Towards Spectral Color Reproduction

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Abstract

Conventional color reproduction 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 photo-sensitive 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 a brief overview of this field and presents some recent advances concerning acquisition and reproduction of multispectral images.

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 have been working on these matters, for example at the University of Chiba in Japan [2,3], Rochester Institute of Technology in the United States [4-8], RWTH Aachen in Germany [9,10], University of Joensuu in Finland [11,12], ENST Paris in France [13-17], University of Burgundy in France [18-20], and Gjøvik University College in Norway [21-29].

Multispectral image acquisition

A multispectral image acquisition system typically contains essentially the same elements as a *color* image acquisition device, the only principal difference is that it has more than three channels. A typical multispectral camera is built from a monochrome camera coupled with a set of K color filters mounted on a rotating filter wheel [3,4,16,18,19] or by using an electronically tunable filter [5,17].

By sampling the spectra and applying matrix notation, we can express the K-channel camera response as the vector

$$\mathbf{c}_K = \mathbf{S}^{\mathrm{T}}\mathbf{r}, \qquad (1)$$

where $\mathbf{S}$ 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.

Equation (1) 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.

Spectral reconstruction

The problem of estimating the spectral reflectances **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 **r** in each pixel is a linear combination of a known set of *P* smooth reflectance functions: $\mathbf{r} = \mathbf{Ra}$, with $\mathbf{R} = [\mathbf{r}_1\ \mathbf{r}_2 \ldots \mathbf{r}_P]$ the matrix of the *P* known reflectances and $\mathbf{a} = [\mathbf{a}_1\ \mathbf{a}_2 \ldots \mathbf{a}_P]^T$ a vector of coefficients.

We have previously proposed [14] a reconstruction operator that minimizes the Euclidian distance $d_E(\mathbf{r}, \mathbf{r}')$ between the original spectrum **r** and the reconstructed spectrum **r**':

$$\mathbf{r}' = \mathbf{RR}^T\mathbf{S}(\mathbf{S}^T\mathbf{RR}^T\mathbf{S})^{-1}\mathbf{c}_K \qquad (2)$$

In [29] 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 [23] (see Figure 1). Neural network-based methods have been found to yield superior performance in the presence of acquisition noise [15,19]. Recently Alsam and Connah [25] proposed to use convex bases as an alternative to linear bases and a method for spectral reconstruction using metamer sets, with promising results, and Mansouri et al [20] proposes to use wavelets as basis functions.

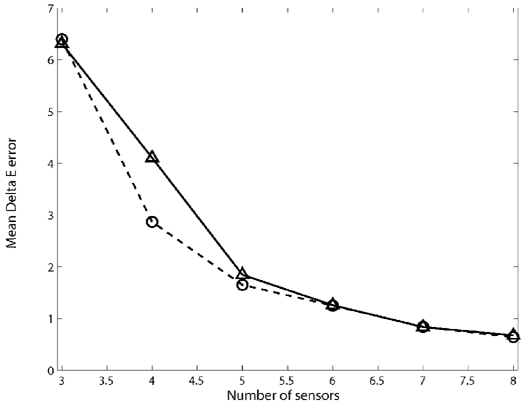

Figure 1. Mean RMS spectral reconstruction error for an evaluation data set of over 1000 natural reflectances [], plotted as function of the number of sensors for an optimised regularised polynomial transform (circles and dashed lines) and a linear, or 1st order polynomial, method (triangles and solid lines) [23]

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 [24] 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 2), 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 3. We also demonstrate that this level is both noise and dataset dependent, by providing results for different magnitudes of noise and different reflectance datasets.

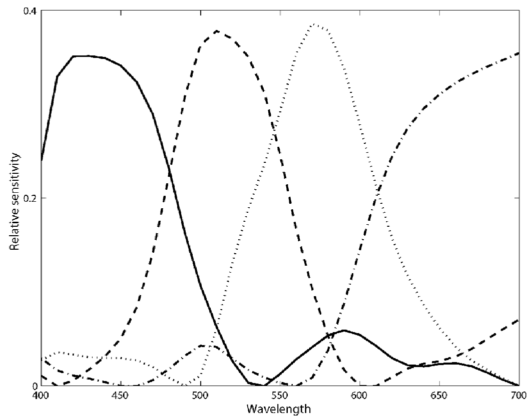

Figure 2. Non-negative sensors formed by varimax rotation with added positivity constraint. [24]

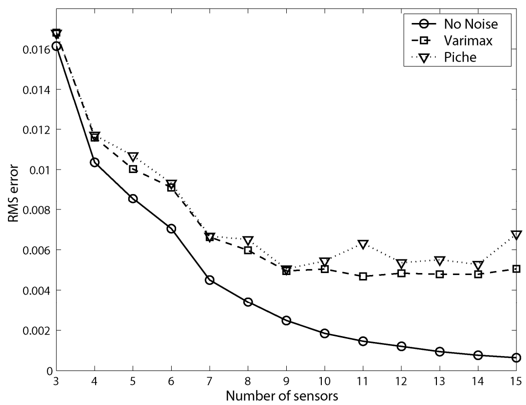

Figure 3. Effect of increasing sensor number with 12 bit quantization and 1% shot noise on Munsell reflectance data [24].

Spectral color reproduction

Even though Professor Hunt pinned down the concept of spectral color reproduction some time back [31], 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 [6-9,21,22,26,27].

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.

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 [32], in which the estimated spectral reflectance $R_{\text{est}}(\lambda)$ of a colorant combination is a weighted sum of the spectral reflectances $P_i(\lambda)$ of the Neugebauer primaries (NP),

$$R_{\text{est}}(\lambda) = \sum_{i=1}^{k} w_i P_i(\lambda). \tag{3}$$

The NPs 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. Currently, the Yule-Nielsen modified spectral Neugebauer (YNSN) model [33], in which the so-called n-factor is introduced in an attempt to model the light interaction between the paper and the colorants, is popular [6]:

$$R_{\text{est}}^{1/n}(\lambda) = \sum_{i=1}^{k} w_i P_i^{1/n}(\lambda). \tag{4}$$

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:

$$\begin{aligned}
w_0 &= (1-c_1)(1-c_2)(1-c_3),\\
w_1 &= c_1(1-c_2)(1-c_3),\\
w_2 &= (1-c_1)\,c_2(1-c_3),\\
w_3 &= (1-c_1)(1-c_2)\,c_3,\\
w_{12} &= c_1 c_2(1-c_3),\\
w_{13} &= c_1(1-c_2)\,c_3,\\
w_{23} &= (1-c_1)\,c_2 c_3,\\
w_{123} &= c_1 c_2 c_3,
\end{aligned} \tag{5}$$

with the relation:

$$\sum_{i=1}^{k} w_i = 1 \text{ and } 0 < w_i < 1 \tag{6}$$

The Neugebauer model requires the measurements of the NPs to evaluate the reflectance of any colorant combination. The value of the *n*-factor depends on 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 [21]. An important problem that was discovered is that the model fails when the paper receives too much ink.

Spectral colorant separation

By the spectral characterization process, 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 have the advantage to require 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 [34].

An optimization method will look for the best colorant combination such that each iteration of the inversion process provides a closer estimation of the desired spectral target. Typically these techniques try to minimize a spectral difference between a spectral target and its estimation.

We currently explore the difference between a colorimetric and spectral reproduction based on the same set of NPs.

Spectral halftoning

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. 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 [35].

In a recent paper we have proposed to use Vector Error Diffusion (VED) for spectral reproduction [27]. 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 [35]. 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 4, the

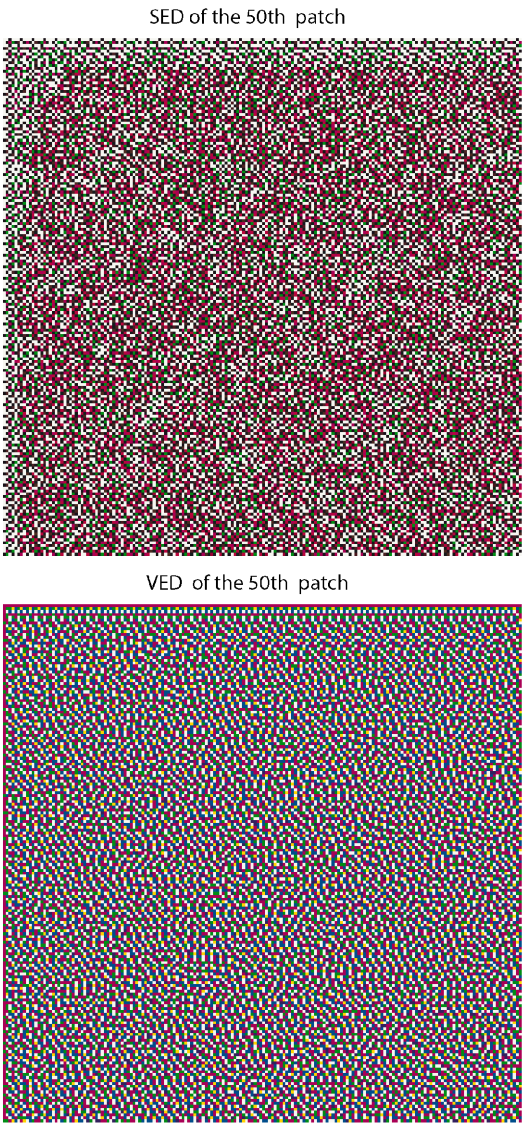

Figure 4. A patch halftoned by scalar error diffusion (above) and vector error diffusion (below). The reduced visual noise (stochastic moiré) achieved by VED is clearly visible [27]

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.

Spectral gamut mapping

So far we have presented two possibilities to reproduce spectral images: one is following the steps of spectral printer characterization, spectral colorant separation and halftoning of each colorant channel by ED, the second is a direct halftoning by spectral VED. Both ways suffer when data (or part of them at least) to be reproduced are located outside the spectral printer gamut. The dimensionality of the spectral data makes it difficult to apply directly extensions of color gamut mapping algorithms. We proposed an alternative approach based on reducing the dimensionality of the problem [22] allowing to map data outside the gamut toward its surface.

Also a full spectral gamut mapping have been introduced based in the inverse spectral printer model. In an inversion problem we are looking for the best colorant combination to reproduce a spectral reflectance. But the spectral reflectance of a colorant combination is the weighted summation of the Neugebauer primaries. So inverting the spectral Neugebauer equations for the weights of the NPs give the closest spectral match for a set of NPs. This technique have shown good results when applied before performing spectral VED, the resulting halftoned image presenting a strong reduction of noise visibility.

Conclusion

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. In particular we have discussed topics such as spectral reconstruction for acquisition of multispectral color images, spectral printer characterization and halftoning considerations for spectral color reproduction. Much has happened in this field over the last decade, but there is still work to be done in order for multispectral color imaging and spectral color reproduction to make it into the mainstream of imaging.

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