Improving Spectral Reconstruction Accuracy from Noisy Camera Captures using Spatial Information

Philipp Urban

Institute of Printing Science and Technology, Technische Universität Darmstadt,
Magdalenenstr. 2, 64289 Darmstadt, Germany
urban@idd.tu-darmstadt.de
www.idd.tu-darmstadt.de/color

Abstract. A Wiener-based method is proposed that estimates reflectances from camera captures considering spatial image information. Motivated by the large influence of noise on the estimation accuracy of the standard Wiener method the new approach combines Wiener denoising with Wiener reflectance estimation. An adaptive selection of spatial-based parameters used for Wiener denoising avoids halo effects and preserves image edges. Experimental results utilizing face images of the Lippmann2000 spectral image database show significant accuracy improvements of the new spatio-spectral Wiener estimation compared to the standard Wiener method.

1 Introduction

The reconstruction of spectral reflectances from camera sensor responses is generally an ill-posed problem since high dimensional reflectances have to be reconstructed from relatively low dimensional camera data. For this reason many different methods have been proposed that use additional information, such as physical properties of reflectances or camera information, to improve reconstruction results.

There are basically two different classes of methods for the reconstruction of spectral refectances: Target-based methods and model-based methods. In some cases the reflectances of the acquired image are approximately known, e.g. if artwork is captured knowing the palette of the artist. For these applications a target using the similar reflectances as the original can be captured and a predefined response-to-reflectance transformation can be fitted to the resulting data. Such transformation can be applied onto the acquired image for estimating its reflectances [1,2].

Unfortunately, the reflectances of the original are often unknown. In this case the model of the camera system and general properties of reflectances such as positivity, smoothness or their distribution can be utilized. These class of methods is often referred as the model-based approach.

In this paper we are considering only linear acquisition systems. If the system is non-linear (e.g. if a gamma transformation is applied within the camera driver) a linearization step is required in advance, see e.g. [3]. We also consider discrete representations of spectra sampled on N equidistant positions within the sensitivity range of the camera system. The typically used camera model is

$$c = DLr + \epsilon = \Omega r + \epsilon \tag{1}$$

where $c \in [0,1]^n$ is the sensor response, $r \in [0,1]^N$ is the captured surface reflectance, ϵ is additive noise and Ω is a $n \times N$ dimensional system matrix. This matrix is the product of the $n \times N$ dimensional matrix D, containing the system sensitivities as row vectors and the $N \times N$ dimensional diagonal matrix L, containing the spectral power distribution of the illuminant as diagonal elements.

One widely used method is the Wiener spectral estimation, which assumes the normal distribution of reflectances $p(r) = \mathcal{N}(0, K_r)$ and noise $p(\epsilon) = \mathcal{N}(0, K_\epsilon)$ and their statistical independence. The Wiener filter matrix has the following form:

$$W = K_r \Omega^T (\Omega K_r \Omega^T + K_\epsilon)^{-1} \tag{2}$$

Based on the assumptions the Wiener estimation Wc is the optimal linear estimation with respect to the spectral root mean square (RMS) error to the actual reflectance. Even though the assumptions are only a rough approximation of the reality (reflectances do not follow a normal distribution rather a mixture of Gaussians [4] and shot noise is statistically dependent from reflectances) the Wiener spectral estimation is successfully used in many application. Unfortunately, the error rates of the Wiener estimation depend strongly on the noise level of the camera system [5]. Small signal-to-noise rations (SNR) cause large spectral RMS errors.

A relatively new approach to limit the influence of noise on the reconstruction accuracy is considering spatial image information. Murakami et al. [6] proposed a spatio-spectral Wiener estimation that reduces the error rates significantly for images with small SNR. An unwanted effect of the method on the image reconstruction are halo effects on edges. For this reason an adaptive spatio-spectral Wiener filter was proposed by Urban et al. [7] that has similar reconstruction accuracy to Murakami's filter but simultaneously preserves edges.

The edge-preserving spatio-spectral estimation will be presented in this paper. Simulation experiments conducted on noisy captures of skin colors of the Lippmann2000 spectral image database [8] will show that the spectral reconstruction accuracy from noisy sensor responses can be significantly improved if spatial image information are considered.

2 The Edge-Preserving Spatio-Spectral Wiener Estimation

The edge-preserving spatio-spectral Wiener estimation is a combination of edge-preserving Wiener denoising and reflectance estimation from the already denoised image. Both estimations can be combined into a single spatially adaptive operator that has to be applied on each pixel of the image.

2.1 Wiener Denoising

Wiener denoising can be derived by Bayesian inference [9] and is defined as follows

$$\acute{c}(i,j) = W_{\mathsf{d}}(i,j)\Big(c(i,j) - \bar{c}(i,j)\Big) + \bar{c}(i,j) \tag{3}$$

$$W_{\mathsf{d}}(i,j) = K_{\mathsf{s}}(i,j)\Big(K_{\mathsf{s}}(i,j) + K_{\epsilon}\Big)^{-1} \tag{4}$$

where $\acute{c}(i,j)$ is the denoised pixel value at position (i,j), $c(i,j)$ is the given noisy pixel value, $\bar{c}(i,j)$ is the estimation of a mean pixel value that is typically calculated by the mean of pixel values within a window around (i,j), $K_{\mathsf{s}}(i,j)$ is the $n \times n$ dimensional spatial covariance matrix and K_{ϵ} is the $n \times n$ dimensional noise covariance matrix. The noise is assumed to be uncorrelated so K_{ϵ} is diagonal and can be usually described with a single variance $K_{\epsilon} = \sigma_{\epsilon}^2 I$. The spatial covariance matrix $K_{\mathsf{s}}(i,j)$ can be calculated from pixels in a neighborhood around position (i,j). To allow for a quick calculation also a global choice of $K_{\mathsf{s}}(i,j) = K_{\mathsf{s}}$ may be considered. In such case a simple Toeplitz matrix may be used utilizing global correlation coefficients in vertical and horizontal directions. Since the correlation may vary in different image regions this results in halo effects around edges.

In order to avoid this negative effect the idea of edge preserving Wiener denoising is the adaptive selection of the covariance matrix $K_{\mathsf{s}}(i,j)$ and the mean value $\bar{c}(i,j)$. This is shown in the next section 2.2.

An interesting byproduct of the Wiener estimation is the knowledge of the posterior uncertainty, i.e. in our case the uncertainty of the denoised pixel value $\acute{c}(i,j)$. In fact, the denoising is only a noise reduction based on statistical assumption of noise and spatial correlation. The resulting denoised pixel value can be seen as a random variable following a normal distribution [9] with mean $\acute{c}(i,j)$ (see eq. (3)) and the following covariance matrix

$$\acute{K}(i,j) = K_{\text{s}}(i,j) - W_{\text{d}}(i,j)K_{\text{s}}(i,j) \tag{5}$$

where $W_{\text{d}}(i,j)$ is defined in eq. (4) and $K_{\text{s}}(i,j)$ is again the spatial covariance matrix. We will need the covariance matrix $\acute{K}(i,j)$ in subsection 2.3 where we present the Wiener reflectance estimation from already noise reduced pixel values.

2.2 How to Modify Wiener Denoising for Edge Preservation?

The modifications of the standard Wiener denoising shown in eq. (3) are limited to the choice of $K_{\text{s}}(i,j)$ and $\bar{c}(i,j)$. The idea is adapted from bilateral filtering [10] that is a common technique for edge preserving spatial smoothing.

Bilateral filtering uses a weighted average of neighboring pixel values for smoothing similar to most smoothing filters. The special edge preserving property of a bilateral filter is based on the combined weighting of neighboring pixels with respect to their spatial and range distance. The range distance is the distance of the pixel values in color space. Typically a Gaussian kernel is used to describe the weighting

$$w_{\text{spatial}}\left[(k,l),(i,j)\right] = \exp\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma^2_{\text{spatial}}}\right) \tag{6}$$

$$w_{\text{range}}\left[(k,l),(i,j)\right] = \exp\left(-\frac{\|c(k,l)-c(i,j)\|_2^2}{2\sigma^2_{\text{range}}}\right) \tag{7}$$

where $w_{\text{spatial}}\left[(k,l),(i,j)\right]$ and $w_{\text{range}}\left[(k,l),(i,j)\right]$ are the spatial and range weights of a pixel at position (k,j) if the filter is applied on pixel (i,j). $\sigma^2_{\text{spatial}}$ and σ^2_{range} are two parameters controlling the decay of the Gaussian kernels.

The combined weight is defined as a normalized product of spatial and range weights

$$w_{\text{bilateral}}\left[(k,l),(i,j)\right] = \frac{w_{\text{spatial}}\left[(k,l),(i,j)\right] w_{\text{range}}\left[(k,l),(i,j)\right]}{\sum_{(\alpha,\beta)\in C(i,j)} w_{\text{spatial}}\left[(\alpha,\beta),(i,j)\right] w_{\text{range}}\left[(\alpha,\beta),(i,j)\right]}. \tag{8}$$

where $C(i,j)$ is an $m \times m$ window around the pixel at position (i,j). A bilateral filter applied on a pixel at position (i,j) weights and sums all pixels within $C(i,j)$ for calculating the new pixel value, i.e.

$$c_{\text{bilateral}}(i,j) = \sum_{(k,l)\in C(i,j)} w_{\text{bilateral}}\left[(k,l),(i,j)\right] c(k,l) \tag{9}$$

But how can we incorporate this idea into the Wiener denoising filter?

First of all we have to change our view onto the bilateral weights from simple constants to random variables. Considering a $m \times m$ window centered at the pixel position (i,j) we have m^2 weights that can be composed into a single m^2 dimensional random vector $w(i,j)$ using lexicographical order. If we order the pixels within the window also lexicographically and arrange them into a $n \times m^2$ dimensional matrix $M(i,j)$, a matrix vector multiplication $M(i,j)w(i,j)$ describes a weighted average of the pixels within the window.

We assume that the random vector $w(i,j)$ follows a normal distribution. In order to preserve edges similar to the bilateral filter we assume that the mean vector $\bar{w}(i,j)$ of the distribution agrees in each component with the bilateral weight, i.e.

$$\forall (k,l) \in C(i,j): \quad \bar{w}_{(k,l)}(i,j) = w_{\text{bilateral}}\left[(k,l),(i,j)\right]. \tag{10}$$

As a consequence Eq. (9) can be written as a simple matrix vector multiplication

$$c_{\text{bilateral}}(i,j) = M(i,j)\bar{w}(i,j). \tag{11}$$

The $m^2 \times m^2$ dimensional covariance matrix $K_w(i,j)$ of the random weight vector $w(i,j)$ can be seen as the uncertainty around the mean $\bar{w}(i,j)$. In order to statistically model the influence of pixels within the window $C(i,j)$ on pixel (i,j) we need to look at this uncertainty. We want to ensure that pixels that are far away from (i,j) or are on the other side of an edge (so that their range difference is large) have a very small influence on pixel (i,j). For this reason the uncertainty has to be very small as well. On the other hand we want to allow pixels that are close and similar to pixel (i,j) to have more variability in their influence on pixel (i,j). With this in mind we can set the standard deviation of each component of the weight vector $w(i,j)$ to be similar to the corresponding component of the mean vector $\bar{w}(i,j)$. As a result and assuming uncorrelated weights the covariance matrix $K_w(i,j)$ is a diagonal matrix with a component-wise square of $\bar{w}(i,j)$ in the diagonal.

The interpretation of the weight vector as a random variable leads us directly to a solution of our original problem of setting $K_{\text{s}}(i,j)$ and $\bar{c}(i,j)$ in a way that

Fig. 1: Portraits of the Lippmann2000 spectral image database considered in the experiments (Rendered for illuminant CIED65 and shown as sRGB images).

the Wiener denoising filter preserves edges. Since $w(i,j)$ is a random variable following a normal distribution and the weighted average $M(i,j)w(i,j)$ of pixels is a simple linear transformation of this normal distribution the resulting distribution is also normal. The mean vector and covariance matrix of this distribution agree with $\bar{c}(i,j)$ and $K_{\mathsf{s}}(i,j)$, respectively, i,e.

$$\bar{c}(i,j) = M(i,j)\bar{w}(i,j) \tag{12}$$

$$K_{\mathsf{s}}(i,j) = M(i,j)K_w(i,j)M(i,j)^T. \tag{13}$$

2.3 Wiener Reflectance Estimation from Noise Reduced Pixels

Now we want to estimate reflectances from the already noise reduced image using a regular Wiener reflectance reconstruction matrix as shown in eq. (2). The only modification of the filter matrix is the noise covariance, since we do not handle any more with the noisy pixels but with pixels that are noise reduced. The covariance matrix of already noise reduced pixels is given in eq. (5) and has to be used to replace the initial noise covariance matrix K_ϵ. The resulting Wiener filter matrix has the following form

$$W_{\mathsf{r}}(i,j) = K_r \Omega^T (\Omega K_r \Omega^T + \acute{K}(i,j))^{-1} \tag{14}$$

$$= K_r \Omega^T (\Omega K_r \Omega^T + K_{\mathsf{s}}(i,j) - W_{\mathsf{d}}(i,j) K_{\mathsf{s}}(i,j))^{-1} \tag{15}$$

2.4 The Edge Preserving Spatio-Spectral Wiener Estimation

The edge preserving spatio-spectral Wiener estimation is a concatenation of edge preserving Wiener denoising and Wiener reflectance reconstruction. For each original noisy pixel $c(i,j)$ the reflectance can be calculated as follows:

$$r_{\mathsf{Reconstruct}}(i,j) = W_{\mathsf{r}}(i,j) W_{\mathsf{d}}(i,j) c(i,j) \tag{16}$$

where $W_{\mathsf{r}}(i,j)$ is defined in eq. (15) and $W_{\mathsf{d}}(i,j)$ is defined in eq. (4).

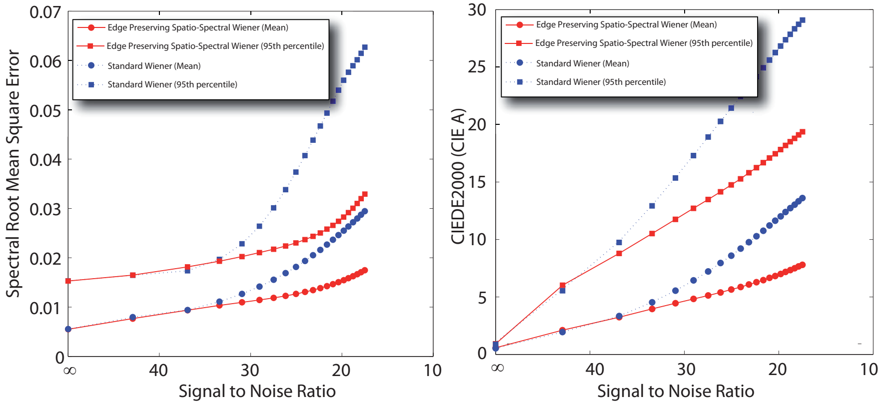

Fig. 2: Average spectral RMS and CIEDE2000 errors obtained by the edge preserving spatio-spectral Wiener and the standard Wiener for all face images of the Lippmann2000 database that were captured by a six-channel camera.

3 Experiments and Results

The aim of the experiments is to compare the performance of the edge-preserving spatio-spectral Wiener reflectance estimation with the standard Wiener estimation. In this paper especially skin colors are investigated. The Lippmann2000 spectral image database [8] was used that includes seven spectral face images that are shown in figure 1. The images were virtually captured by a modified six channel Sinar 54H camera [11] using the camera model in eq. (1). The ideal camera response image was disturbed by Gaussian noise resulting in images with different signal-to-noise-ratio (SNR). These images were reconstructed by both methods and the spectra were compared with the initial spectral images using spectral root-mean-square and CIEDE2000 differences. The spectral covariance matrix used by both methods were calculated from reflectances of 1269 Munsell color chips freely available at the Information Technology Dept., Lappeenranta University of Technology, Finland. For the spatio-spectral Wiener method a rectangular 5×5 window was used. The decay parameters within the bilateral weights (see eq. (6) and (7)) were chosen as follows: $\sigma_{\text{spatial}} = 2$ and $\sigma_{\text{range}} = 0.1$.

The overall performance can be seen in figure 2. Figure 3 shows an image reconstructed from captures with different signal-to-noise-ratios. To demonstrate the edge preserving properties of the spatio-spectral Wiener estimation method figure 4 shows a cutout image including multiple edges.

Fig. 3: Spectral reconstructions from a six-channel capture of a Lippmann2000 image shown as sRGB renderings. Different noise levels were considered reaching from zero noise to large noise levels.

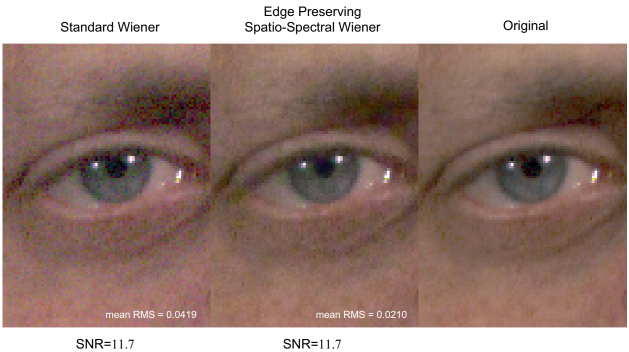

Fig. 4: Enlarged cutout of spectral reconstructions for the highest noise level shown in figure 3 (images are rendered for sRGB). The spatio-spectral reconstruction does not show the hue shift of the standard Wiener method. The edge preserving performance can be seen especially at the specular highlights (sharp edges without any halo effect).

4 Discussion

It can be seen from figure 2 that both methods perform similar for noise free captures. Indeed, it can be shown that the spatio-spectral Wiener estimation reduces to the standard Wiener method in case of vanishing noise. This can be seen by setting K_ϵ to zero within the matrix $W_{\mathrm{d}}(i,j)$ (see eq. (4)). For captures with large SNR values the performance of both methods is therefore very similar. This behavior changes for increasing noise. Spectral reconstructions by the standard Wiener reflectance estimation show significant worse error rates than the spatio-spectral method. At the highest noise level the errors of the standard Wiener estimation are nearly twice the size of the spatio-spectral Wiener. Figure 3 shows that the spectral errors of the standard Wiener method result in a distinct hue shift for high noise levels. This is not observable for the spatio-spectral Wiener. The edge preserving performance of the spatio-spectral Wiener is shown in figure 4. Here a cutout of the image in figure 3 for the highest noise level is shown alongside the original image. The edges do not show any halo effects, which is typical for many smoothing or noise reduction methods. Especially the specular highlights show sharp edges. It should be noted, that the standard Wiener method is applied on each pixel independently to its neighbors. Therefore, it preserves edges by construction as can be seen in the left image of figure 4.

5 Conclusion

In this paper, a new approach for spectral image reconstruction was proposed that utilizes spatial image information to reduce the influence of noise on the reconstruction accuracy. It combines edge preserving Wiener denoising and Wiener reflectance estimation to a single adaptive reconstruction matrix using local propagation of the noise covariance matrix. Experimental results on the Lippmann2000 spectral image database show significant improvements to the standard Wiener reflectance estimation method for high noise levels. For large signal-to-noise ratios both methods perform similar in terms of spectral root-mean-square errors.

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