Optimal Spectral Sensitivities of a Multispectral Image Acquisition System

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Abstract

In recent years the development and design of multispectral color image acquisition devices has received great attention from the color scientific community. And the use of these multispectral devices has grown dramatically to achieve different purposes. Here we tackle the optimal design of a polyvalent three-channel multispectral system, with three channels, which would be able to reconstruct the spectral reflectances of objects to be imaged and the spectral power distribution of the illumination, as well as to provide illuminant invariant descriptors.

To achieve the optimal design of such a polyvalent multispectral device we test different spectral sensitivity of the different channels.

Introduction

Up to date the main objectives of the multispectral devices have been: (1) to provide accurate color characterization, and (2) to reconstruct scene surface spectral reflectances and/or the illuminant spectral power distribution (SPD). The first purpose, which can fail due to metamerism, can be achieved if the spectral sensitivities of the device satisfy the Luther-Ives condition.[1-2] The second purpose, which provides a more complete characterization, is achieved by using "optimal" filters coupled to monochrome digital cameras or by the design of "optimal" spectral sensitivities for the different camera channels.[3-9]

All the research to recover both the surface spectral reflectance and the illuminant spectral power distribution from the image data takes into account the statistical properties of the objects that are to be imaged and of the illuminants to be used. For example low-dimensional linear models,[10-11] which have already been proved accurate to recover spectral functions, benefit from the spectral correlation of a set of empirical spectra. If the basis functions used in these linear models are calculated, for example, to minimize the mean squared error, then they are all orthogonal eigenvectors and may be obtained from a principal component analysis (PCA).

Simultaneously several authors, trying to solve the color constancy problem, have shown that a particular linear combination of log RGB responses is invariant to light intensity and light color.[12-14] Therefore this combination defines invariant descriptors to the changes in the illuminant over a scene, solving the one-dimensional color constancy problem at a pixel, which is appropriate for object recognition. So far these invariant descriptors rely on two assumptions: (1) the camera spectral sensitivities must be sufficiently narrow (not far from delta functions), and (2) illumination spectra are close to Planckian spectra. More recently Lenz *et al.*[15] have shown how to use transformation groups to calculate different independent invariants for a given class of transformations.

In this paper we study what would be the optimal design of a three-channels multispectral camera in order to perform three different tasks simultaneously: to provide natural illuminant invariant descriptors and to allow spectral recovery of both the objects spectral reflectance and the spectral power distribution of natural illumination.

Spectral Recovery Based on Linear Models

Low-dimensional linear representation of object spectral reflectances has been proved extensively in the literature to be very efficient (see Ref. 4 for a review). Most authors agree that a dimension between 3 and 5 is necessary to achieve a high degree of recovery accuracy, depending on the different databases statistical properties.

Similarly several authors have shown that the natural illumination spectra (*i.e.* daylight, skylight and twilight) variance can be explained with the linear combination of 3 to 5 basis functions in the visible spectral range (see Ref. 16 for an overview).

If a Principal Component Analysis (PCA) is used to obtain those basis functions, then they can have negative values, as shown in Figures 1 and 2. So it is impossible to have real sensors with the same spectral transmittance as the basis functions.

Therefore alternative sensors must be selected in order to recover spectral functions from the response of these real sensors. This is accomplished in this paper by using an inversion recovery algorithm (see for example Refs. 4 and 9) and an exhaustive search method to obtain the best set of Gaussian sensors.

Invariant Descriptors

Very recently several authors[12-14] have defined invariant descriptors that remain constant despite the change in light intensity and light color. These invariant descriptors to the illumination changes in a scene are linear combination of the log RGB responses and solve the one-dimensional color constancy problem at a pixel in artificial systems.

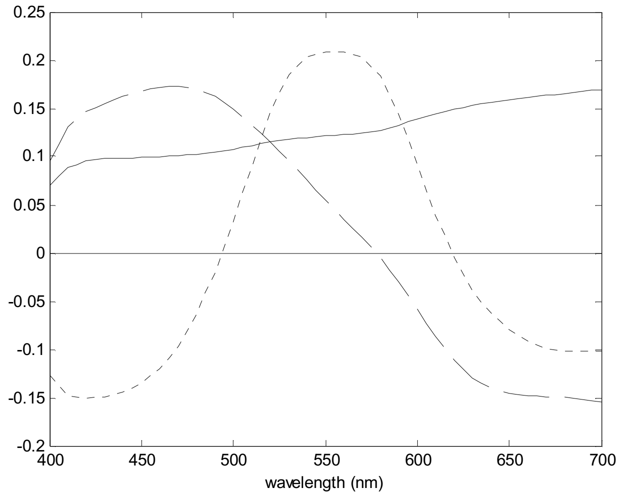

Figure 1. Spectral distribution of the first three ColorChecker reflectance eigenvectors

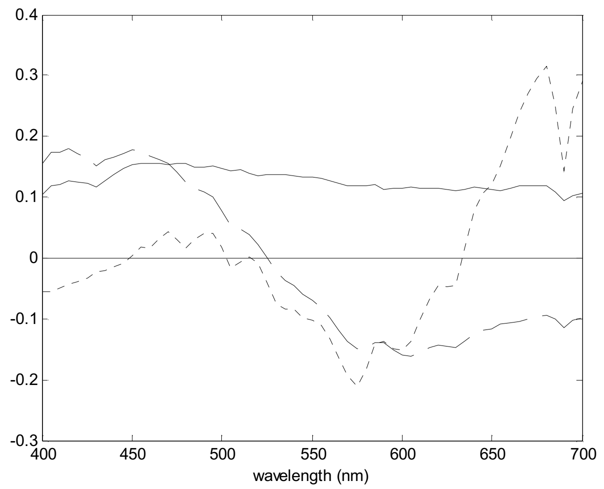

Figure 2. Spectral distribution of daylight eigenvectors.

Considering the definition of this invariant parameter, accurate one-dimensional color constancy is obtained when the three sensors have very narrow spectral sensitivities (not far from delta functions) and when illumination spectra are close to Planckian spectra.

Nevertheless if the sensors are broadband (as is the case in commercial cameras), the accuracy of the invariant descriptors can be checked by representing, for example, for any group of objects and illuminants the log (B/R) versus the log (G/R), being R, G, and B, the response of the three sensors, respectively. If the invariant is valid for a set of sensors this representation will generate for each object under whatever illuminant, points over a straight line whose slopes must be similar for all the objects in the scene (see ref. 12 for the proof and a detailed discussion).

The constraint of Planckian spectra was overcome by Marchant and Onyango[13-14] to include natural illumination as daylight.

Optimal Sensor Search and Experiments

Here we look for the optimal three Gaussian spectral sensitivities that would provide simultaneously illuminant invariant descriptors and accurate estimation of both the spectral reflectances of objects and the natural illuminant SPD.

To achieve this objective we have made an exhaustive but discrete search to find the best set of three Gaussian sensors that would provide this triple use. We restrict our study to a set of three sensors that are Gaussian functions of wavelength, all having the same bandwidth, and investigate the influence of their spectral location and bandwidths, allowing the peak sensitivity of each sensor to be at any wavelength from 400 nm to 700 nm in 5 nm steps, and the full width at medium height (FWMH) to vary from 10 nm to 200 nm.

In our search both the reflectance spectra (assuming that the illuminant SPD is known) and the illuminant SPD (we assume that a reference white, with a known spectral reflectance, is included in the acquired scene) are estimated using the response of the different camera channels and linear models with basis functions obtained from two PCAs: one applied to the 24 spectral reflectances of the GretagMacbeth ColorChecker (the first three eigenvectors are shown in Figure 1), and the other from a set of 2600 daylight SPDs (see Ref. 16 and Figure 2).

We performed an evaluation of the quality of the multispectral acquisition system by calculating a goodness of fit coefficient (GFC) previously used by other authors,[16-17] and the root mean squared error (RMSE) of the 24 recovered Macbeth ColorChecker spectral reflectances as well as CIELAB color differences. The same triple evaluation was done over a set of 64 recovered natural illuminants SPDs (22 daylight, 21 skylight, 21 twilight) with a high range of correlated color temperatures CCTs (from 3750 K to 100,000 K).

To test the ability to provide accurate invariant descriptors we represent, for each one of the 24 spectral reflectances and all the 64 illuminants, the logarithm of the ratio between the response of one sensor and other sensor (*i.e.* log (B/R)) versus that of other two sensors (for example, log (G/R)). In case the invariant is accurate this representation will generate straight lines (*i.e.* correlation coefficient values close to unity) for each spectral reflectance considered (24 in our case) all of them with very similar slopes (*i.e.* with low standard deviations).

Our exhaustive search shows that the best results are obtained when the three sensors have a FWMH of approximately 46 nm (remember that we have imposed the restriction of three sensors with an equal bandwidth) and their peak sensitivities are located in 450 nm, 550 nm and 615 nm respectively. Figure 3 shows the spectral sensitivities of the three optimal sensors. It is quite remarkable the close agreement of these optimal sensors with most of commercial cameras peaks sensitivities.

The results obtained with these optimal sensors are shown in Table 1 and Table 2. Three examples of spectral reflectance recoveries are included in Figure 4, three illumination SPD reconstructions in Figure 5, and the invariant descriptor check in Figure 6.

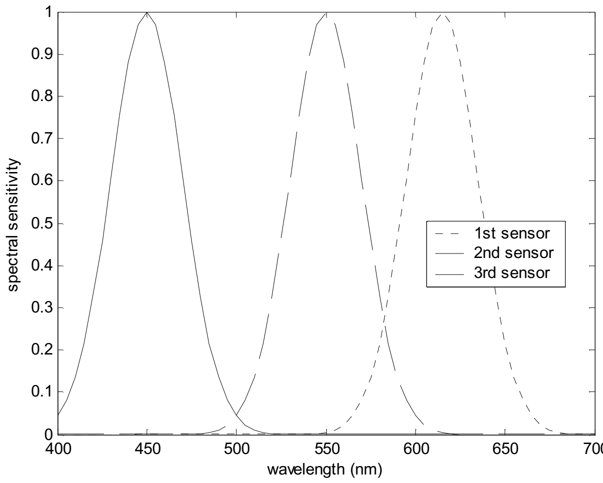

Figure 3. Optimized Gaussian spectral sensor sensitivities.

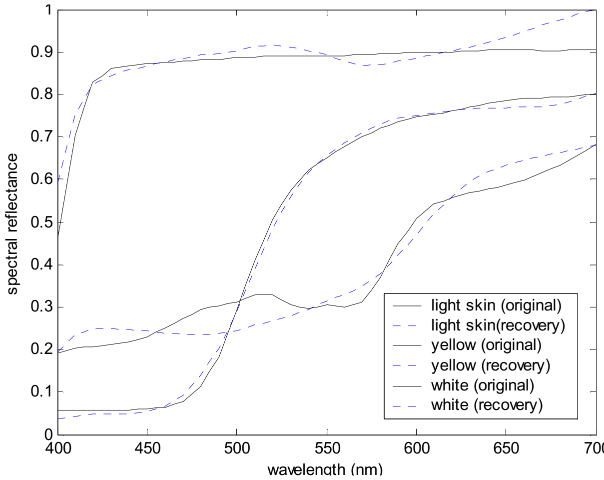

Figure 4. Example of three spectral reflectance reconstructions

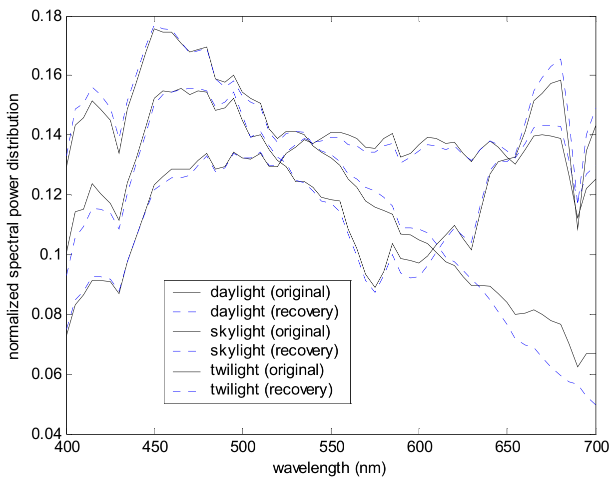

Figure 5. Example of three natural illuminants SPD recoveries

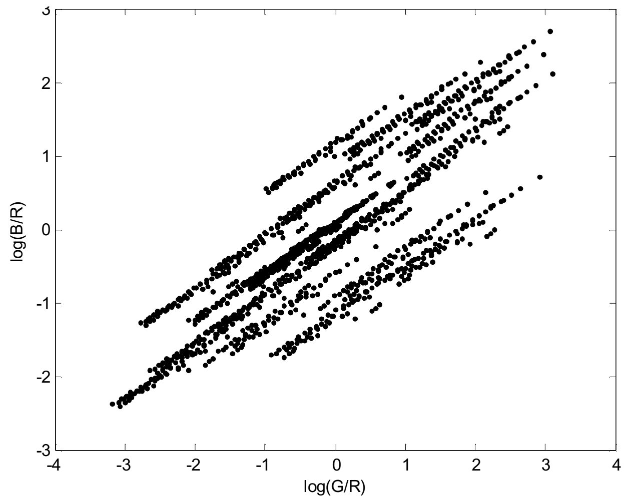

Figure 6. Representation of log (B/R) versus log (G/R) for the 24 ColorChecker surfaces under the 64 illuminants.

Table 1. Spectral reflectance recovery results obtained with the optimal sensor over the 24 ColorChecker chips.

	GFC	CIELAB	rmse
mean	0.9887	1.7148	0.2147
standard deviation	0.0147	1.5871	0.1169
10% percentile	0.9614	3.8751	0.3503

Table 2. Natural illumination spectral recovery results obtained with the optimal sensor over the 64 SPDs tested.

	GFC	CIELAB	rmse
mean	0.9955	0.3294	0.0260
standard deviation	0.0058	0.3214	0.0446
10% percentile	0.9868	0.8051	0.0632

Table 3. Invariant results obtained with the optimal sensors.

	slope	correlation coefficient
mean	0.6445	0.9751
standard deviation	0.0207	0.0039

Conclusions

Although increasing the number of the channels in the image acquisition system will allow better accuracy, here we have shown that with only three but well chosen sensors it is possible to obtain a polyvalent image acquisition system that would provide good recoveries of both spectral reflectances and natural illuminant SPDs as well as illuminant invariant descriptors.

The results obtained will be useful for future designs of polyvalent multispectral color image acquisition systems.

Our future intention is to increase the number of sensors, to reduce the constraints assumed in this paper and to consider the influence of noise.

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Biography

Javier Hernandez-Andres received his Ph.D. in Physics from the University of Granada in 1999. Since 1995 he is working in the Department of Optics at the University of Granada, Spain, where he is now an associate professor. His current research interests include color science, color vision, multispectral color imaging and atmospheric optics. He is a member of the Optical Society of America and the Spanish Optical Society.