, such as illumination and background.

After matching spectral reflectance, dynamic range and appearance between original scene and reproduction image it is necessary to consider other physical limitations such as the color gamut and intensity range of color displaying devices. In order to compensate the limitations of the reproducing device (either display or hardcopy) it is necessary to perform a mapping from image representation space to physical display space. It raises the question of what is the best mapping strategy and how to assess the quality of matching. Image quality assessment has relayed on time-consuming psychophysical experiments. Increasingly accurate color appearance models have been proposed but these models were devised using solid uniform color patches and spatial color appearance models have been a very active area of research.[14,15]

Colorimetric Color Imaging

Colorimetric color imaging is based on transformation of device color space to a device-independent color space based on linear transformation.[2,16] This can be achieved by calibration procedures usually by measuring colorimetric values under certain illumination condition and associating these measurements with what is captured, displayed or printed. The colorimetric modeling generally consists of a non-linear transformation followed by a linear color transformation. Colorimetric color imaging works fine under controlled illumination. For some applications such as portraiture it is possible to estimate spectral properties of skin from conventional trichromatic cameras and doing so it introduces flexibility on changing illumination.[17] An example of this application is shown in Figure 1 in which a portrait scene taken under illuminant with spectral radiance $E_1(\lambda)$ is captured by a HDTV camera giving signals *R, G, B*.[17] These device color signals are then converted to device independent *X, Y, Z* values using color transformation $\boldsymbol{M}_1$. Spectral reflectance $R(\lambda)$ image is then estimated from colorimetric signals using eigenvector (it could be directly derived from camera signals as normally performed, but in this example it is converted from colorimetric values in order to be consistent with the colorimetric color reproduction flow). Then colorimetric values *X', Y', Z'* are calculated for a new illuminant with spectral radiance $E_2(\lambda)$. A pre-calculated transformation $\boldsymbol{M}_2$.obtained by display calibration transforms the colorimetric values to display device space color values R_c, G_c, B_c. A pre-calculated color transformations $\boldsymbol{M}_3$.is used to transform display color values to printing values R_p, G_p, B_p so when the portrait image is printed and viewed under illuminant with spectral radiance $E_3(\lambda)$ the measured colorimetric values *X'', Y'', Z''* are going to match with *X', Y', Z'*.

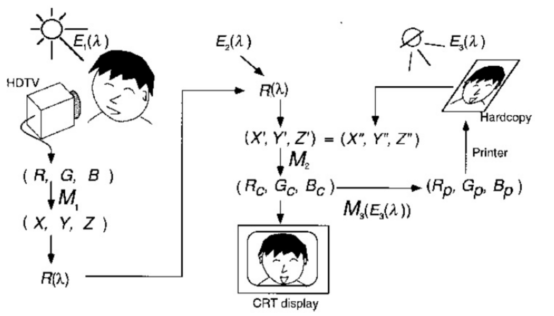

Figure 1. Example of colorimetric color imaging with spectral estimation

Another example of colorimetric color reproduction system is the European MARC project that demonstrated the feasibility of an end-to-end scene to hardcopy colorimetric color-management system for artwork reproduction.[18] This project was very successful in producing high-quality reproductions that matched the original paintings under controlled illumination.

Spectral Color Imaging

The example of Figure 1 has a spectral estimation that relies on trichromatic capture because skin color can be very accurately reconstructed using only three-color channels. However, when scenes with a myriad of colors are involved, such as artwork imaging, it is necessary to increase spectral sampling in order to estimate accurately spectral properties of the material. Technical issues concerned with multi-channel image acquisition and reconstruction, such as number of required basis functions, compression, imaging artifacts, type of transformation, reconstruction space and reproduction quality metrics have been studied extensively.[4-10,19-27] In contrast to the abundance of research concerning image-capture aspects of spectral imaging, there has been much less research on the spectral color reproduction of hardcopy.[10, 28-36] At MCSL, an algorithm was developed by Tzeng comprising several steps.[31-34] At first, *a priori* analysis was performed to determine an optimal ink set.[31] In this analysis, the spectral properties of the colorants used to create the original object were measured or estimated and analyzed statistically. The possible statistical colorants were correlated to real inks in an existing database resulting in an optimal ink set.[32] A printer overprint model was next derived.[33] The spectral reflectance of the ink overprints were predicted using Kubelka-Munk theory.[37] The Yule-Nielsen modified Neugebauer equations were used to predict spectral reflectance from dot areas.[38] More details on the use of this model for developing printer profiles are given by Iino and Berns.[28,29] Using this approach, Tzeng was successful in reproducing the colors of the GretagMacbeth ColorChecker color rendition chart using the Dupont WaterProof proofing process with six inks.[34] The average color difference between the original rendition chart and the reproduction for illuminant D50 and the 2° observer was 1.9 ΔE^*_{94} with maximum of 5.8. The research by Tzeng was fundamental and not focused on the high-speed requirements to create color separations for high-resolution images. Essentially, Tzeng used images with limited number of pixels (corresponding to the various target colors such as the ColorChecker). Extending his research to images with millions of pixels was a research topic at MCSL.[10,36] In one earlier work, an end-to-end spectral reproduction from scene to hardcopy was obtained using as input, a liquid-crystal tunable filter (LCTF) attached with a camera loaded with negative film and as output, six-color MatchPrint proofing.[7] We extended the spectral-based ink separation research from proofing to ink-jet printing using initially a four-color ink-jet printer[10] performing spectral color reproduction from scene to hardcopy using a trichromatic digital camera and a four-color inkjet printer, in order to verify the feasibility and accuracy of spectral imaging and reproduction using systems that do not require fabrication especially for this purpose. For this feasibility study, we developed an end-to-end spectral color reproduction system comprising a spectral image-acquisition system[23] and a spectral-based printing system.[10] A scene was captured using broadband multi-channel imaging of the visible spectrum. The spectral reflectance of each pixel was estimated from the digital signals.[23] The spectral reflectance image was processed by a spectral-based color-separation algorithm, and prints produced. The goal of this research was to produce hardcopy results that are spectrally matched to original colors. We used off-the-shelf trichromatic digital camera combined with multiple filtration, image processing, and four-color ink-jet printing. Both scene input and printed output were defined spectrally. The spectral-based printing separation algorithm produced the least metameric reproduction to the original scene using a computationally feasible approach. The goal of this end-to-end color-reproduction research was the examination of the possibilities and limitations of commercial input and output devices. Results showed an average end-to-end system accuracy of 1.5 ΔE_{00} and spectral reflectance rms error of 0.9% between measured and reproduced reflectances for a printed target of 55 colors.

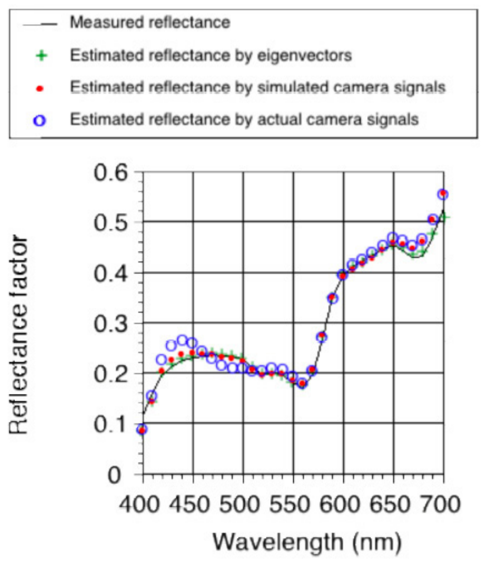

Figure 2. Influence of noise introduction on spectral curve estimation accuracy.

Figure 2 shows an example of how going from theoretical eigenvector reconstruction to simulated estimation and reconstruction from actual imaging will introduce noise and has influence on the accuracy of spectral reflectance curve estimation.

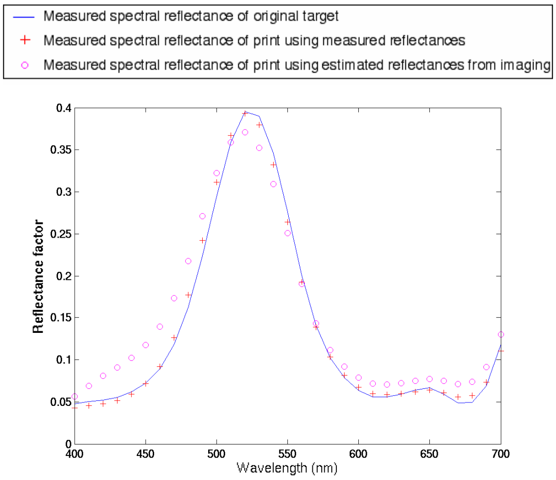

Figure 3. Influence of noise introduction on spectral-based printing estimation accuracy.

Figure 3 shows an example of how progressively going from a theoretical printer simulation to a whole imaging chain from capture to printing introduces noise making measured spectral curves of the print diverge from the original measurement.

This research was further extended to digital imaging capturing system with more spatial resolution and six-color printing.[36] More details can be found at www.art-si.org

High-Dynamic Range Imaging

High-dynamic range (HDR) images are becoming widely available. Computer generated images are the most common sources but a growing number of alternatives exist for natural imaging capture.[13,39] The development of HDR displays has lagged the availability of HDR content, and most HDR images must be tonally compressed to be viewed with typical electronic displays. In order to support this dynamic range compression, many researchers have proposed methods for rendering high-contrast HDR images to non-HDR displays.[13] Such rendering methods are basically strategies to perform tone mapping. The abundance of proposed tone mapping algorithms lead to researchers in HDR image rendering to perform psychophysical evaluation experiments comparing a HDR image or scene with a tone-mapped image. However, as stated in the CIE TC8-08: Spatial Appearance Modeling and HDR Rendering, it is necessary to make comparisons of rendered images against an original to evaluate its accuracy of appearance. Since it is not practical to have an original natural HDR scene always available under controlled observation condition, it is necessary to build display devices that improves dynamic range capabilities by many orders of magnitude compared to current displays in order to show the HDR scene. Such HDR displays can be built based on a proposed display system using a combination of off-the-shelf components consisting of a Digital Light Projector (DLP) and a Liquid Crystal Display (LCS) panel.[40] Such HDR display is based on a dual modulation principle, where the LCD panel is used as an optical filter that modulates a high intensity but lower resolution image coming from the DLP projector. Such a HDR display system was built[41] and calibrated[42] before compared with an original scene as shown in Figure 4.

A framework for HDR video sequence rendering evaluation was proposed. In this framework, HDR images with XYZ tristimulus values image sequences are converted to six channel images using HDR display characterization. The same HDR images are tone-mapped and rendered to a CRT display. A system with processing capability for HDR video sequences is also presented as well as procedure to calibrate both CRT and HDR displays. A calibrated CRT monitor was placed next to the HDR display to allow side-by-side evaluations. The captured HDR scene is displayed on both HDR and CRT displays. The colorimetric values XYZ_m of the original scene are measured. The capture produced a raw linear data that was processed to give a reconstructed XYZ_r tristimulus image. This image is the reference and starting point for both display rendering and tone-mapping rendering for the CRT display.

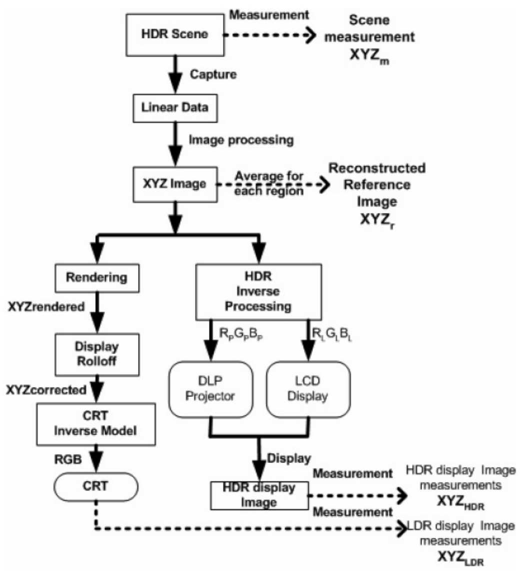

Figure 4. Processing flowchart for HDR imaging

The built HDR display system was capable of showing 14-bit dynamic range data. The XYZ reference values were rescaled to fit within the range of the HDR display. Using a HDR display inverse model, a sextuplet of values ($R_PG_PB_P$ values for the DLP and $R_LG_LB_L$ values for the LCD) to drive the HDR display. The HDR image was then rendered to be displayed on the CRT display considering angular and spatial non-uniformity. Ratios between colorimetric values are used to compare accuracy of the reproduction but a more appropriate metric has to be devised to compare images in this emerging and fascinating field of HDR imaging.

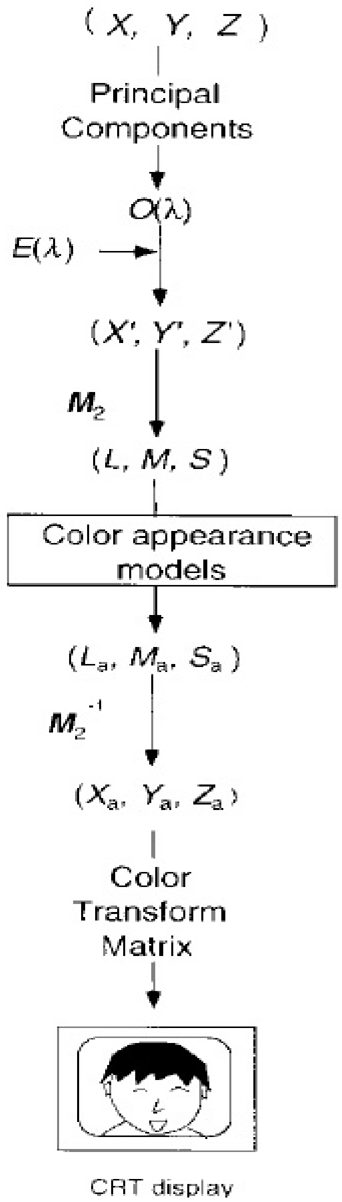

Figure 5. Corresponding color reproduction diagram.

Color Imaging Appearance Modeling

Figure 5 shows a schematic diagram of a corresponding color reproduction system that takes in account color appearance modeling.[43] By using color appearance models, the tristimulus values X_c, Y_c, Z_c after chromatic adaptation can be calculated from the tristimulus values X', Y', Z' obtained by colorimetric color reproduction. The first step is a transformation $\boldsymbol{M}_2$ from tristimulus values X', Y', Z' to cone fundamental tristimulus values L, M, S. Thereafter, the calculated L, M, S values are used to estimate fundamental tristimulus values L_a, M_a, S_a corresponding to the cone responses after the chromatic adaptation by using color appearance models. The tirstimulus values X_a, Y_a, Z_a are calculated by the inverse matrix of $\boldsymbol{M}_2$ and displayed using color transformation based on display calibration.

Psychophysical experiments showed that color appearance models derived from color patches did not perform at it best when used for complex images.[43] Color appearance modeling can be optimized for a particular type of scene, such as portraiture.[44] However, for a general application, a simple spatial model has to be proposed.[14,15]

Color Image Quality Metrics

A perceptual color difference was proposed as an alternative color difference metric for complex images instead of the conventional color difference equation.[45] This color difference is derived based on Mahalanobis distance by using covariance matrices for differences of each color attribute. The covariance matrices for each class of images can be obtained by psychophysical experiments using just noticeable difference in paired comparisons. The Mahalanobis distance, commonly used in pattern recognition analyses, makes uniform the influence of the distribution of each attribute considering the correlation between each term. The Mahalanobis distance can be applied in a color space using metric lightness, chroma and hue angle, as follows;

$$\Delta \boldsymbol{d} = \sqrt{\begin{bmatrix} \Delta \boldsymbol{L} & \Delta \boldsymbol{C} & \Delta \boldsymbol{h} \end{bmatrix} \begin{bmatrix} \sigma_{LL} & \sigma_{LC} & \sigma_{Lh} \\ \sigma_{CL} & \sigma_{CC} & \sigma_{Ch} \\ \sigma_{hL} & \sigma_{hL} & \sigma_{hh} \end{bmatrix}^{-1} \begin{bmatrix} \Delta \boldsymbol{L} \\ \Delta \boldsymbol{C} \\ \Delta \boldsymbol{h} \end{bmatrix}}$$

where σ_{LL}, σ_{CC}, σ_{hh} are the variances of metric lightness, chroma, hue angle, respectively. $\Delta \boldsymbol{L}$, $\Delta \boldsymbol{C}$ and $\Delta \boldsymbol{h}$ are respectively difference of the metric lightness, chroma and hue angle difference between two images, for instance the original and the reproduction. On the other hand, σ_{LC} (σ_{CL}), σ_{Lh} (σ_{hL}), σ_{Ch} (σ_{hC}) are the covariances between metric lightness and chroma, and lightness and hue angle, and chroma and hue angle, respectively. The variance-covariance matrix can be easily derived using three-dimensional threshold of color-difference perceptibility as shown above.[1,46,47] The resultant matrices were compared for different classes of images and we reported that the information in the resulting matrix can give very useful trends and clues about which kind of transformation can minimize the perceptual color difference in images when a transformation such as a gamut mapping is required.

Other image quality considerations

Each imaging paradigm presented above is focused in a particular aspect of color image quality. Spectral color imaging is particularly important to critical applications in which identification of materials and illumination-independence is relevant. In the other hand, the main benefit of HDR imaging is increasing visibility. Color appearance models are critical for cross-media reproduction. Due to the limitations and scope for this paper, other important image quality factors were omitted. In particular, the pursuit of fitting more and more pixels in the same physical package in imaging sensors has lead to smaller and smaller pixels resulting in loss of sensitivity and consequently increasing noise levels.[48] We also cannot forget that in a consumer market, color preference from the users is more critical than color accuracy and fidelity.[49,50]

Conclusion

Image quality is a complex problem that is one of the biggest challenges in imaging Advanced research on spectral color imaging and high-dynamic range imaging combined with color appearance modeling and image quality assessments are big steps towards a modeling for a total image quality concept. However, there are still a lot of work to be performed extending current technologies for a more comprehensive image representation and rendering that matches perfectly with our perception. The researches mentioned in this paper were executed while the author was at Chiba University, Japan between 1993 and 1997; at Munsell Color Science Laboratory, RIT, Rochester, NY, USA from 1997 to 2003 and at Pixim Inc. between 2003 and 2005. Further details can be found in the referenced papers.

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References

1. G. Wyszecki and W. S. Stiles, Color Science, 2nd ed., John Wiley & Sons, New York, 1982.
2. R. S. Berns, Billmeyer and Saltzman's Principles of Color Technology, John Wiley & Sons, , 2000.
3. E. Giorgianni and T. E. Madden, Digital Color Management: Encoding Solutions, Addison-Wesley, Reading, MA, 1998.
4. B. Hill, (R)evolution of color imaging systems, in Proc. of the First European Conference on Color in Graphics, CGIV'2002, Imaging and Vision, IS&T, Springfield, VA, 2002, pp. 473-479.
5. S. Tominaga, Spectral Imaging by a multi-channel camera, *J. Electronic Imaging* **8**, 332-341 (1999).
6. M. Hauta-Kasari, K. Miyazawa, S. Toyooka, and J. Parkkinen, Spectral vision system for measuring color imagers, *J. Opt. Soc. Am. A* **16**, 2352-2362 (1999).
7. M. Rosen and X. Jiang, Lippmann2000: A spectral image database under construction, in Proc. of the International Symposium on Multispectral Imaging and Color Reproduction for Digital Archives, Chiba University, Japan, 1999, pp. 117-122.
8. H. Haneishi, T. Hasegawa, A. Hosoi, Y. Yokoyama, N. Tsumura, and Y. Miyake, System design for accurately estimating the spectral reflectance of art paintings, *Appl. Opt.* **39**, 6621-6632 (2000).
9. F. Schmitt, H. Brettel and J. Y. Hardeberg, Multispectral Imaging Development at ENST, *Display and Imaging* **8**, 261-268 (2000).
10. F. H. Imai, D. R. Wyble, R. S. Berns and D. Tzeng, A feasibility study of spectral color reproduction, *J. Imaging Sci. Technol.* **47**, 554-553 (2003).
11. B. A. Wandell, Foundations of vision, Sinauer Associates, Inc., 1995.

12. M. D. Fairchild, Color appearance models, 2nd Ed., John Wiley & Sons, 2005.
13. E. Reinhard, G. Ward, S. Pattanaik and P. Debevec, High dynamic range imaging, Acquisition, display, and image-based lighting, Morgan Kauffman, 2006.
14. G. M. Johnson and M. D. Fairchild, A top down description of s-CIELAB and CIEDE2000, *Color Res. Appl.* **28**, 425-435 (2003).
15. M.D. Fairchild and G.M. Johnson, "The iCAM framework for image appearance, image differences, and image quality," *J. Electronic Imaging, 13* 126-138 (2004).
16. R. W. G. Hunt, The reproduction of colour, 6th Edition, John Wiley & Sons, 2004.
17. F. H. Imai, N. Tsumura, H. Haneishi and Y. Miyake, Principal component analysis of skin color and its applications to colorimetric color reproduction on CRT display and hardcopy, *J. Imaging Sci. Technol.* **40**, 422-430 (1996).
18. J. Cupitt, K. Martinez, and D. Saunders, A methodology for art reproduction in colour: the Marc project, *Computers and the History of Art* **6**, 1-19 (1996).
19. L. T. Maloney, Evaluation of linear models of surface spectral reflectance with small numbers of parameters, *J. Opt. Soc. Am. A* **10**, 1673-1683 (1986).
20. T. Jaaskelainen, J. Parkkinen and S. Toyooka, Vector-subspace model for color representation, *J. Opt. Soc. A* **7**, 725-730 (1990).
21. D. H. Marimont and B. A. Wandell, Linear models of surface and illuminant spectra, *J. Opt. Soc. Am. A* **9**, 1905-1913 (1990).
22. M. J. Vrhel and H. J. Trussel, Color correction using principal components, *Color Res. and Appl.* **17**, 328-338 (1992).
23. F. H. Imai, R. S. Berns, and D. Tzeng, A comparative analysis of spectral reflectance estimation in various spaces using a trichromatic camera system, *J. Imaging Sci. Technol.* **44**, 280-287 (2000).
24. D. Connah, S. Westland and M. G. A. Thomson, Recovering spectral information using digital camera systems, Coloration Technology **117**, 309-312 (2001).
25. Y. Murakami, T. Obi, M. Yamaguchi, N. Ohyama and Y. Komiya, Spectral reflectance estimation from multi-band image using color chart, *Opt. Commun.* **188**, 47-57 (2001).
26. J. Y. Hardeberg, F. Schmitt and H. Brettel, Multispectral color image capture using a Liquid Crystal Tunable Filter, *Optical Engineering* **41,** 2532-2548 (2002).
27. M. R. Rosen, F. H. Imai, M. D. Fairchild and N. Ohta, Data-efficient methods applied to spectral image capture, *J. Soc. Photogr. Sci. Technol. Japan* **65**, 353-362 (2002).
28. K. Iino and R. Berns, Building Color Management Modules Using Linear Optimization I. Desktop color system *J. Imaging Sci. Tech*. **42**, 79-94 (1998).
29. K. Iino and R. Berns, Building Color Management Modules Using Linear Optimization II. Prepress System for Offset Printing, *J. Imaging Sci. Tech* **42**, 99-144 (1998).
30. M. Kouzaki, T. Itoh, T. Kawaguchi, N. Tsumura, H. Haneishi and Y. Miyake, Spectral Color Reproduction for Hardcopy System by using Vector Error Diffusion Method, in Proc. of First International Symposium on Multispectral Imaging and High Accurate Color Reproduction, Chiba University, 1999, pp. 106-109.
31. D. Tzeng and R. S. Berns, Spectral-based ink selection for multiple-ink printing I. Colorant Estimation of Original Objects, in Proc. of Sixth IS&T/SID Color Imaging Conference, IS&T, Springfield, VA, 1998, pp.106-111.
32. D. Tzeng and R. S. Berns, Spectral-based ink selection for multiple-ink printing II. Optimal Ink Selection, in Proc. of Seventh IS&T/SID Color Imaging Conference, IS&T, Springfield, VA, 1999, pp. 182-187.
33. D. Tzeng and R. S. Berns, Spectral reflectance prediction of ink overprints by Kubelka-Munk turbid media theory, in Proc. of TAGA/ISCC Symposium in Vancouver B.C., 1999, pp. 682-697.
34. D. Tzeng, R. S. Berns, Spectral-based Six-color Separation minimizing Metamerism, in Proc. of Eighth IS&T/SID Color Imaging Conference, IS&T, Springfield, VA, 2000, pp. 342-347.
35. D. R. Wyble and R. S. Berns, A critical review of spectral models applied to binary color printing, *Color Res. Appl.* **25**, 5-19 (2000).
36. Y. Chen, R. S. Berns, and L. A. Taplin, Six color printer characterization using an optimized cellular Yule-Nielsen spectral Neugebauer model, *J. Imaging Sci. Technol.* **48**, 519-528 (2004).
37. P. Kubelka and F. Munk, Ein Beitrag zur Optik der Farbanstriche, *Zeit Tekn. Phy*. **12**, 593-601 (1931).

38. J. A. C. Yule and W. J. Nielsen, The penetration of light into paper and its effect on halftone reproduction, in *Proc. of TAGA,* 65-75 (1951).
39. W. Bidermann, A. El Gamal, S. Ewedemi, J. Reyneri, H. Tian, D. Wile and D. Yang, A 0.18 m High Dynamic Range NTSC/PAL Imaging System-on-Chip with Embedded DRAM Frame Buffer," in Proc. of ISSSCC, 2003.
40. H. Seetzen, L, Whitehead and G. Ward, High Dynamic Range Display using low and high resolution modulators, *Society for Information Display International Symposium Digest,* 2003.
41. F. H. Imai, D. Kuo and R. J. Motta, Colorimetric characterization of a HDR display system, in *Proc. of the 10th Congress of the International Colour Association AIC Colour 05*, University of Granada, Spain, 2005, pp. 653-656.
42. F. H. Imai, D. Kuo and R. J. Motta, Design of a framework for HDR sequence rendering evaluation, in *Proc. of IS&T & SID Color Imaging Conference,* IS&T, Springfield, VA, 2005, pp. 14-19.
43. F. H. Imai, N. Tsumura, H. Haneishi and Y. Miyake, Prediction of color reproduction for skin color under different illuminants based on the color appearance models, *J. Imaging Sci. Technol.* **41**, 166-173 (1997).
44. F. H. Imai, N. Tsumura, H. Haneishi and Y. Miyake, Improvement of incomplete chromatic adaptation model for facial pattern images, *J. Imaging Sci. Technol.* **42**, 264-268 (1998).
45. F. H. Imai, N. Tsumura, and Y. Miyake, Perceptual color difference metric for complex images based on Mahalanobis distance, *J. Electronic Imaging* **10**, 385-393 (2001).
46. K. Witt, Three-dimension threshold of color-difference perceptibility in painted samples: Variability in painted samples. Variability of observers in four CIE color regions, *Color Res. Appl.* **12**, 128-134 (1987).
47. J. Uroz, Colour difference perceptibility for large-size printed images, M. Sc. Thesis, University of Derby, Derby, UK (1999).
48. J. Farrell, F. Xiao and S. Kavusi, Resolution and light sensitivity tradeoff with pixel size, in *Proc. of SPIE* **6069**, SPIE, Bellingham, WA, 211-218, 2006.
49. M. Tsukada, C. Funayama and J. Tajima, Automatic color preference correction for color reproduction, in *Proc. of SPIE* **4300**, SPIE, Bellingham, WA, 216-223, 2001.
50. S. R. Fernandez, M. D. Fairchild and K. Braun, Analyses of observer and cultural variability white generating 'preferred' color reproduction of pictorial images, *J. Imaging Sci. Technol.* **49**, 96-104 (2005).