14th European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September 4-8, 2006, copyright by EURASIP

RECENT ADVANCES IN ACQUISITION AND REPRODUCTION OF MULTISPECTRAL IMAGES

Jon Y. Hardeberg

The Norwegian Color Research Laboratory, Department of Computer Science and Media Technology
Gjøvik University College, P.O.Box 191, N-2802 Gjøvik, Norway
Phone: +47-61135215, fax: +47-61135240, email: jon.hardeberg@hig.no, web: www.colorlab.no

ABSTRACT

Conventional color imaging science and technology is based on the paradigm that three variables are sufficient to characterize a color. Color television uses three color channels, and silver-halide color photography uses three photosensitive layers. However, in particular due to metamerism, three color channels are often insufficient for high quality imaging e.g. for museum applications. In recent years, a significant amount of color imaging research has been devoted to introducing imaging technologies with more than three channels – a research field known as multispectral color imaging. This paper gives an overview of this field and presents some recent advances concerning acquisition and reproduction of multispectral images.

1. INTRODUCTION

Already in 1853, the mathematician Hermann Grassmann, the inventor of linear algebra, postulated that three variables are necessary and sufficient to characterize a color [1]. This principle, the three-dimensionality of color, has since been confirmed by thorough biological studies of the human eye. This is the reason why analog and digital color images are mostly composed of three color channels, such as red, green and blue (RGB).

However, for digital image acquisition and reproduction, three-channel images have several limitations. First, in a color image acquisition process, the scene of interest is imaged using a given illuminant. Due to metamerism, the color image of this scene under another illuminant cannot be accurately estimated. Furthermore, since the spectral sensitivities of the acquisition device generally differ from the standardized color matching functions, it is also impossible to obtain precise device-independent color. By augmenting the number of channels in the image acquisition and reproduction devices we can remedy these problems, and thus increase the color image quality significantly.

Multispectral color imaging systems are developing rapidly because of their strong potential in many domains of application, such as physics, museum, cosmetics, medicine, high-accuracy color printing, computer graphics, etc. Several academic research groups worldwide are working on these matters, for example at the University of Chiba in Japan [2, 3], Rochester Institute of Technology in the United States [4–9], ENST Paris in France [10–14], and Gjøvik University College in Norway [15–21].

After this brief general introduction we explain the concept of metamerism in Section 2. In Sections 3 and 4 we present concepts, research challenges, and recent advances within respectively acquisition and reproduction of multispectral images.

2. COLOR AND METAMERISM

Aristotle viewed all color to be the product of a mixture of white and black, and this was the prevailing belief until Sir Isaac Newton's prism experiments provided the scientific basis for the understanding of color and light [22]. Newton showed that a prism could break up white light into a range of colors, which he called the spectrum, and that the recombination of these spectral colors re-created the white light.

An important fact of color is that the perceived color of a given object is not merely a function of the spectral reflectance of the surface of the object, which we denote $r(\lambda)$, but also of the spectral distribution of the illumination $l(\lambda)$, and the spectral sensitivities of the three types of photosensitive cells (cones) in the eye $s_i(\lambda)$. The cone responses c_i, $i = 1,2,3$, can be modeled relatively simply as

$$c_i = \int_{\lambda_{\min}}^{\lambda_{\max}} l(\lambda) r(\lambda) s_i(\lambda) d\lambda. \quad (1)$$

This equation forms the basis of *colorimetry* – the quantification of color [23, 24].[1] By uniformly sampling the spectra above with a proper wavelength interval, we can rewrite Equation 1 in a matrix form as

$$\mathbf{c} = \mathbf{S}^t \mathbf{L} \mathbf{r}. \quad (2)$$

This matrix notation has several advantages, in particular it enables us to use techniques based on matrix algebra, such as vector space projections, to solve problems related to color (for more details, see e.g. [11]).

From Equation 1, and the fact that the reflectance spectra are continuous functions, while the sensor response only has three values, it is clear that there are several different spectra that can appear as the same color to the observer. A set of two such spectra having different spectral compositions but giving rise to the same psychophysical characterization are called *metamers*.

For imaging, metamerism is both a curse and a blessing. Without metamerism there would be no color image reproduction as we know it. Technologies such as photography, printing, and television, are all based on metamerism. The reproduced images have spectral distributions that show little or no similarity to those of the original scene, rather they are created in order be *perceived* as equal by a standard human observer.

[1] Note that the complexity of the Human Visual System extends far beyond that described by Equation 1, for instance is the perceived color of an object highly dependent on its surrounds and viewing conditions. Such phenomenons are currently being researched in the field of color appearance modeling [25].

On the downside, perhaps the most striking objectionable effect of metamerism is seen when surfaces that have matching colors seen under one illuminant, do not match under another. This is an important problem for example in the clothing industry. Even more relevant to imaging is the case of creating an exact reproduction of for instance a painting. The imaging professional typically spends a lot of time and energy tweaking the color reproduction process to match the original colors perfectly under a reference illuminant – but in the end, when a customer displays the print for example in a typical office fluorescent light, it does not have the desired colors.

3. MULTISPECTRAL COLOR IMAGE ACQUISITION

A multispectral color image acquisition system mostly contains essentially the same elements as a color image acquisition device, the only principal difference is that it has more than three channels. Figure 1 illustrates schematically the different elements of a multispectral camera using a set of K different color filters. The K channels are acquired sequentially by changing the filter, typically either by using a rotating filter wheel [3, 4, 14, 26, 27], or an electronically tunable filter [5, 12].

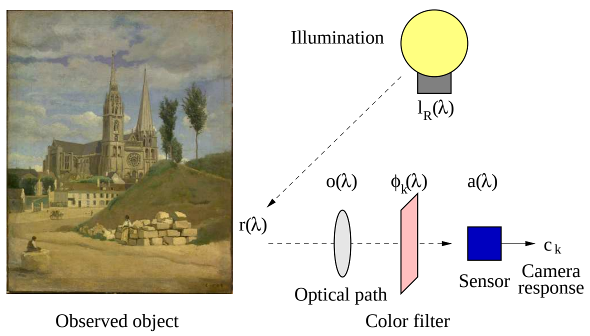

Figure 1: Schematic view of the image acquisition process. Only one color filter is shown in this figure. For conventional color imaging, three color filters would be used, and for multispectral color imaging, we need more than three.

By sampling the spectra and applying matrix notation, similarly to what we did with Equation 1, we can express the K-channel camera response as the vector

$$\mathbf{c}_K = [c_1 c_2 \dots c_K]^t = \Theta^t \mathbf{r}, \tag{3}$$

where Θ is the known N-line, K-column matrix of the spectral transmittances of the filters multiplied by the camera sensitivities, the optical path transmittance, and the spectral distribution of the illuminant, that is, the matrix elements of Θ can be expressed as

$$\theta_{kn} = [\phi_k(\lambda_n) a(\lambda_n) o(\lambda_n) l_R(\lambda_n)]. \tag{4}$$

Equation 3 represents a basic linear model of the image acquisition system, and this model can typically be used for further interpretation of the multispectral image data.

3.1 Spectral reconstruction

The problem of estimating the spectral reflectances $\tilde{\mathbf{r}}$ from the camera responses $\mathbf{c}_K$ is central in the design and optimization of a multispectral color imaging system.

One approach is to take advantage of *a priori* knowledge concerning the spectral reflectances that are to be imaged, by assuming that the reflectance $\mathbf{r}$ in each pixel is a linear combination of a known set of P smooth reflectance functions: $\mathbf{r} = \mathbf{Ra}$, with $\mathbf{R} = [\mathbf{r}_1 \mathbf{r}_2 \dots \mathbf{r}_P]$ the matrix of the P known reflectances and $\mathbf{a} = [a_1 a_2 \dots a_P]^t$ a vector of coefficients. We have previously proposed [11] a reconstruction operator that minimizes the Euclidian distance $d_E(\mathbf{r}, \tilde{\mathbf{r}})$ between the original spectrum $\mathbf{r}$ and the reconstructed spectrum $\tilde{\mathbf{r}}$:

$$\tilde{\mathbf{r}} = \mathbf{RR}^t \Theta (\Theta^t \mathbf{RR}^t \Theta)^{-1} \mathbf{c}_K. \tag{5}$$

In [28] we compared the performance of a number of linear methods for reflectance reconstruction including the one presented above. Methods based upon smoothness minimization, linear models of reflectance and least squares fitting were compared using two simulated 6-channel camera systems. The smoothness methods were generally found to deliver the best performance on the test data sets. Furthermore, they deliver equivalent performance on training data, even compared to those methods that make explicit use of a priori knowledge of the training data.

Spectral reconstruction continues to be an active field of research. One trend is to apply non-linear methods such as polynomial regression [17] (see Figure 2). Neural network-based methods have been found to yield superior performance in the presence of acquisition noise [13, 27]. Recently Alsam and Connah [19] proposed to use convex bases as an alternative to linear bases and a method for spectral reconstruction using metamer sets, with promising results.

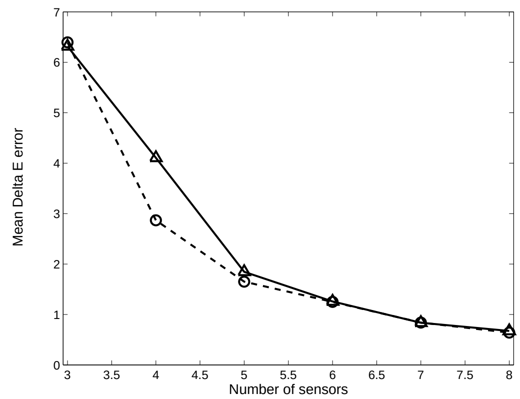

Figure 2: Mean RMS spectral reconstruction error for an evaluation data set of over 1000 natural reflectances [29], plotted as function of the number of sensors for an optimised regularised polynomial transform (circles and dashed lines) and a linear, or 1st order polynomial, method (triangles and solid lines) (from [17]).

3.2 How many channels?

The surface reflectance functions of natural and manmade surfaces are invariably smooth. It is desirable to exploit this smoothness in a multispectral imaging system by using as few sensors as possible to capture and reconstruct the data. In a recent paper [18] we investigated the minimum number of sensors to use, while also minimizing the spectral reconstruction error.

We do this by deriving different numbers of optimized sensors, constructed by transforming the characteristic vectors of the data (Figure 3), and simulating reflectance reconstruction with these sensors in the presence of noise. We find an upper limit to the number of optimized sensors one should use, above which the noise prevents decreases in error. For a set of Munsell reflectances, captured under educated levels of noise, we find that this limit occurs at approximately nine sensors, see Figure 4. We also demonstrate that this level is both noise and dataset dependent, by providing results for different magnitudes of noise and different reflectance datasets.

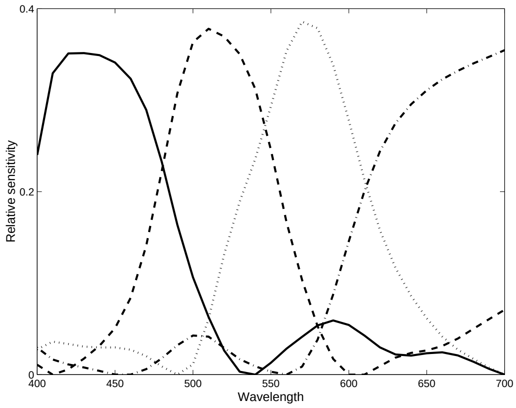

Figure 3: Non-negative sensors formed by varimax rotation with added positivity constraint. (From [18].)

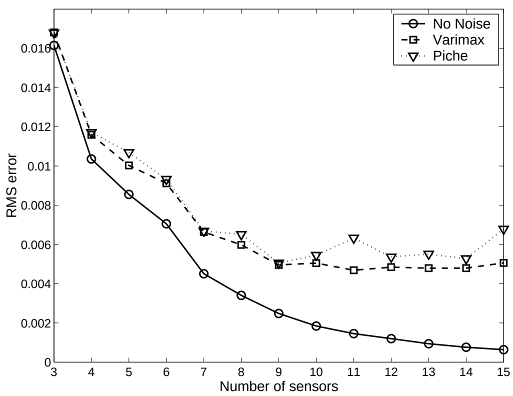

Figure 4: Effect of increasing sensor number with 12 bit quantization and 1% shot noise on Munsell reflectance data. (From [18].)

4. MULTISPECTRAL COLOR IMAGE REPRODUCTION

Even though Professor Hunt pinned down the concept of *spectral color reproduction* some time back [30], the idea of creating a reflective physical image, in which the spectral reflectance of the original scene is reproduced, have not been much explored since. Besides a few early photographic techniques, it is only recently that this idea has been taken up in color imaging research. [7–9, 15, 16, 20, 21]

The main idea behind our research in this area is that it is possible to reproduce multispectral color images faithfully on printed media, using a multi-channel image reproduction system. Our goal is thus to reproduce images with a spectral match to an original scene, or a reference image, in order to eliminate the problems of the conventional metameric matches that can be achieved with four-color printing processes. A metameric match is only correct under a given viewing illuminant, while a spectral match is correct under any illuminant.

Although conceptually simple, the realization of a multispectral color image reproduction system requires many challenging research problems to be solved, some of which are briefly presented in the following sections.

4.1 Spectral printer characterization

In order to use a printer for spectral reproduction it is crucial to model its behaviour precisely. A landmark printer model for halftone prints is the Neugebauer model [31], in which the estimated spectral reflectance $\hat{R}(\lambda)$ of a colorant combination is a weighted sum of the spectral reflectances $\mathrm{NP}_i(\lambda)$ of the Neugebauer primaries (NP),

$$\hat{R}(\lambda) = \sum_{i=1}^{k} w_i \mathrm{NP}_i(\lambda). \tag{6}$$

The NP are all the possible combinations of colorants that the printer can print. For example a three ink printer (CMY) will produce $2^3 = 8$ NPs. Today, the Yule-Nielsen modified spectral Neugebauer (YNSN) model [32], in which the so-called n factor is introduce in an attempt to model the light interaction between the paper and the colorants, is popular [9]:

$$\hat{R}^{1/n}(\lambda) = \sum_{i=1}^{k} w_i \mathrm{NP}_i^{1/n}(\lambda). \tag{7}$$

For both models, the weights w_i are calculated from the colorant values c_1, c_2 and c_3 (in the case of a three-primary printer) using the Demichel model, as follows:

$$\begin{array}{rcl} w_0 & = & (1-c_1)(1-c_2)(1-c_3), \\ w_1 & = & c_1(1-c_2)(1-c_3), \\ w_2 & = & (1-c_1)c_2(1-c_3), \\ w_3 & = & (1-c_1)(1-c_2)c_3, \\ w_{12} & = & c_1c_2(1-c_3), \\ w_{13} & = & c_1(1-c_2)c_3, \\ w_{23} & = & (1-c_1)c_2c_3, \\ w_{123} & = & c_1c_2c_3. \end{array} \tag{8}$$

The Neugebauer models require the measurements of the primaries NP to evaluate the reflectance of any colorant combination. The value of the n factor depends the printing technology: for instance for amplitude modulated halftoning a value around 2 is typically used, while for frequency modulated halftoning, it is used as an optimization factor.

We have obtained promising results for an eight-channel inkjet system using the YNSN model [15]. An important problem that was discovered is that the model fails when the paper receives too much ink.

Using the YNSN model, a relationship between colorant values and resulting spectral reflectance is established: this is denoted the forward printer model. However, in practice for spectral reproduction it is the inverse relationship that is needed; the inverse model converts from the desired spectral reflectance to required colorant values. Since the YNSN model is not analytically invertible, iterative methods are often used. It is also possible to use large size look-up tables but they require a large number of data to be built. The iterative methods has the advantage to need just a few measurements, but the iteration process can fall into local minima, and therefore fail to obtain the optimal solution. To alleviate this problem we recently proposed an alternative method of inverting the Neugebauer model [33].

Furthermore, recent investigations have been carried out concerning spectral gamut limitations [16], and optimal design of colorants for spectral reproduction [20].

4.2 Halftoning considerations

Once a set of colorant values for each pixel is obtained, commonly it is necessary to apply a halftoning process to convert the pixel values typically ranging from 0 to 255 on eight bits to binary levels indicating whether an ink drop of a certain color is laid down at a certain location or not.

This halftoning is typically done by error diffusion (ED) performed separately on each channel. In ED the output pixel value (0 or 1) of an ink channel is determined by a thresholding condition. Then the difference (i.e. the error) between the input pixel value and output pixel value is weighted by a weight filter and diffused to the neighboring pixels. Several possibilities exist for filter weights, e.g. Floyd-Steinberg [34] and Jarvis-Judice-Ninke [35], aiming to break up unwanted patterns typically found in ED. This operation is performed for each colorant channel separately in a raster scan mode. Clustered-dot screens are not suitable because of moiré issues when using a high number of primaries. It has been observed that the fact that the ED is performed independently for each channel introduces unwanted objectional patterns, this can be called stochastic moiré [36].

In a recent paper we have proposed to use Vector Error Diffusion (VED) for spectral reproduction [21]. The VED technique halftones a picture considering each pixel value of an image as a vector of data, thus performing the halftoning of all the channels simultaneously. For colorimetric VED, the error metric determining the combination of inks to be printed is typically calculated as the Euclidean distance in colour space between the desired colour and the colours of the Neugebauer Primaries [36]. The NP giving the smallest error is chosen, and the resulting error is diffused to the neighboring pixels.

The extension from colorimetric VED to spectral VED is relatively straightforward; the error metric is the Euclidean distance in spectral reflectance space. Using this approach we have obtained very promising simulation results on a 7-channel inkjet printer. For each pixel the spectral reflectance is directly converted into a dot distribution and is ready to be printed. We thus completely avoid the difficult problem of establishing the inverse model, as discussed earlier. As it can be seen in Figure 5, the effect of stochastic moiré is greatly reduced.

However, spectral VED is a time consuming process, and further work should be done to increase the performance of the algorithm. A study of the primaries interaction and the spectral gamut of the printer should bring improvement and allow to deal with data outside of the printer gamut [16].

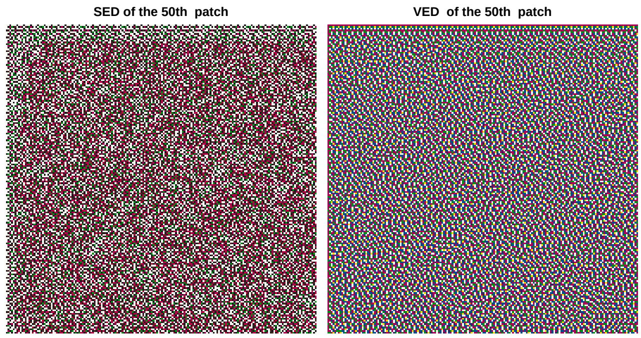

Figure 5: A patch halftoned by scalar error diffusion (left) and vector error diffusion (right). The reduced visual noise (stochastic moiré) achieved by VED is clearly visible. (From [21]).

5. SUMMARY

In this paper we have given a brief overview of the field of multispectral color imaging, as well as a few of our recent advances in the field.

REFERENCES

[1] Hermann Günter Grassmann. Zur Theorie der Farbenmischung. *Annalen der Physik und Chemie*, 89:69, 1853. English translation “Theory of Compound Colors” published in Philosophical Magazine, vol 4(7), pp. 254–264 (1854). Reprinted in [37], pp 10–13.

[2] Y. Miyake, Y. Yokoyama, N. Tsumura, H. Haneishi, K. Miyata, and J. Hayashi. Development of multiband color imaging systems for recordings of art paintings. In *Color Hardcopy and Graphic Arts IV*, volume 3648 of *SPIE Proceedings*, pages 218–225, 1999.

[3] Hiroaki Sugiura, Tetsuya Kuno, Norihiro Watanabe, Narihiro Matoba, Junichiro Hayachi, and Yoichi Miyake. Development of a multispectral camera system. In *Sensors and Camera Systems for Scientific, Industrial and Digital Photography Applications*, volume 3965 of *SPIE Proceedings*, pages 331–339, 2000.

[4] Peter D. Burns and Roy S. Berns. Analysis multispectral image capture. In *Proceedings of IS&T and SID's 4th Color Imaging Conference: Color Science, Systems and Applications*, pages 19–22, Scottsdale, Arizona, November 1996.

[5] Francisco H. Imai, Mitchell R. Rosen, and Roy S. Berns. Comparison of spectrally narrow-band capture versus wide-band with a priori sample analysis for spectral reflectance estimation. In *Proceedings of IS&T and SID's 8th Color Imaging Conference: Color Science, Systems and Applications*, pages 234–241, Scottsdale, Arizona, 2000.

[6] Roy S. Berns and Francisco H. Imai. Pigment identification of artist materials via multi-spectral imaging. In *Proceedings of IS&T and SID's 9th Color Imaging Conference: Color Science, Systems and Applications*, pages 85–90, Scottsdale, Arizona, 2001.

[7] Timothy Kohler and Roy S. Berns. Reducing metamerism and increasing gamut using five or more colored inks. In *IS&T's Third Technical Symposium On Prepress, Proofing, and Printing*, pages 24–29, 1993.

[8] Di-Yuan Tzeng and Roy S. Berns. Spectral-based six-color separation minimizing metamerism. In *Proceedings of IS&T*

and SID's 8th Color Imaging Conference: Color Science, Systems and Applications, pages 342–347, Scottsdale, Arizona, 2000.

[9] Lawrence Taplin and Roy S. Berns. Spectral color reproduction based on a six-color inkjet output system. In *Proceedings of IS&T and SID's 9th Color Imaging Conference: Color Science, Systems and Applications*, pages 209–214, Scottsdale, Arizona, 2001.

[10] Henri Maître, Francis Schmitt, Jean-Pierre Crettez, Yifeng Wu, and Jon Y. Hardeberg. Spectrophotometric image analysis of fine art paintings. In *Proceedings of IS&T and SID's 4th Color Imaging Conference: Color Science, Systems and Applications*, pages 50–53, Scottsdale, Arizona, 1996.

[11] Jon Y. Hardeberg. *Acquisition and Reproduction of Color Images: Colorimetric and Multispectral Approaches*. Dissertation.com, Parkland, Florida, USA, 2001. Available at http://www.dissertation.com/library/1121350a.htm. (Revised second edition of Ph.D dissertation, Ecole Nationale Supérieure des Télécommunications, Paris, France, 1999).

[12] Jon Y. Hardeberg, Francis Schmitt, and Hans Brettel. Multispectral color image capture using a Liquid Crystal Tunable Filter. *Optical Engineering*, 41(10):2532–2548, 2002.

[13] Alejandro Ribés, Francis Schmitt, and Hans Brettel. Reconstructing spectral reflectances of oil pigments with neural networks. In *Proceedings of 3rd International Conference on Multispectral Color Science*, pages 9–12, Joensuu, Finland, June 2001.

[14] Alejandro Ribés, Hans Brettel, Francis Schmitt, Haida Liang, John Cupitt, and David Saunders. Color and multispectral imaging with the crisatel multispectral system. In *Proc. IS&T's 2003 PICS Conference*, pages 215–219, Rochester, New York, 2003.

[15] Jon Y. Hardeberg and Jérémie Gerhardt. Characterization of an eight colorant inkjet system for spectral color reproduction. In *CGIV'2004, Second European Conference on Colour in Graphics, Imaging, and Vision*, pages 263–267, Aachen, Germany, April 2004.

[16] Arne M. Bakke, Ivar Farup, and Jon Y. Hardeberg. Multispectral gamut mapping and visualization – a first attempt. In *Color Imaging: Processing, Hardcopy, and Applications X, Electronic Imaging Symposium*, volume 5667 of *SPIE Proceedings*, pages 193–200, San Jose, California, January 2005.

[17] David Connah and Jon Y. Hardeberg. Spectral recovery using polynomial models. In *Color Imaging: Processing, Hardcopy, and Applications X*, volume 5667 of *SPIE Proceedings*, pages 65–75, San Jose, California, January 2005.

[18] David Connah, Ali Alsam, and Jon Y. Hardeberg. Multispectral imaging: How many sensors do we need? *Journal of Imaging Science and Technology*, 50(1), 2006.

[19] Ali Alsam and David Connah. Recovering natural reflectances with convexity. In *Proceedings of the 9th Congress of the International Colour Association, AIC Color 2005*, pages 1677–1680, Granada, Spain, May 2005.

[20] Ali Alsam and Jon Y. Hardeberg. Optimal colorant design for spectral colour reproduction. In *IS&T/SID's Twelfth Color Imaging Conference*, Scottsdale, Arizona, November 2004.

[21] Jérémie Gerhardt and Jon Y. Hardeberg. Spectral colour reproduction by vector error diffusion. In *To be presented at CGIV'2006, Third European Conference on Colour in Graphics, Imaging, and Vision*, Leeds, UK, June 2006.

[22] Isaac Newton. New theory about light and colors. *Philosophical Transactions of the Royal Society of London*, 80:3075–3087, 1671. Excerpts reprinted in [37], pp 3–4.

[23] Günter Wyszecki and W. S. Stiles. *Color Science: Concepts and Methods, Quantitative Data and Formulae*. John Wiley & Sons, New York, 2 edition, 1982.

[24] *Colorimetry*, volume 15:2004 of *CIE Publications*. Central Bureau of the CIE, Vienna, Austria, 2004.

[25] Mark D. Fairchild. *Color Appearance Models*. Addison-Wesley Publishing Company, 1997.

[26] A. Mansouri, F. S. Marzani, J. Y. Hardeberg, and P. Gouton. Optical calibration of a multispectral imaging system based on interference filters. *Optical Engineering*, 44(2), 2005.

[27] Alamin Mansouri. *Etude, conception et réalisation d'un système multispectral de vision pour des applications de proximité, et développement d'algorithmes de reconstruction de la réflectance*. PhD thesis, Université de Bourgogne, Dijon, France, November 2005.

[28] David Connah, Jon Y. Hardeberg, and Stephen Westland. Comparison of spectral reconstruction methods for multispectral imaging. In *Proceedings of the IEEE International Conference on Image Processing*, Singapore, October 2004.

[29] H. Owens. *Colour and spatiochromatic processing in the human visual system*. PhD thesis, University of Derby, Derby, UK, 2002.

[30] R. W. G. Hunt. *The Reproduction of Colour in Photography, Printing and Television*. Fountain Press, Kings Langley, UK, 3 edition, 1975. (Currently available in its 6th edition.).

[31] H. E. J. Neugebauer. Die theoretischen Grundlagen des Mehrfarbendruckes. *Zeitschrift für wissenschaftliche Photographie, Photophysik und Photochemie*, 36(4):73–89, April 1937.

[32] J. A. C. Yule and W. J. Nielsen. The penetration of light into paper and its effect on halftone reproductions. In *Proceedings of the Technical Association of the Graphic Arts (TAGA)*, volume 3, page 65, 1951.

[33] Ali Alsam, Jérémie Gerhardt, and Jon Y. Hardeberg. Inversion of the spectral Neugebauer printer model. In *Proceedings of the 9th Congress of the International Colour Association, AIC Color 2005*, pages 473–476, Granada, Spain, May 2005.

[34] Robert W. Floyd and Louis Steinberg. An adaptive algorithm for spatial greyscale. *Proceedings of the Society for Information Display*, 17(2):75–77, 1976.

[35] J. F. Jarvis, C. N. Judice, and W. H. Ninke. A survey of techniques for the display of continuous tone pictures on bilevel displays. *Computer Graphics and Image Processing*, 5:13–40, 1976.

[36] H. Haneishi, T. Suzuki, N. Shimoyama, and Y. Miyake. Color digital halftoning taking colorimetric color reproduction into account. *Journal of Electronic Imaging*, 5(5):95–106, January 1996.

[37] D. MacAdam, editor. *Selected Papers on Colorimetry — Fundamentals*, volume 77 of *Milestone Series*. SPIE Optical Engineering Press, Bellingham, Washington, 1993.

ACKNOWLEDGEMENTS

I want to express my deepest gratitude to all those who have collaborated with me on different projects within this field, in particular Professor Francis Schmitt, who got me started in this area, as well as my colleagues and students Ali Alsam, David Connah, Ambroise Marin, Jeremie Gerhardt, and Arne Magnus Bakke.