A Spatially Adaptive Wiener Filter for Reflectance Estimation

Philipp Urban, Mitchell R. Rosen, Roy S. Berns;
Munsell Color Science Laboratory, Chester F. Carlson Center for Imaging Science,
Rochester Institute of Technology, 54 Lomb Memorial Drive, Rochester, New York 14623

Abstract

Wiener filtering has many applications in the area of imaging science. In image processing, for instance, it is a common way of reducing Gaussian noise. In color science it is often used to estimate reflectances from camera response data on a pixel by pixel basis. Based on a priori *assumptions the Wiener filter is the optimal linear filter in the sense of the minimal mean square error to the actual data. In this paper we propose a spatially adaptive Wiener filter to estimate reflectances from images captured by a multispectral camera. The filter estimates pixel noise using local spatial neighborhood and uses this knowledge to estimate a spectral reflectance. In the hypothetical case of a noiseless system, the spatially adaptive Wiener filter equals the standard Wiener filter for reflectance estimation. We present results of various simulation experiments conducted on a multispectral image database using a 6-channel acquisition system and different noise levels.*

Introduction

Estimation of reflectance spectra from camera responses is generally an ill-posed problem since a high dimensional signal is reconstructed from a relatively low dimensional signal. Associated with the development of multispectral camera systems many techniques were developed to tackle this problem. The basic approach to achieve a good estimation of scene reflectance spectra is to utilize as much information from the underlying capturing process as possible. Success is commonly evaluated through the spectral root mean square difference from the measured reflectance spectrum or color differences (e.g. CIEDE2000 [1]) for a set of selected illuminants. We will give a short and by far not exhaustive overview of reflectance reconstruction methods in the following text.

Information used by reflectance estimation methods may include the knowledge of the acquisition illuminant, the channel sensitivities of the camera, noise properties of the system and *a priori* knowledge of the source reflectance.

Most of the methods listed below require *a priori* knowledge of the spectral sensitivities of the camera system and of the acquisition illuminant. A common approach is to consider properties of natural reflectance spectra as additional *a priori* knowledge. These properties include positivity, boundedness and smoothness. Low effective dimensionality [2]. of natural reflectances is the reason why many methods use a low-dimensional linear model to describe spectra such as introduced in this context by Maloney and Wandell [3].

Some methods utilize a low dimensional linear model of reflectances to calculate the smoothest reflectance of all device metameric spectra (all spectra that lead to the given sensor response)[4, 5, 6]. Other methods use nearest neighbor type approaches within higher dimensional linear models [7] or adaptive principle component analysis (PCA) [8]. It was observed that a combination of multiple techniques can lead to improved reconstructions [9]. DiCarlo and Wandell extended the linear model in order to find reflectances lying on a submanifold that may describe the set of captured reflectances more accurate [10].

When camera sensitivities are not available, some approaches treat the system as a black box and use captured color-targets with known reflectances in order to construct a response-to-reflectance transformation [11, 12, 13]. The accuracy of these target-based methods is by construction highly dependent on the training target [14].

If additional information about the captured spectra is known, e.g. by a low resolution spectral sampling of the image [15] or by capturing printed images knowing the model of the printing device [16, 17], the accuracy of the spectral reconstruction can be further improved.

A special linear estimation technique widely used in spectral reconstruction is the Wiener filter. Based on the assumption of a normal distribution of reflectances and system noise and the assumption that noise is statistically independent of the reflectances, it is the optimal linear filter in the sense of the minimal mean square error to the actual reflectance. The Wiener filter has the form

$$r = K_r\Omega^T(\Omega K_r\Omega^T + K_\varepsilon)^{-1}c \tag{1}$$

where K_r is the covariance matrix of reflectance spectra, K_ε is the covariance matrix of additive noise, c is the sensor response, Ω is the device lighting matrix described in detail in eq. (2) and r is the reconstructed spectrum.

Several factors can prevent the Wiener filter from performing optimally in the sense of the minimal mean square error:

1. The reflectance covariance matrix K_r can only be approximated suboptimally. A minimal knowledge approach uses a Toeplitz matrix [18]. Other approaches use a representative set of reflectances to estimate the covariance matrix [19]. Shen and Xin [20, 21] proposed a method that adaptively selects and weighs these training spectra in order to estimate the reflectance covariance matrix based on the actual sensor response. A Bayesian approach of Zhang and Brainard highly related to the Wiener filter estimates the covariance

matrix using a low dimensional space of reflectance weights [22].

2. The Wiener filter cannot ensure the positivity and boundedness of the estimation. Both are important properties of natural reflectances. In the approach of Zhang and Brainard [22] that performs a Gaussian fit in a low dimensional space of reflectance weights all weights that correspond to reflectance functions with negative values have been excluded. This technique shall ensure the positivity of reconstructions.
3. Noise plays an important role in image acquisition systems. The accuracy of the Wiener estimation is highly dependent on the magnitude of system noise. Furthermore, the Wiener filter assumes signal-independent noise and disregards the signal-dependent shot noise. In eq. (3) the noise sources in electronic imaging devices are sketched and a commonly used noise model is introduced. An additional problem is the estimation of the noise covariance matrix. The accuracy of the Wiener reconstruction is highly dependent on the quality of the noise covariance estimation. Shimano [23] proposed a method for estimating this noise covariance matrix and achieved a good performance in terms of colorimetric and spectral RMS errors compared to multiple methods described above [24].

The first two problems above are not addressed in this paper. If desired, the algorithms proposed by other authors can be incorporated to the proposed spatially adaptive Wiener filter.

Our paper focuses solely on the noise problem. The observation of the large dependency of the Wiener estimation on the magnitude of the noise variance leads to the idea of reducing noise based on the local pixel neighborhood in order to improve the reconstruction of the Wiener filter.

The idea of combining spectral reflectance reconstruction with spatial noise reduction is not new. In a recent article Murakami *et al.* [25] proposed a spatio-spectral Wiener filter, which was called 3D Wiener (merging of 2 spatial dimension and 1 spectral dimensions in a single Wiener filter). In Murakami's *et al.* article a sequence of spatial Wiener filtering followed by spectral Wiener filtering was investigated as well and called 2D+1D Wiener filter. The 2D Wiener filter is applied channel-wise on the sensor-response image. The noise variance is estimated globally from the resulting image and used in the subsequent spectral 1D Wiener filter.

The approach proposed in this paper goes beyond 2D+1D Wiener filtering but does not go far as 3D Wiener filtering. In contrast to Murakami's *et al.* 2D+1D approach our 2D noise reduction is performed on all channels simultaneously using a single Wiener filter. The noise covariance matrix is updated locally and propagated to the spectral Wiener filter. Both steps can be combined as a single operator, which enables a simple parallel computing, similar to Murakami's *et al.* 3D Wiener filter. We will derive the spatially adaptive Wiener filter by Bayesian inference. Its noise reduction and propagation properties will be especially emphasized.

Model of a Linear Acquisition System

In this paper we consider linear acquisition systems. The discrete model of a n-channel capturing system is given by the following formula

$$c = DLr = \Omega r \tag{2}$$

where $c \in [0,1]^n$ is the sensor response, $r \in [0,1]^N$ the vector representing the spectral reflectance and Ω the $n \times N$ dimensional system matrix defined by the product of the matrix D containing the spectral sensitivities of the system as row vectors, and the diagonal matrix L, containing the spectral power distribution of the acquisition illuminant as diagonal elements. All vector representations of spectra are samples of continuous spectra at N equidistant wavelengths.

Noise Model

There are two categories of noise in electronic imaging devices: signal-independent and signal-dependent noise. Signal-independent noise includes thermal noise, reset noise and amplifier noise. It can be well modeled by a normal distribution with zero mean. Signal-dependent noise results from the measurement uncertainty due to the quantum nature of light and is called *photon shot noise* or simply *shot noise*. Shot noise follows a Poisson distribution, which can be well approximated by a signal dependent normal distribution if the number of photons detected by the device is large. The general noise model for an image acquisition system is given by the following formula

$$c = \Omega r + \varepsilon = \Omega r + G(\Omega r)\varepsilon_1 + \varepsilon_2 \tag{3}$$

where

$$G(\Omega r) = G((\omega_1,\dots,\omega_n)^T r) = \begin{pmatrix} g(\omega_1^T r) & & 0 \\ & \ddots & \\ 0 & & g(\omega_n^T r) \end{pmatrix} \tag{4}$$

models the signal dependency and $\varepsilon_1 \sim \mathcal{N}(0, K_1 = \sigma_1^2 I)$ and $\varepsilon_2 \sim \mathcal{N}(0, K_1 = \sigma_2^2 I)$ follow normal distributions with zero mean. Since ε_1 and ε_2 can be assumed as statistically independent the overall noise

$$\varepsilon \sim \mathcal{N}(0, G(\Omega r)K_1 G(\Omega r)^T + K_2) \tag{5}$$

is also normally distributed with zero mean.

Derivation of the Spatially Adaptive Wiener Filter

In image processing applications Wiener filtering is a common technique to remove Gaussian noise from images. The Wiener filter is the optimal linear filter in the sense of the minimal mean-square error to the noiseless image. In multispectral imaging the Wiener filter is used to optimally reconstruct spectral reflectances from camera responses in the sense of the minimal mean-square error to the original reflectances. In this context the filter is applied on a pixel-by-pixel basis, without adding information of the local pixel-neighborhood. The idea of the spatially adaptive Wiener filter is to combine both methods in order to add more information of the underlying process to the reconstruction. In the following text indexes i and j identify the spatial pixel position within the image.

Noise Reduction in the Spatial Domain

We will introduce the Wiener noise-reducing filter by means of Bayesian inference (see e.g. [26]). Bayesian inference uses prior knowledge of the distribution $p(c'_{ij})$ of noiseless sensor responses c'_{ij} in combination with a likelihood model $p(c_{ij}|c'_{ij})$ of the current sensor response c_{ij} given a noiseless sensor response c'_{ij}. Using this a priori knowledge, the distribution $p(c'_{ij}|c_{ij})$ of the noiseless sensor responses c'_{ij} given the actual sensor response c_{ij} can be estimated by Bayes'theorem. We make the following assumptions about the a priori distributions

$p(c_{ij}|c'_{ij})$**:** Our likelihood model has the following form $c_{ij} = c'_{ij} + \varepsilon$, where ε is additive noise following a normal distribution with zero mean and covariance matrix K_ε. We can assume uncorrelated noise with a diagonal covariance matrix $K_\varepsilon = \sigma_\varepsilon^2 I$ that can be estimated based on captured targets [23]. The distribution of $p(c_{ij}|c'_{ij})$ is therefore also normal with mean c'_{ij} and a covariance matrix K_ε. Since c'_{ij} is not known *a priori* we assume the mean to be c_{ij}, which results in the following distribution

$$p(c_{ij}|c'_{ij}) = \mathscr{N}(c_{ij}, K_\varepsilon) \tag{6}$$

$p(c'_{ij})$**:** We assume a normal distribution of noise-free sensor responses

$$p(c'_{ij}) = \mathscr{N}(\bar{c}_{ij}, K_{ij}). \tag{7}$$

We estimate the mean $\bar{c}_{ij}$ and covariance matrix K_{ij} based on a local pixel neighborhood C_{ij} of the actual pixel c_{ij}. This neighborhood can be chosen for instance as a $2m+1 \times 2m+1$ rectangular window, i.e. $C_{ij} = \{c_{kl} \mid k \in \{i-m, \ldots, i+m\},\ l \in \{j-m, \ldots, j+m\}\}$. In case of such rectangular window the distribution has the following mean and covariance matrix

$$\bar{c}_{ij} = \frac{1}{(2m+1)^2} \sum_{c \in C_{ij}} c \tag{8}$$

$$K_{ij} = \frac{1}{(2m+1)^2 - 1} \sum_{c \in C_{ij}} (c - \bar{c}_{ij})(c - \bar{c}_{ij})^T \tag{9}$$

In order to calculate the posteriori distribution $p(c'_{ij}|c_{ij})$ of the noiseless sensor response c'_{ij} given the actual sensor response c_{ij} we can use Bayes'theorem. The resulting distribution is again normal and has the following form

$$p(c'_{ij}|c_{ij}) = \frac{p(c'_{ij})p(c_{ij}|c'_{ij})}{p(c_{ij})} \tag{10}$$

$$= \mathscr{N}(W_{ij}(c_{ij} - \bar{c}_{ij}) + \bar{c}_{ij}, K_{ij} - W_{ij}K_{ij}). \tag{11}$$

where

$$W_{ij} = K_{ij}(K_{ij} + K_\varepsilon)^{-1} \tag{12}$$

is the noise-reducing Wiener filter. The maximum a posteriori estimate is the mean $W_{ij}(c_{ij} - \bar{c}_{ij}) + \bar{c}_{ij}$ of the posteriori distribution. This value is the minimum mean square error estimator for the noiseless sensor response given the noisy sensor response c_{ij}.

Reflectance Reconstruction from the Noise-Reduced Pixels

We propose the Wiener filter for the spectral reflectance reconstruction from the previously noise-reduced pixels. We will derive this filter by means of Bayesian inference as well. The prior distribution is the distribution $p(r_{ij})$ of reflectances r_{ij} and the likelihood model $p(c'_{ij}|r_{ij})$ is the distribution of noise-reduced sensor responses c'_{ij} given a reflectance spectrum r_{ij}. We make the following assumption about the prior distributions:

$p(c'_{ij}|r_{ij})$**:** Our likelihood model has the following form $c'_{ij} = \Omega r_{ij} + \hat{\varepsilon}$, where $\hat{\varepsilon}$ is additive noise already attenuated by the Wiener filter in eq. (12). This results in a normal distribution with mean Ωr_{ij} and a covariance matrix that equals the covariance matrix of the posteriori distribution $p(c'_{ij}|c_{ij})$ shown in eq. (11), i.e.

$$p(c'_{ij}|r_{ij}) = \mathscr{N}(\Omega r_{ij}, K_{ij} - W_{ij}K_{ij}) \tag{13}$$

$p(r_{ij})$**:** We assume a normal distribution of reflectance spectra with zero mean

$$p(r_{ij}) = \mathscr{N}(0, K_r). \tag{14}$$

The covariance matrix K_r can be estimated using a Toeplitz matrix [18] or by using a representative set of reflectance spectra $r_1, \ldots, r_q$ as follows

$$K_r = \frac{1}{q-1} \sum_{i=1}^{q} (r_i - \bar{r})(r_i - \bar{r})^T, \quad \bar{r} = \frac{1}{q} \sum_{i=1}^{q} r_i \tag{15}$$

The posteriori distribution $p(r_{ij}|c'_{ij})$ of spectral reflectances r_{ij} given the noise-reduced sensor response c'_{ij} can be calculated by Bayes'theorem and is again normal

$$p(r_{ij}|c'_{ij}) = \frac{p(r_{ij})p(c'_{ij}|r_{ij})}{p(c'_{ij})} \tag{16}$$

$$= \mathscr{N}(\hat{W}_{ij}c'_{ij}, K_r - \hat{W}_{ij}\Omega K_r). \tag{17}$$

where

$$\hat{W}_{ij} = K_r\Omega^T(\Omega K_r \Omega^T + K_{ij} - W_{ij}K_{ij})^{-1} \tag{18}$$

is the reflectance reconstructing Wiener filter based on already noise-attenuated sensor responses. The maximum a posteriori estimate is the mean $\hat{W}_{ij}c'_{ij}$ of the posteriori distribution. This value has the minimum mean square difference to the actual reflectance spectrum given the noise-reduced sensor response.

The Spatially Adaptive Wiener Filter

We can combine the noise-attenuating and the reflectance reconstructing Wiener filter by inserting the mean of the posteriori distribution defined in eq. (11) into the mean of the posteriori distribution defined in eq. (17). The result is the spatially adaptive Wiener filter

$$\mathscr{W}_{ij}(c_{ij}) = \hat{W}_{ij}W_{ij}(c_{ij} - \bar{c}_{ij}) + \hat{W}_{ij}\bar{c}_{ij} \tag{19}$$

where $\bar{c}_{ij}$ is the mean sensor response in a pixel neighborhood of c_{ij} (see e.g. eq. (9)), W_{ij} is defined in eq. (12) and $\hat{W}_{ij}$ is defined in eq. (18).

The spatially adaptive Wiener filter reduces to the traditional reflectance reconstructing Wiener filter in case of vanishing noise, i.e.

$$K_\varepsilon \to 0 \Rightarrow \mathscr{W}_{ij}(c_{ij}) \to K_r\Omega^T(\Omega K_r \Omega^T)^{-1}c_{ij} \tag{20}$$

Figure 1. *sRGB renderings of spectral images used in experiments. Left:* FruitsandFlowers*, Middle:* YoungGirl*, Right:* WomanFace.

Experiments

The spatially adaptive Wiener filter was tested on three images that are part of a spectral image database freely available on the website *www.multispectral.org*. Figure 1 shows the images rendered as sRGB images for illuminant CIE-D65. For our simulation experiments we used spectral sensitivity measurements of a modified Sinar 6-channel camera, which are shown in Figure 2. The acquisition illuminant was CIE-D65. In a first step the spectral camera sensitivities and the acquisition illuminant were used to render a camera response 6-channel image from each of the three spectral images.

In a second step we added different amounts of noise to each of the three 6-channel images by means of the noise model introduced in eq. (3). For this purpose signal-dependent and signal-independent noise were added based on all combinations of $\sigma_1 = 0, 0.002, \ldots, 0.01$ and $\sigma_2 = 0, 0.002, \ldots, 0.01$, which result in 36 different images for each of the three corresponding spectral images. These images were used to estimate the spectral reflectances using the standard Wiener filter (see eq. (1)) and the spatially adaptive Wiener filter (see eq. (19)).

To estimate the spectral reflectance covariance matrix K_r, spectral reflectance measurements of 1269 Munsell color chips were used according eq. (15). The Munsell spectra are available from the Information Technology Dept., Lappeenranta University of Technology, Finland. The noise covariance matrix K_ε was set to $K_\varepsilon = (\sqrt{0.5}\sigma_1 + \sigma_2)^2 I$. For the spatially adaptive Wiener filter a simple 3×3 window was used.

Results and Discussion

Figure 3 shows the average and 95 percentile spectral RMS reconstruction error against the signal to noise ratio for all images. A detailed breakdown is shown in Figures 4-6, where the average spectral RMS error is plotted against the signal-dependent and signal-independent noise. The table shows the numerical results for $\sigma_1 = \sigma_2 = 0, 0.002, \ldots, 0.01$.

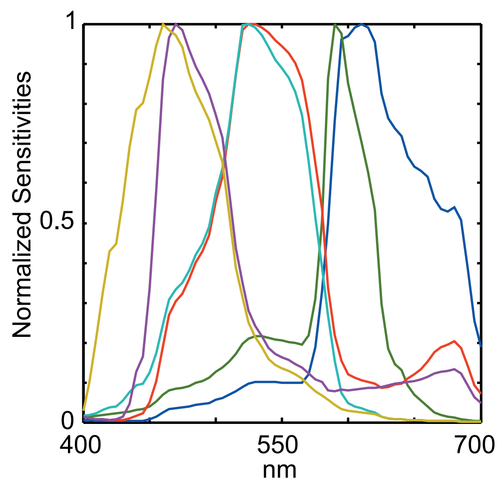

Figure 2. *Normalized spectral sensitivities of the modified Sinar 6-channel camera*

For the noise-free images the results for the Wiener filter and the spatially adaptive Wiener filter are similar, which validate the claim in eq. (20). For all other noise levels, both signal-dependent and signal-independent, the spatially adaptive Wiener filter outperforms the normal Wiener filter. The higher the noise level the larger the difference between the spectral RMS reconstruction errors. The results show that the improvement with respect to error rates in case of high noise levels is significant. For the test images *YoungGirl* and *WomanFace* it can reach up to 25% for the highest noise level. Not only the average spectral RMS errors are reduced also the 95 percentile, standard deviation and maximal errors are diminished.

To calculate the spatially adaptive Wiener filter two $n \times n$ matrices have to be inverted for each pixel, where n is the number of channels of the image acquisition system. As a consequence the numerical complexity to calculate the spatially adaptive Wiener filter is much higher than the complexity of the normal

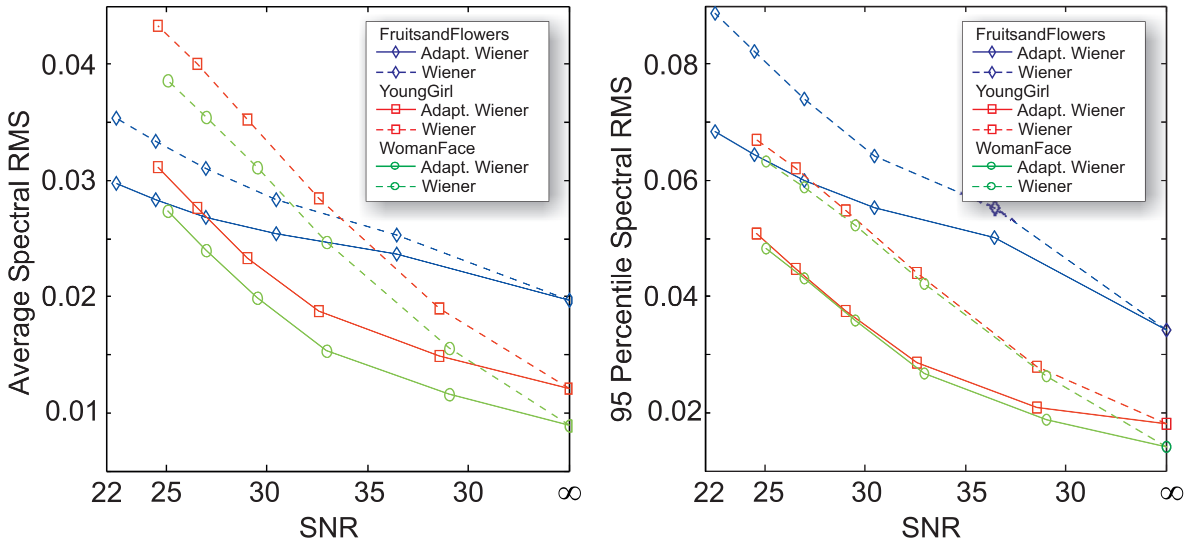

Figure 3. *Average (left) and 95 percentile (right) spectral RMS error against signal to noise ratio (SNR).*

Wiener filter. The decision to favor the spatially adaptive Wiener filter over the normal Wiener filter therefore strongly depends on the application and factors like noise level, number of channels n, available hardware, real-time requirements etc.

Spectral RMS results

	Adaptive Wiener			Wiener		
			FruitandFlowers			
σ_1, σ_2	Mean	Std	Max	Mean	Std	Max
0.000	0.020	0.007	0.066	0.020	0.007	0.066
0.002	0.024	0.012	0.082	0.025	0.013	0.084
0.004	0.025	0.013	0.087	0.028	0.016	0.095
0.006	0.027	0.015	0.099	0.031	0.018	0.111
0.008	0.028	0.016	0.099	0.033	0.021	0.125
0.010	0.030	0.017	0.104	0.035	0.023	0.133
			YoungGirl			
σ_1, σ_2	Mean	Std	Max	Mean	Std	Max
0.000	0.012	0.004	0.026	0.012	0.004	0.026
0.002	0.015	0.004	0.038	0.019	0.006	0.044
0.004	0.019	0.006	0.048	0.028	0.010	0.060
0.006	0.023	0.008	0.059	0.035	0.013	0.073
0.008	0.028	0.010	0.064	0.040	0.014	0.080
0.010	0.031	0.011	0.075	0.043	0.015	0.089
			WomanFace			
σ_1, σ_2	Mean	Std	Max	Mean	Std	Max
0.000	0.009	0.004	0.019	0.009	0.004	0.019
0.002	0.012	0.005	0.029	0.016	0.007	0.038
0.004	0.015	0.007	0.041	0.025	0.012	0.055
0.006	0.020	0.010	0.060	0.031	0.016	0.072
0.008	0.024	0.012	0.061	0.035	0.018	0.075
0.010	0.027	0.014	0.067	0.039	0.019	0.077

Conclusion

A spatially adaptive Wiener filter for reflectance estimation from camera signals was derived using Bayesian inference. For this purpose a noise-reducing Wiener filter and a spectral reconstruction Wiener filter were combined to a single filter using local propagation of the noise covariance matrix. The filter reduces to the normal spectral reconstruction Wiener filter in case of vanishing noise. In case of signal-dependent as well as signal-independent noise it outperforms the normal Wiener filter in terms of spectral RMS errors.

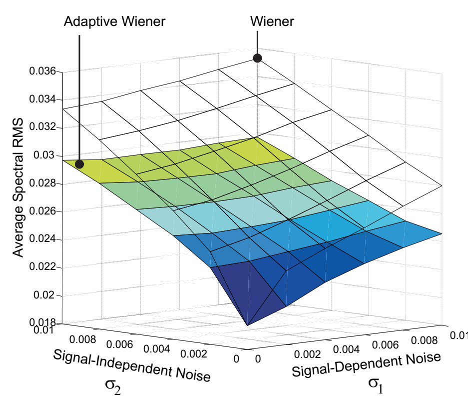

Figure 4. *Average spectral RMS errors for image:* FruitAndFlowers

References

[1] CIE Publication No. 142. Improvement to Industrial Colour Difference Evaluation. Vienna, 2001. CIE Central Bureau.

[2] J. Y. Hardeberg. On the spectral dimensionality of object colours. In *CGIV*, pages 480–485, Poitiers, France, 2002. IS&T.

[3] L. T. Maloney and B. A. Wandell. Color constancy- A method for recovering surface spectral reflectance. *Optical Society of America, Journal, A: Optics and Image Science*, 3:29–33, 1986.

[4] C. Li and M. R. Luo. The estimation of spectral reflectances using the smoothness constraint condition. pages 62–67, Scottsdale Ariz., 2001.

[5] V. Cheung, S. Westland, C. Li, J. Hardeberg, and D. Connah.

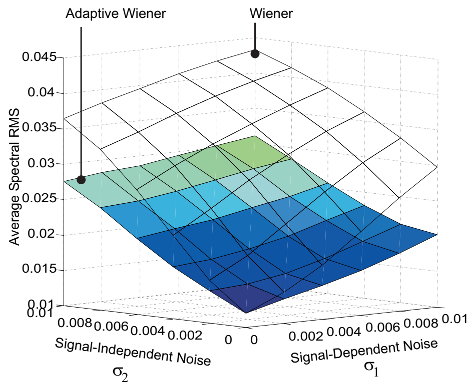

Figure 5. *Average spectral RMS errors for image:* YoungGirl

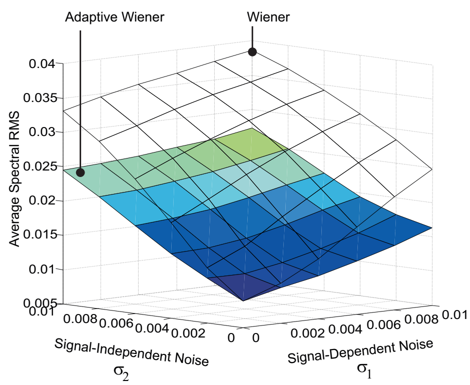

Figure 6. *Average spectral RMS errors for image:* WomanFace

Characterization of trichromatic color cameras by using a new multispectral imaging technique. *Journal of the Optical Society of America A*, 22(7):1231–1240, 2005.

[6] P. Morovic and G. D. Finlayson. Metamer-set-based approach to estimating surface reflectance from camera RGB. *Journal of the Optical Society of America A*, 23(8):1814–1822, 2006.

[7] M. Shi and G. Healey. Using reflectance models for color scanner calibration. *Journal of the Optical Society of America A*, 19:645–656, 2002.

[8] X. Zhang and H. Xu. Reconstructing spectral reflectance by dividing spectral space and extending the principal components in principal component analysis. *Journal of the Optical Society of America A*, 25(2):371–378, 2008.

[9] H. L. Shen, J. H. Xin, and S. J. Shao. Improved reflectance reconstruction for multispectral imaging by combining different techniques. *Optics Express*, 15(9):5531–5536, 2007.

[10] J. M. DiCarlo and B. A. Wandell. Spectral estimation theory: beyond linear but before Bayesian. *Journal of the Optical Society of America A*, 20(7):1261–1270, 2003.

[11] F. H. Imai and R. S. Berns. Spectral estimation using trichromatic digital cameras. In *Intl. Sym. Multispectral Imaging and Color Reproduction for Digital Archives*, pages 42–49, Chiba University, 1999.

[12] Y. Zhao and R. S. Berns. Image-based spectral reflectance reconstruction using the matrix R method. *Color Research and Application*, 32(5):343–351, 2007.

[13] C. Li and M. R. Luo. A novel approach for generating object spectral reflectance functions from digital cameras. In *IS&T/SID*, pages 99–103, Scottsdale Ariz., 2005.

[14] M. Mohammadi, M. Nezamabadi, R. Berns, and L. Taplin. Spectral imaging target development based on hierarchical cluster analysis. In *IS&T/SID, 12th Color Imaging Conference*, pages 59–64, Scottsdale Ariz., 2004.

[15] Y. Murakami, K. Ietomi, M. Yamaguchi, and N. Ohyama. Maximum a posteriori estimation of spectral reflectance from color image and multipoint spectral measurements. *Applied Optics*, 46(28):7068–7082, 2007.

[16] G. Sharma. Targetless scanner color calibration. *Journal of Imaging Science and Technology*, 44:301–307, 2000.

[17] G. Sharma. Set theoretic estimation for problems in subtractive color. *Color Research and Application*, 25:333–348, 2000.

[18] J.A.S. Viggiano. Minimal-knowledge assumptions in digital still camera characterization I.: Uniform distribution, Toeplitz correlation. *IS&T/SID, 9th Color Imaging Conference*, pages 332–336, 2001.

[19] 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.

[20] H. L. Shen and J. H. Xin. Spectral characterization of a color scanner by adaptive estimation. *Journal of the Optical Society of America A*, 21(7):1125–1130, 2004.

[21] H. L. Shen and J. H. Xin. Spectral characterization of a color scanner based on optimized adaptive estimation. *Journal of the Optical Society of America A*, 23(7):1566–1569, 2006.

[22] X. Zhang and D. H. Brainard. Bayesian color correction method for non-colorimetric digital image sensors. In *IS&T/SID*, pages 308–314, Scottsdale Ariz., 2004.

[23] N. Shimano. Recovery of spectral reflectances of objects being imaged without prior knowledge. *IEEE Transactions on Image Processing*, 15(7):1848–1856, 2006.

[24] N. Shimano, K. Terai, and M. Hironaga. Recovery of spectral reflectances of objects being imaged by multispectral cameras. *Journal of the Optical Society of America A*, 24(10):3211–3219, 2007.

[25] Y. Murakami, K. Fukura, M. Yamaguchi, and N. Ohyama. Color reproduction from low-SNR multispectral images using spatio-spectral Wiener estimation. *Optics Express*, 16(6):4106–4120, 2008.

[26] Ali Mohammad-Djafari. Bayesian inference for inverse problems in signal and image processing and applications. *International Journal of Imaging Systems and Technology*, 16(5):209–214, 2006.

Author Biography

Philipp Urban received his M.S. degree in Mathematics from the University of Hamburg in 1999 and his Dr. degree in the field of color science from the Hamburg University of Technology in 2005. From 1999 until 2006 he was part of the research group "Vision Systems" at the Hamburg University of Technology and worked for Ratio Entwicklungen GmbH (ICC-member) where he developed color managing systems. Since 2006 he is a visiting scientist at the Munsell Color Science Laboratory at the Rochester Institute of Technology. His research interests are color science and multispectral imaging.