Algorithms for spectral color stimulus reconstruction with a seven-channel multispectral camera

Stephan Helling *Enrico Seidel*
Aachen University of Technology
Aachen, Germany

Wolfram Biehlig
JENOPTIK LDT GmbH
Gera, Germany

Abstract

A mobile seven-channel multispectral camera with optical bandpass filters has been realized. The filters are arranged in a filter wheel rotating between lens and greyscale sensor (CCD). The time required for a complete multispectral exposure was brought down to less than one second. The main part of this paper deals with the algorithms applied to reconstruct spectral color stimuli information from the seven sampling values of the camera. Different methods have been simulated and tested. Results are presented. As the camera is handy enough to offer mobile applications, the illuminant problem for the use under varying light conditions has been studied. Finally, a solution for geometric inter-channel distortions due to glass filters within the optical path inside the camera is pointed out.

Introduction

A variety of multispectral cameras with four or more spectral channels have been proposed and realized [10]. Channel responsivity curves vary from narrow-band gaussian type to specifically adapted distributions. An advanced concept [9] for professional quality color reproduction uses 16 channels with gaussian transmission distribution, realized by optical interference filters. The filters cover the range of the visible light equidistantly from 400 nm to 700 nm. A halogen lamp is used as light source. The filters are arranged in a filter wheel that rotates between the lamp and the object being inserted into a drawer. With this setup it is possible to record the spectral reflectances of surface colors very accurately resulting in remarkably low color distance CIE ΔE_{94} between the original color and the reproduction. Total recording time ranges in the order of minutes.

New seven-channel camera

To close the gap between the high quality 16-channel camera technology on one hand and the common three-channel technology on the other hand, a seven-channel camera covering the range of almost all natural colors has been realized. It consists of an industrial grey scale camera ($1029 * 1292$ pixels, 8 bit) with a filter wheel rotating between CCD chip and objective. The wheel contains seven gaussian bandpass filters, which are arranged equidistantly from 400 nm to 700 nm with a half-power bandwidth of 40 nm (fig. 1). The time required for a complete multispectral exposure is

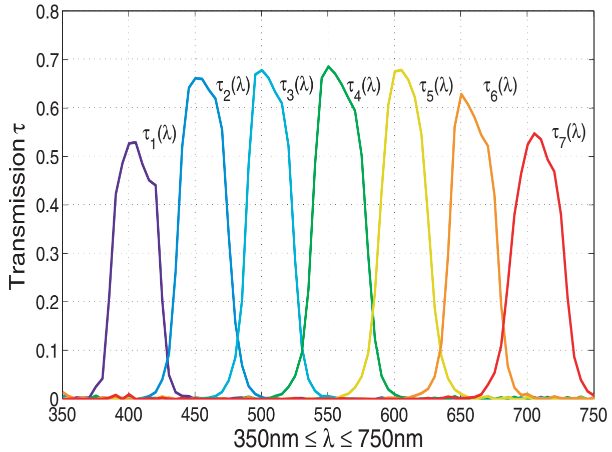


Figure 1: Gaussian type channel sensitivities of multispectral camera covering the range of visual light from 400 *nm to* 700 *nm.*

less than one second, due to the fact that the filter wheel rotates continuously during a multispectral exposure. Though recording of moving objects is not yet possible, a significant decrease in recording time is realized compared to other multispectral cameras that casually need exposure times in the size of minutes. Due to the small dimensions of the camera, it additionally provides the advantage of mobility. Accordingly, it is not restricted to the use in a studio but can be taken outside, too. As outdoor light conditions are subject to fluctuations, a spectral reconstruction method has been developed that is virtually light independent. Simulations with different illuminants show good results.

Camera Modeling

On one hand, the creation of an exact spectral reconstruction function can be done based on the physical transfer function of the camera [4, 5]. In a second approach, the camera can be regarded as a black box. So first, a model of the camera has been implemented that provides each channel's output signals corresponding to any given spectral stimulus at the input.

All spectral data (filter transmissions, sensor sensitivity, illuminant and the object's spectral reflectance) are therefore sampled between $\lambda_{min} = 350\,nm$ and $\lambda_{max} = 750\,nm$ (81 samples), which reduces the integrals to matrix and vector operations. In the end, there is a camera model (matrix $\mathbf{H}$) that predicts the seven output signals as function of the spectral illuminant, the object's spectral reflectance and exposure time. Nonlinear effects (e.g. CCD distortion and black offset) are added and result in good agreement between the model and the real camera's behaviour.

The camera's output signals basically have an integral characteristic. This results in the fact, that an infinite number of different color stimuli lead to the same channel signals at the camera's output. Secondly, the transfer function cannot be analytically inverted: numerical calculations are required in order to obtain the original spectral stimulus from the camera signal.

Spectral Reconstruction

Having defined a camera model $\mathbf{H}$, the inverse transfer function $\mathbf{H}_{inv}$ is calculated in the next step, which cannot be done analytically due to the fact that the matrix $\mathbf{H}$ is not a square matrix. Several methods aiming at a numerical inversion of $\mathbf{H}$ were implemented and tested: pseudo inverse, regression, Wiener inverse and optimized Wiener inverse [3]. These four methods were compared by presenting a spectral data set of a large number of reflectance spectra of natural colors (like Vrhel's set [1]) to the model and calculating ΔE_{94} between the original and the reconstructed colors. The ColorChecker DC has been recorded as well by the camera and results of the reconstructions have been compared with high accurate spectral measurements of the ColorChecker taken in advance.

The simple pseudo inverse $\mathbf{H}^+$ of the transfer function $\mathbf{H}$ shows the poorest performance (see Fig. 2a for spectral reconstruction considering a yellow color as example). All of the reconstructed spectra suffer from a strong ripple content resulting from the seven gaussian type channel sensitivities. Therefore, this method is not adequate for spectral reconstruction, as natural spectra usually have a flat distribution. Nevertheless, the Lab color values derived from these spectra are better than initially expected, because over- and undershoots cancel out each other under certain conditions when calculating XYZ tristimulus values.

In order to find an inverse transfer function $\mathbf{H}_{inv}$ using regression (Fig. 2b), a representative spectral data set $\mathbf{F}$ (like Vrhel's set) is presented to the camera model and all channel signals $\mathbf{Y}$ are measured. This way a transfer function $\mathbf{H}$ is obtained that regards the camera as a black box, with no physical characteristics of the camera being invested. The pseudo inverse $\mathbf{H}^+$ of this function $\mathbf{H}$ can be derived from $\mathbf{F}$ and $\mathbf{Y}$. Very good reconstruction results are generated. Nevertheless, an important disadvantage of this method must be seen in the fact that the spectral data used to gain the inverse transfer function is preliminarily fixed, so the inverse transfer function is trained on this set. As a consequence, spectra from the utilised data set are reconstructed very well, whereas other spectra tend to be reconstructed badly. This means that in order to guarantee good reconstruction results, information about the expected spectra is needed in advance [6, 7, 8]. This can be the case when digitizing paintings, where the color pigments can be measured spectrally beforehand. But, unfortunately, this method is not practical in order to obtain a generally useable inverse transfer function.

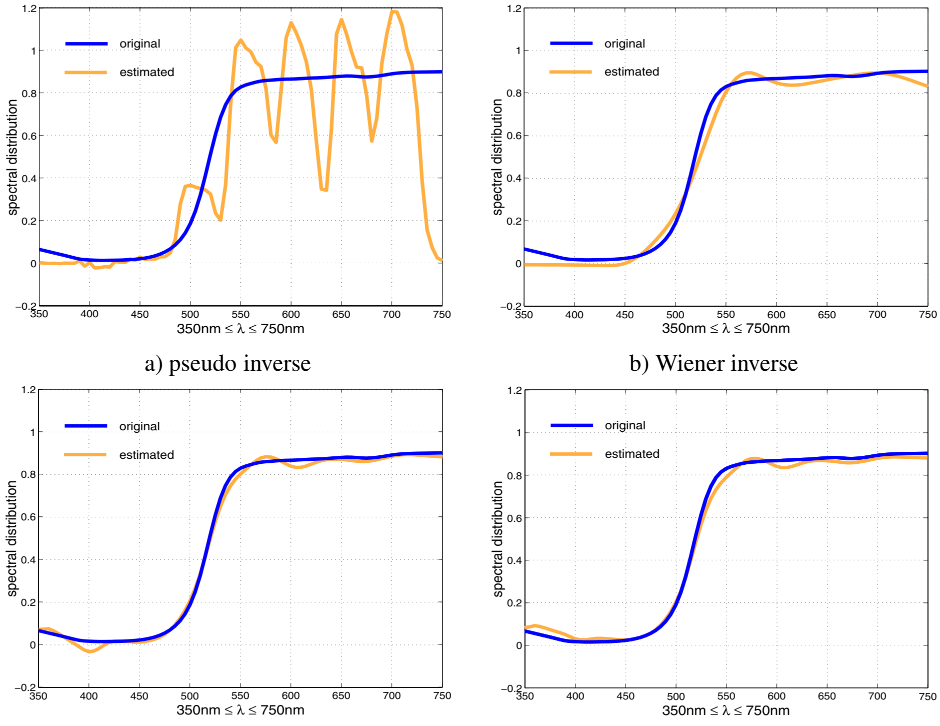
The third reconstruction method utilizes the Wiener inverse (Fig. 2c), which takes into account that natural spectra usually have a quite flat distribution. Thus, such spectral distributions own a very high auto correlation coefficient ($\rho \approx 0.99$). The Wiener matrix, which is part of the inverse transfer function, contains this coefficient and higher orders of it. It must be noted that this inverse transfer function is not trained on a special spectral data set. In fact, the original physical transfer function $\mathbf{H}$ is invested. This characteristic suggests the good general usability of the inverse function, as there is no spectral data needed for training. Reconstructions tend to be good over a wide variety of test spectra.

A variant of the Wiener inverse can be obtained by calculating the correlation coefficients ρ of the Wiener matrix from a spectral data set (Fig. 2d). This way, the inverse transfer function will be optimized to work on this data set. Similar to the regression, this method will produce good results, if there is *a priori* knowledge about the expected spectra. But, as well, it suffers from the shortcoming that other spectra not showing the same degree of autocorrelation potentially are reconstructed badly.

Table 1 shows average and maximum CIE ΔE_{94} achieved by the different reconstruction methods. Figure 3 shows the corresponding distributions.

Table 1: Comparison of CIE ΔE_{94} color distances between original and reproduced colors achieved by different spectral reconstruction methods for ColorChecker DC. Reconstruction methods are denoted as follows: a) pseudo inverse, b) Wiener inverse with $\rho = .99$, c) Wiener inverse, trained on spectral data set, d) regression.

	camera		simulation	
method	$\Delta E_{94,av}$	$\Delta E_{94,max}$	$\Delta E_{94,av}$	$\Delta E_{94,max}$
a)	2.67	6.24	2.45	5.08
b)	1.04	7.34	.517	1.86
c)	1.1	7.96	.501	2.63
d)	.864	7.66	.376	1.58



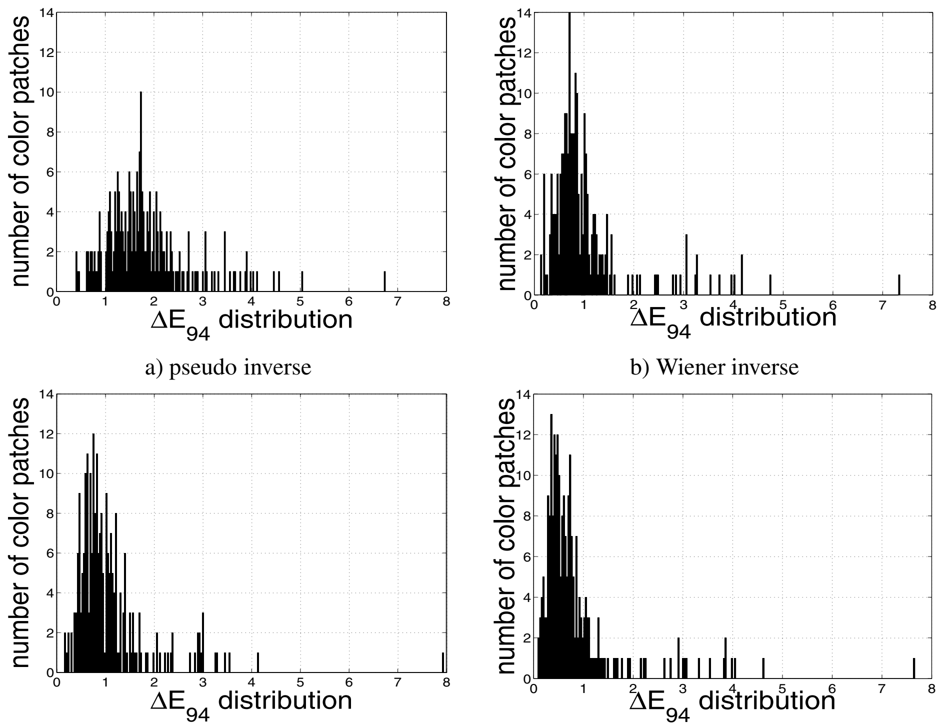
a) pseudo inverse

b) Wiener inverse

c) Wiener inverse, trained on data set

d) regression

Figure 2: Comparison of four reconstruction methods considering a yellow color as example.



a) pseudo inverse

b) Wiener inverse

c) Wiener inverse, trained to data set

d) regression

Figure 3: Histograms of CIE ΔE_{94} values between original and reproduced colors achieved by different spectral reconstruction methods for ColorChecker DC. The very high, single maximum value of about $8\Delta E_{94}$ results from a dark, black color tone, where the signal-to-noise-ratio is very bad.

Effects of different illuminants on spectral reconstruction

The color stimulus ϕ_λ recorded by the camera consists of the inseparable product of both the illuminant $S(\lambda)$ and the object's reflectance spectra $\beta(\lambda)$. The camera signal y_i of channel i can be described as

$$y_i = k_i \int_{\lambda_{min}}^{\lambda_{max}} S(\lambda)\,\beta(\lambda)\,o(\lambda)\,\tau_i(\lambda)\,E(\lambda)\,d\lambda \qquad (1)$$

with $o(\lambda)$: spectral transfer function of lens system, $\tau_i(\lambda)$: transmission distribution of filter i, $E(\lambda)$: sensitivity of CCD, $\lambda_{min} = 350\,nm$, $\lambda_{max} = 750\,nm$. In case the spectral distribution of the illuminant is known (e.g. in a studio), the reflectance spectra can be easily calculated by dividing the estimated color stimulus $\widehat{\phi_\lambda}$ by the illuminant's spectral distribution $S(\lambda)$. Yet, the camera proposed in this paper is intended for mobile use, so, as light conditions are subject to change, no information about the illuminant can be taken into account during spectral reconstruction. Consequently, a method had to be developed in order to minimize the effect of illumination on spectral reconstruction.

The basic assumption is that the illuminant spectra $S(\lambda)$ is relatively flat, so it can be considered constant within each of the seven wavelength sections defined by the filters. Being no function of wavelength λ it can be written in front of the integral as a constant multiplier $\overline{S_i}$. The new equation for the channel signal y_i is

$$y_i = k_i \overline{S_i} \int_{\lambda_{min}}^{\lambda_{max}} \beta(\lambda)\,o(\lambda)\,\tau_i(\lambda)\,E(\lambda)\,d\lambda. \qquad (2)$$

The set of amplification constants $\overline{S_i}$ can be measured simply by recording the white reference, whose spectral characteristic ideally should be $\beta_{white}(\lambda) \equiv 1$. In this case, all factors in the integral are known and can be calculated as function of the camera model, which is important for simulation purposes. The set of constant factors $\overline{S_i}$ will then be used to rescale the set of image separations of the recorded object. The result is a simulation of recording with equal energy white as light source. Any given light source can be used afterwards as illuminant during spectral reconstruction. The normalised channel signal $\widetilde{y_i}$ finally is

$$\widetilde{y_i} = y_{white,i} \frac{\int_{\lambda_{min}}^{\lambda_{max}} \beta(\lambda)\,o(\lambda)\,\tau_i(\lambda)\,E(\lambda)\,d\lambda}{\int_{\lambda_{min}}^{\lambda_{max}} \beta_{white}(\lambda)\,o(\lambda)\,\tau_i(\lambda)\,E(\lambda)\,d\lambda}. \qquad (3)$$

In case of ideally flat light distributions $S(\lambda)$ there is no reproduction error at all, but it must be annotated that this method is slightly erroneous, if the light distribution contains peaks. Anyhow, simulations with different illuminants (see table 2) showed that this error is virtually independent from the illuminant and negligible compared to the benefit of light independent multispectral exposures.

Table 2: Influence of different light sources on average ΔE_{94} between original and reconstructed colors. Illumination during exposure has virtually no effect on spectral reconstruction.

illuminant	$\Delta E_{94,av}$
A	0.641
B	0.344
C	0.344
D65	0.347
E	0.388
Xe	0.367

Geometric inter-channel distortions

As the filter wheel is arranged within the optical path inside the camera, i.e. between CCD sensor and lens, there is a geometric influence on the optical transfer function in addition to the spectral filter characteristic. Due to a variation of filter thickness and the virtual impossibility to arrange all filters absolutely coplanarly in the filter wheel, there are geometric translations and focus differences between the channels. The geometric translations ranging up to +/-5 pixels in both x and y direction lead to parasitic rainbow colors on objects' edges in the reconstructed color image. Unfortunately, this distortion is neither spatially constant over one channel nor constant between the images of the same channel of different objects. In fact, it depends from object distance, camera zoom and aperture, so that a correction has to be recalculated by the software for each multispectral exposure.

Figure 4: Translation vectors are determined for a set of subregions. Orientation and length vary throughout the image.

To achieve this, the image is initially divided into a set of subregions, in order to take into account the nonuniformity of the translation vector over the image. One of the pictures, usually the one containing the best signal-to-noise-ratio, is defined as reference. Translation vectors are now calculated individually for each region for all other pictures (fig. 4). The calculation is based on a correlation analysis between the reference and the translated sample region. High correlation coefficients (close to 1) indicate a good congruency of reference and sample. A downhill type algorithm is used for

finding the coefficient's maximum as function of translation vector for each picture region.
Finally, a vector array with the same size as the original image is produced. It contains the calculated translation vectors for the selected regions. The vectors for the rest of the pixels are generated by bilinear interpolation. In order to gain best results and completely abolish rainbow edges, subpixel translations turned out to be indispensable.
Also, a good contrast within the analysed region of the images is needed, otherwise fixed-pattern-noise will possibly generate wrong geometric fits.

Conclusion

A mobile seven-channel multispectral camera has been realized and simulated on a computer. Different methods of spectral reconstruction based on the seven color samples were implemented, tested and compared. The ColorChecker DC has been used for these purposes. The color distance ΔE_{94} between the original and the reconstructed colors was used as a quality criteria for the spectral reconstruction. The comparison showed that the Wiener estimation produces the best results, if no *a priori* information about the expected spectra is available. If this information existed, regression turned out to be the most suitable reconstruction method.
A convenient method was shown that allows multispectral images to be taken without any knowledge about the illuminant used during exposure, as long as the spectral distribution of the light source is reasonably flat. Also, a solution for correcting geometric inter-channel distortions was given.

References

[1] M.J. Vrhel, R. Gershon, L.S. Iwan, "Measurement and Analysis of Object Reflectance Spectra", Color Res. Appl. 19, No. 1, 1994, pp. 4-9

[2] G. Wyszecki, W.S. Stiles, "Color Science - Concepts and Methods, Quantitative Data and Formulae", Second Edition, John Wiley & Sons, New York, 2000, ISBN 0-471-39918-3

[3] F. König, "Die Charakterisierung von Farbsensoren", PdD Thesis, Aachen, 2001

[4] G.E. Healy, R. Kondepudy, "Radiometric CCD Camera Calibration and Noise Estimation", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 16, No. 3, March 1994

[5] J.Y. Hardeberg, H. Brettel, F. Schmitt, "Spectral characterisation of electronic cameras", Signal and Image Processing Department, École Nationale Supérieure des Télécommunications, Paris, France

[6] H. Haneishi, T. Hasegawa, A. Hosoi, Y. Yokoyama, "System design for accurately estimating spectral reflectance of art paintings", Department of Information and Image Science, Chiba University

[7] F. Imai, R. Berns, "High-Resolution Multi-Spectral Image Archives - A Hybrid Approach", Munsell Color Science Laboratory, Rochester Institute of Technology, Rochester, New York

[8] Y. Yokoyama, N. Tsumura, H. Haneishi, Y. Miyake, "A New COlor Management System Based on Human Perception and its Application to Recording and Reproduction of Art Paintings", The Fifth Color Imaging Conference: Color Science, Systems and Applications

[9] W. Praefke: "Multispektrale Verarbeitung und Reproduktion von Farbtönen"; Fortschritt-Berichte VDI, Nr. 680, PhD Thesis, Aachen, 2001

[10] J. Hardeberg, F. Schmitt, H. Brettel, J-P. Crettez, H. Maître, "Multispectral Image Acquisition and Simulation of Illuminant Changes", Colour Imaging: Vision and Technology, Wiley 1999

Biography

Stephan Helling received his diploma degree in Electrical Engineering from the Aachen University of Technology in 2001. He is now engaged in research on multispectral imaging systems with focus on multispectral cameras. He is member of the German Society for Color Science and Application DfwG.