Separating illuminant and surface reflectance spectra from filtered trichromatic camera measurements

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Abstract

We show how illuminant and reflectance spectra can be accurately measured or separated, up to a multiplicative factor, at each pixel of a scene by using a CCD digital camera instead of a spectroradiometer. In order to obtain suitable spectra of both illuminants and reflectances in a scene, we may use a 6-channel measure from the digital 3-channel RGB camera. This is accomplished by taking two images of the scene, and using a colour filter during the second. No other practical or theoretical restrictions are needed to apply this separation algorithm, which is based on the validity of low-dimensional linear models for representing illuminant and reflectance spectra.

Introduction

A colour signal [1], or radiance spectrum, can be defined as any function which represents the spectral power distribution (SPD) of the product of the spectral reflectance of one pixel of an object and the SPD of the light source that illuminates it. The ability to separate the surface reflectance spectrum from the illuminant spectrum at each pixel is useful for many tasks, and it is still one of the unsolved problems in multispectral colour science. For example, surface spectral reflectance data can be used to classify minerals [2] or to simulate the colour appearance of an object under illuminant changes, which would be desirable for visually guided robots, automatic terrain classiffication by remote sensing or for better colour reproduction in colour displays, among many other applications [3]. Achieving this spectral signal separation by means of digital cameras and multispectral techniques would be specially useful, leading the way to use portable digital cameras -instead of spectrometers- to render high spatial resolution colour images.

In this work we use the Wiener estimation method [4] to obtain the spectral colour signal of a scene from the simulated responses of a trichromatic camera coupled with a filter, instead of using a spectrometer [2,3]. We then separate this radiance spectra into spectral reflectance and illuminant components by using the method proposed by Ho *et. al.* [3], which has been also used by other authors but always making use of spectral radiance measurements from a spectrometer [2,3] instead of using a trichromatic camera and a filter. We find that spectral reflectance and illuminant can be accurately obtained at each pixel, up to a multiplicative factor, from trichromatic camera measurements of a scene by making use of finite-dimension linear models for reflectance and illuminant spectra.

Method

The RGB digital camera had spatial resolution 1280 × 1024 pixels (QImaging, model Retiga 1300, QImaging Corp., Canada) and 12 bits intensity resolution per channel. Several hyperspectral colour signal data from various scene fragments [5] were used as training spectra for the Wiener estimation method to obtain the matrix relating colour signals and camera responses (recovery matrix). The "matrix-training set" **S**, used to obtain the recovery matrix, was formed from 30 different fragments taken from 30 scenes, each fragment of size 151 × 151 pixels. The six camera responses r_i to the color signals (i = 1,..,6 for red, green, and blue sensors, respectively and three additional responses for the camera coupled with a blue plastic filter) were computed. The six camera responses for each pixel formed the response matrix **R** for the entire colour signal set. The recovery matrix **D** was then computed from the pseudoinverse of **R** (denoted by superscript +) by

$$\mathbf{D} = \mathbf{S}\mathbf{R}^{+} \tag{1}$$

An estimate $\hat{\mathbf{S}}_1$ of a set of test spectra $\mathbf{S}_1$ may then be obtained from a given set of camera responses $\mathbf{R}_1$ by applying the transformation matrix **D**, that is

$$\hat{\mathbf{S}}_1 = \mathbf{D}\mathbf{R}_1 \tag{2}$$

Once we have estimated the spectral colour signal from camera responses usign the Wiener method, we can apply Ho *et. al.* algorithm [3] to separate illuminant and reflectance components of this colour signal. This method is based on the use of finite-dimensional linear models for surface reflectance and illuminant spectra [2,3]. For example, performing a principal component analysis (PCA) [6] over a set of previously registered spectral measurements, or training spectra, provides a set of vectors (called eigenvectors or principal components) which can be linearly combined to obtain the spectral estimation of a reflectance and an illuminant spectrum. The weights in these linear combinations are chosen to minimize the mean square error of the estimation in the space of spectral curves over all the training spectra. Hence, we have

$$E(\lambda) \approx \sum_{i=1}^{m} V_i(\lambda)\varepsilon_i \, , \; O(\lambda) \approx \sum_{j=1}^{n} W_j(\lambda)\sigma_j \tag{3}$$

where V_i and ε_i are respectively the eigenvectors and coefficients used in this linear combination for reconstructing N sampled wavelengths of the illuminant spectrum E. For surface reflectance, W_j and σ_j are respectively the reflectance basis vectors and coefficients for reconstructing the surface reflectance spectrum $O(\lambda)$. We use a training set of 10^5 hyperspectral reflectance measurements [5] to perform a PCA and construct W_j, and a set of 2600 daylight spectral measurements [7] to construct V_i. These two training sets were not used to test the system later, on the contrary of previous works [2,3]. The colour signal or radiance spectrum is the product of the illuminant and the reflectance spectra, and can be expressed as

$$S(\lambda) \approx \sum_{i=1}^{m}\sum_{j=1}^{n} \varepsilon_i \sigma_j V_i W_j \quad (4)$$

We can solve this equation in two ways [2,3]. First, we can write an equation for each λ and solve for the combinations $\varepsilon_i\sigma_j$ if $N > n{\cdot}m$ (which is known as *linear method* [2]). On the other hand, we can try to minimize the distance

$$\left\| S(\lambda) - \sum_{i=1}^{m}\sum_{j=1}^{n} \varepsilon_i \sigma_j V_i W_j \right\|^2 \quad (5)$$

deriving with respect to the coefficients σ_j, ε_i and equalling to zero [3], if we do this we obtain two sets of equations in each set of coefficients which can be iteratively solved to obtain the separated reflectance and illuminant spectra (this method is called *non-linear method* [2]). Since the surface reflectance and illuminant spectral curves are obtained up to a multiplicative factor [2,3], we will normalize all the curves in order to compare their relative spectral shape [3].

In this work we test these algorithms by separating illuminant and surface reflectance curves from a set of 68403 colour signals recovered from simulated camera responses in 3 different scenes of size 151x151 pixels; the reflectances of these recovered signals were not included in the PCA of the surface spectral reflectances.

Imai *et al*. [8] suggest that "mononumerosis" should be avoided when evaluating the quality of spectral matches. By this term they mean that *several* metrics should be used to assess color reconstruction from both colorimetric and spectral standpoints. Here, we measure the accuracy of the estimations by using two kinds of metric [9,10]: a spectral metric like GFC (which stands for the goodness-fit-coefficient [4,7,9]) and CIELAB distance ΔE^*_{ab}.

Results

We show in this section the accuracy of the normalized spectra obtained after applying the separation algorithm [3] to the radiance spectra obtained from the responses of the trichromatic camera with the blue filter and without any filter, instead of using spectrometer data.

In Table 1 we show some mean ± standard deviation (SD) values for the GFC and ΔE^*_{ab} metrics when estimating illuminant curves with different numbers (m and n; we simulated for m = 1,..,4 and n = 2,..,12 in the complete study) of basis vectors for illuminants and reflectances using the linear method explained before. Table 2 is identical for reflectance estimations using the linear method. Table 3 shows the results for these two metrics when estimating illuminant curves using the non-linear method and Table 4 is for reflectances using also the non-linear method.

We found m=2 and n=11 as the optimum dimensions for the lineal method (if we make a balance between reflectances and illuminants and the two metrics used for each), while choosing m=2 and n=4 lead to the best results with the non-linear method. These differences in the optimum dimensions of the two spaces for the two methods were not considered before by other authors using this same separation algorithm [2,3].

Table 1. Mean and SD values for GFC and CIELAB ΔE^*_{ab} metrics for illuminant spectra and the linear method. In bold type are the best results balanced between reflectances and illuminants and the two metrics used.

m	*N*	GFC	ΔE^*_{ab}
2	4	0.964±0.083	5.6±5.0
2	7	0.992±0.010	1.9±1.6
2	8	0.994±0.007	1.8±1.4
2	11	**0.994±0.008**	**1.4±0.8**
3	3	0.996±0.006	1.2±0.9
3	7	0.992±0.005	2.0±0.8
3	8	0.995±0.004	1.3±0.9
3	10	0.960±0.042	2.2±1.6

Table 2. Mean and SD values for GFC and CIELAB ΔE^*_{ab} metrics for reflectance spectra and the linear method. In bold type are the best results balanced between reflectances and illuminants and the two metrics used.

m	*n*	GFC	ΔE^*_{ab}
2	4	0.951±0.062	6.7±4.2
2	7	0.969±0.023	4.2±2.0
2	8	0.968±0.021	4.3±2.0
2	11	**0.957±0.031**	**4.1±2.1**
3	3	0.921±0.043	4.2±2.0
3	7	0.948±0.021	3.5±1.9
3	8	0.944±0.032	4.1±1.9
3	10	0.871±0.131	3.6±2.0

Table 3. Mean and SD values for GFC and CIELAB ΔE^*_{ab} metrics for illuminant spectra and the non-linear method. In bold type are the best results balanced between reflectances and illuminants and the two metrics used.

m	*n*	GFC	ΔE^*_{ab}
2	4	**0.992±0.008**	**1.9±1.4**
2	7	0.991±0.011	1.8±1.6
2	8	0.991±0.011	1.9±1.6
2	11	0.991±0.012	1.7±1.5
3	3	0.984±0.018	3.3±2.6
3	7	0.982±0.017	2.9±1.7
3	8	0.982±0.018	2.8±1.7
3	10	0.982±0.018	2.7±1.6

Table 4. Mean and SD values for GFC and CIELAB ΔE^*_{ab} metrics for reflectance spectra and the non-linear method. In bold type are the best results balanced between reflectances and illuminants and the two metrics used.

m	*n*	GFC	ΔE^*_{ab}
2	4	**0.990±0.006**	**1.7±1.4**
2	7	0.987±0.015	1.6±1.4
2	8	0.987±0.018	1.6±1.5
2	11	0.987±0.023	2.1±1.6
3	3	0.976±0.024	2.8±1.9
3	7	0.980±0.023	2.3±2.1
3	8	0.980±0.021	2.3±2.1
3	10	0.980±0.022	2.3±2.1

Figure 1a shows the spectral curves of surface reflectance, and Figure 1b for illuminant spectra, for the median value of the GFC metric among the test set of 68403 spectral curves of colour signals when using the linear method. Figure 2 is analogous for the non-linear method. In each case the best number of eigenvectors *m* and *n* was used according to the results shown in Tables 1 to 4.

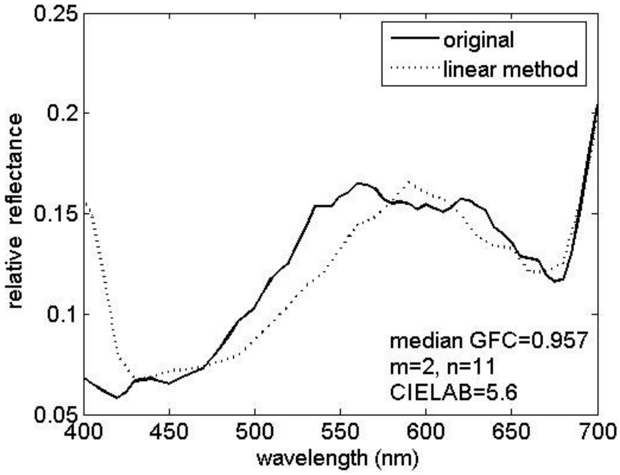

Figure 1a. *Surface reflectance SPDs recovered using the linear method.*

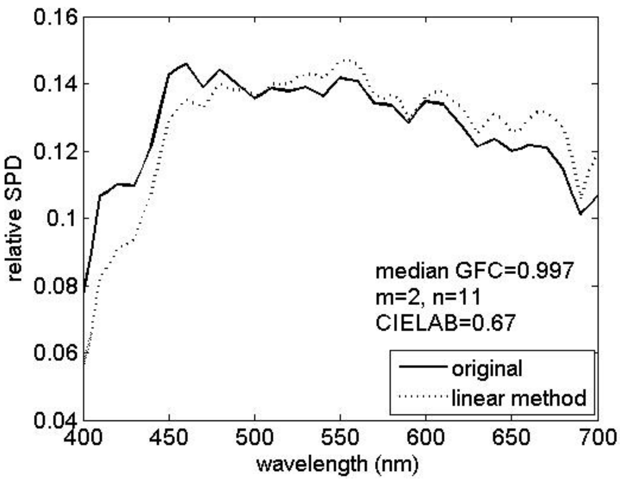

Figure 1b. *Illuminant SPDs recovered using the linear method.*

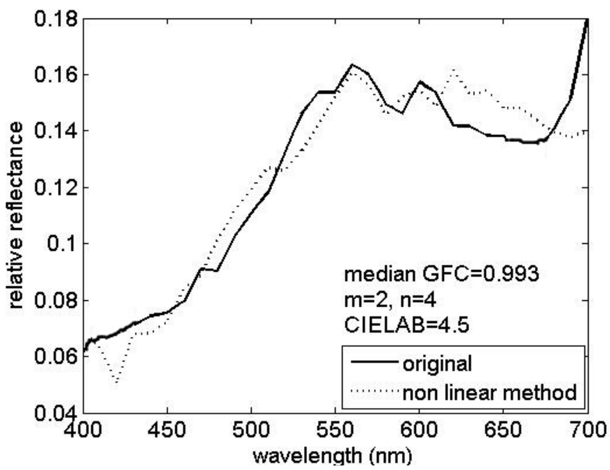

Figure 2a. *Surface reflectance SPDs recovered using the non-linear method.*

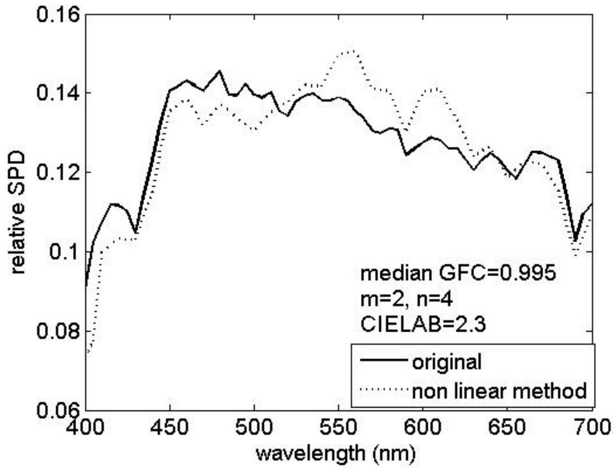

Figure 2b. *Illuminant SPDs recovered using the non-linear method*

Conclusions

We can see how the two methods permit to accurately separate illuminant and reflectance information from a given radiance spectrum at a pixel, which was estimated from the responses of a trichromatic camera with a blue filter and without filter instead of using a spectrometer and any other additional measurement for spacial correlation or *a priori* illuminant estimation. The results seem even better if we remember that the test spectra composing the radiance colour signal were not included in the PCA to train the system. The linear method separates illuminants with slightly better accuracy than the non-lineal method, but this last obtains much better reflectances. The optimum dimensions of reflectance and illuminant spaces obtained for each method are different, a fact not accouted for by other authors [2].

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Author Biography

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