An Adaptive-PCA Algorithm for Reflectance Estimation from Color Images

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Abstract

This paper deals with the problem of spectral reflectance estimation from color camera outputs. Because the reconstruction of such functions is an inverse problem, stabilizing the reconstruction process is highly desirable. One way to do this is to decompose reflectance function on a basis functions like PCA. The present work proposes an algorithm making PCA adaptive in reflectance estimation from a color camera output. We propose to adapt the PCA basis derivation by selecting, for each sample, the more relevant elements from the training set elements. The adaptivity criterion is achieved by a likelihood measurement. Finally, the spectral reflectance estimation results are evaluated with the commonly used goodness-of-fit coefficient (GFC) and ΔE color difference, and prove the reliability of the proposed methods.

1. Introduction

In conventional color imaging, each pixel is characterized by 3 components such as red, green and blue. These components are necessary and sufficient to characterize any color observable by humans. However, such three-dimensional representation of color has several limitations. First, in a color image acquisition process, the scene is acquired using a given illuminant making it impossible to estimate the scene color accurately under another illuminant in the absence of additional information on the spectral reflectance. Multispectral imaging systems remedy this problem by increasing the number of acquisition channels. In doing so, scene surface reflectance recovery from the camera output becomes easier. However, multispectral systems are still heavy and unaffordable for many applications where color cameras are still widely used. Therefore, finding appropriate mathematical methods to estimate the spectral reflectance from color camera output is of great importance as it is crucial for the success of many tasks as classification, segmentation, etc.

In the next sections, we first formulate the problem of reflectance estimation in the general case and then we give some related works introducing the linear model. The Section 3 describes the experimental set-up and the Section 4 is dedicated to the algorithm we propose to make PCA adaptive in task of reflectance estimation. We finally give the results in Section 5 before concluding.

2. Problem formulation and related works

The generally used spectral model of the acquisition chain in either color or multispectral system is illustrated in Figure 1.

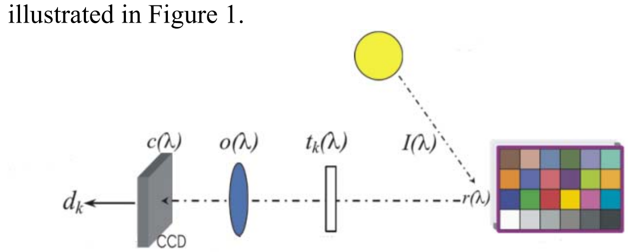

Figure 1: Synopsis of the spectral model of the acquisition process in color/multispectral systems.

In this Figure, I(λ) represents the spectral radiance of the illuminant, r(λ) is the spectral reflectance of the surface, o(λ) is the spectral transmittance of the optical system, $t_k(\lambda)$ denotes the spectral transmittance related to the k^{th} filter, c(λ) is the spectral sensitivity of the camera and η_k represents the spectral noise for the k^{th} channel, k=1…K. The camera output d_k, related to the channel k for a single pixel of the image, is given by

$$d_k = \int_{\lambda_{\min}}^{\lambda_{\max}} I(\lambda) r(\lambda) o(\lambda) c(\lambda) t_k(\lambda) d\lambda + \eta_k . \quad (1)$$

If the noise is assumed removed by preprocessing [1], and assuming a linear opto-electronic transfer function, we can replace I(λ), c(λ), o(λ) and $t_k(\lambda)$ by the spectral

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sensitivity $S_k(\lambda)$ of the k^{th} channel. Then, Equation (1) becomes:

$$d_k = \int_{\lambda_{min}}^{\lambda_{max}} S_k(\lambda) r(\lambda) d\lambda. \quad (2)$$

By regularly sampling the spectral range to N wavelengths, Equation 2 can be written in matrix notations as follows:

$$d_k = \mathbf{S}_k^T(\lambda)\mathbf{r}(\lambda), \quad (3)$$

where $\mathbf{S}_k(\lambda)=[s_k(\lambda_1)\ s_k(\lambda_2)\dots\ s_k(\lambda_N)]^T$ is the vector containing the spectral sensitivity of the acquisition system related to the k^{th} channel, $\mathbf{r}(\lambda)=[r(\lambda_1)\dots\ r(\lambda_N)]^T$ is the vector of the sampled spectral reflectances of the scene, and ^{T} is the transpose vector operator. Considering a system with all channels, Equation 3 can be written as:

$$\mathbf{d} = \mathbf{S}^T\mathbf{r}, \quad (4)$$

where **d** is the vector containing all d_k camera outputs and $\mathbf{S} =[s_1\dots s_K]^T$ is the matrix containing the channels' spectral sensitivities $\mathbf{S}_k$. The final goal is to recover $\mathbf{r}(\lambda)$ from the camera output given by Equation 4. This is obtained by finding an operator **Q** that satisfies:

$$\tilde{\mathbf{r}} = \mathbf{Qd}. \quad (5)$$

Depending on how the matrix **S** is determined, three main paradigms of spectral reflectance estimation exist.

-If **S** is obtained by a direct physical system characterization, the operator **Q** is the inverse or the pseudo-inverse of **S**. Thus $\mathbf{Q}=\mathbf{S}^+$, where $^+$ is the pseudo-inverse operator.

-If **S** is obtained indirectly by matching a set of M color patches (for which we know the theoretical reflectance) and an image of these patches is captured by the camera, then we have a set of corresponding pairs ($\mathbf{d}_m$, $\mathbf{r}_m$), for m=1,...,M, where $\mathbf{d}_m$ is a vector of dimension K containing the camera responses, and $\mathbf{r}_m$ is a vector of dimension N representing the spectral reflectance of the m^{th} patch. The reflectances $\mathbf{r}_m$ are gathered in the matrix **R** and the camera outputs for the M patches are gathered in the matrix **D**. The operator **Q** is directly obtained by calculation of this matching. Any optimization method can fulfill this aim (neural networks, least squares regression…). Thus, the operator **Q** is obtained from

$$\mathbf{R} = \mathbf{QD} \quad (6)$$

through the pseudo-inverse of $\mathbf{D}$

$$\mathbf{Q} = \mathbf{RD}^+ \quad (7)$$

which, as $J=K$, becomes

$$\mathbf{Q} = \mathbf{RD}^{-1}. \quad (8)$$

-The third paradigm for spectral reflectance estimation consists in directly interpolating the camera outputs d_k. Then, no knowledge about the matrix **S** is required. However, rigorous conditions about filters' shapes and number make this technique ineffective for reflectance estimation from color cameras.

The final goal is to estimate the spectral reflectance functions **r** from the camera outputs **d**. In order to do so, several methods exist in the literature mainly when estimating reflectance from color cameras outputs [2-6]. Most of these approaches use pseudo-inverse calculus or Wiener estimation to overcome the noise amplification. An alternative to those methods is the linear model. Using the linear model to estimate reflectance from camera response seems to be trivial since we have assumed a linear opto-electronic transfer function allowing us to use the matrix notation in Equations 4 and 5. Moreover, it offers an alternative to imposing smoothness on reflectance functions. This is expressed by assuming that $\mathbf{r}(\lambda)$ can be approximated by a linear combination of a small number of basis functions [7]. Thus, a set of basis functions B_m (m=1…M) are defined such that each reflectance r_i can be written as:

$$\mathbf{r}_i = B_m a_{i,m}, \quad (9)$$

where $a_{i,m}$ is the weight of the m^{th} basis function related to the i^{th} sample. The basis functions are themselves functions of the wavelength but free of constraints such as being positive or constrained to be limited to the range [0 1]. Their number M is chosen to conserve maximum of energy. Equation 4 can be written as:

$$\mathbf{d} = \mathbf{S}^T\mathbf{Ba}, \quad (10)$$

where the columns of the N*M matrix $\boldsymbol{B}$ contain the M basis functions of a linear model of reflectance spectra and the M*J matrix **a** holds the weights that define the particular spectrum that we wish to reconstruct. When gathering $\mathbf{S}^T$ and $\boldsymbol{B}$ in a unique operator, this latter is a square matrix that could be easily inverted when K=M. We can rewrite Equation 10 as:

$$\mathbf{a} = (\mathbf{S}^T\mathbf{B})^{-1}\mathbf{d}, \quad (11)$$

which allows us to compute **a** after which one can easily estimate **r** from:

$$\tilde{\mathbf{r}} = \mathbf{Ba}. \quad (12)$$

In this context, methods belonging to the second paradigm, although implicitly, use decomposition techniques. For example, methods based on neural networks are also methods taking benefits from basis decomposition [8-9].

Within the linear model, PCA analysis was largely used as a decomposition basis [7, 10-11]. In a previous work [12], we performed a comparison by experimenting with two bases: PCA and wavelets analysis in the case of multispectral imaging. The goal was to study, in the same tasks of reflectance representation and estimation, the performance of training-set-dependent basis represented here by PCA and training-set-independent basis such as wavelets. A principal result we obtained was that PCA analysis performs better in the case of reflectance estimation from a multispectral system with broad-band filters (which is the case of conventional color systems) due to the fact that the low number of channels is compromised by its training set dependency. However the error remains significant. From this last observation, we propose to improve this approach by making it more adaptive.

3. Experimental set-up

We build our experiments on the comparison of the results presented using classic PCA cited in [11]. So, in one hand, we have two color images, one of the Macbeth DC containing 192 patches and one of the Macbeth CC containing 24 patches. In the other hand, we have measured by a spectrophotometer the reflectances $\mathbf{r}_p(\lambda)$ ($p=1\ldots24$) of the Macbeth CC patches. These latter are sampled at 10nm intervals in the range [400-700] yielding for each spectrum $\mathbf{r}(\lambda)$ to a vector of 31 values. The fact that we have a color image of the Macbeth CC provides us a set of *24* RGB tri-stimuli that we note $\mathbf{t}_p$. The objective is to estimate the $\mathbf{r}(\lambda)$ of each patch among the 192 Macbeth DC patches. We note that having the corresponding pairs ($\mathbf{r}_p(\lambda)$, $\mathbf{t}_p$) of the Macbeth CC allows us the mapping:

$$\mathbf{t}_p = \mathbf{Sr}, \tag{14}$$

where $\mathbf{S}$ is a 3x31 matrix whose rows contain the product of the illuminant and one of the channels' sensitivities. To stabilize the inversion, we use the classic PCA basis decomposition for each $\mathbf{r}_p(\lambda)$ like in Equation 12. So the last equation becomes (for all the tri-stimuli noted $\mathbf{T}$):

$$\mathbf{T} = \mathbf{SBA}, \tag{15}$$

$\mathbf{SB}$ is a 3x3 matrix and therefore we can write:

$$\mathbf{A} = (\mathbf{SB})^{-1}\mathbf{T} \ . \tag{16}$$

Since $\mathbf{R}=\mathbf{BA}$, we can deduce the reflectance for the 192 Macbeth DC patches using the following equation:

$$\mathbf{R} = \mathbf{B}(\mathbf{SB})^{-1}\mathbf{T} \tag{17}$$

4. Proposed algorithm

Deriving a basis consisting of three components from a large training set using PCA is suitable (for the representativeness) and means that all the elements of this set participate in the derived three components of the basis. However, for the reconstruction of a particular spectrum with a particular shape, all the elements of the training set are neither necessary nor appropriate. From this observation, we propose to adapt the training-set to each spectrum we wish to reconstruct. To do so, we derive a PCA basis in two steps: firstly, we derive a PCA basis from the whole training set and we perform a first estimation of reflectance from each tri-stimulus using this basis. Then, we measure the likelihood between the estimated reflectance and each element of the training-set. A new training set is built by keeping only those elements whose similarity falls in the range [95%-100%]. Then, we perform a new PCA analysis from this new set to derive a new basis consisting of new three components with which we perform the final reflectance estimation. The likelihood is calculated using the non centered correlation coefficient, largely used and known in the community as Goodness-of-Fit Coefficient (GFC) expressed by the formula:

$$GFC = \frac{\left|\sum_j R_m(\lambda_j)R_r(\lambda_j)\right|}{\left(\left|\sum_j [R_m(\lambda_j)]^2\right|\right)^{1/2}\left(\sum_j [R_r(\lambda_j)]^2\right)^{1/2}}$$

where $R_m(\lambda_j)$ is the value measured by the spectrophotometer in the wavelength λ_j, and $R_r(\lambda_j)$ represents the reconstructed value related to the same wavelength. The algorithm is presented below

Begin
Derive a basis $\mathbf{B}_1$ *from the training-set* $\mathbf{r}_p$
for each tri-stimulus $\mathbf{t}_i$ *where* i=1..192
Estimate an intermediate $\mathbf{r}_i^{inter}$ *as* $\mathbf{r}_i^{inter} = \mathbf{B}_1 (\mathbf{SB}_1)^{-1} \mathbf{t}_i$
Calculate the GFC between $\mathbf{r}_i^{inter}$ *and each* $\mathbf{r}_p$
$\mathbf{G} = \underset{p}{Max}(\mathrm{GFC}(\mathbf{r}_i^{inter}, \mathbf{r}_p))$
$\boldsymbol{New\_}\mathbf{r}_p = \{ \mathbf{r}_p \ / \ 0.95.\boldsymbol{G} \leq \mathrm{GFC}(\mathbf{r}_i^{inter}, \mathbf{r}_p) \leq \mathbf{G}\}$
Derive a basis $\boldsymbol{B}_2$ *from the training-set* $\boldsymbol{New\_}\mathbf{r}_p$
Estimate the final $\mathbf{r}_i$ *as* $\mathbf{r}_i = \mathbf{B}_2 (\mathbf{S}\,\mathbf{B}_2)^{-1} \mathbf{t}_i$
end for
end

5. Results

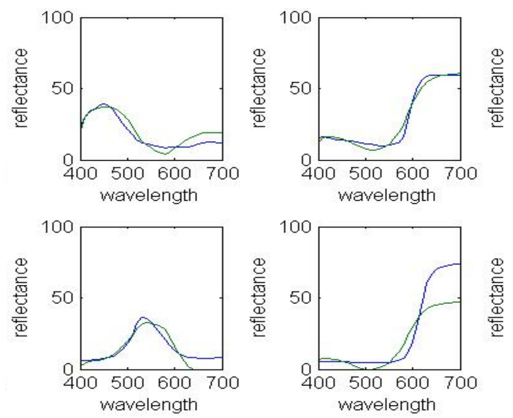
The results of this experiment were evaluated in terms of objective metrics and visual curve comparison. Figure 2 shows examples of four reconstructions of the same patches using Classic PCA (**a.**) and adaptive PCA (**b.**). For objective evaluation, we used GFC, and since this method is applied with the aim of reflectance recovery from a conventional color camera, we added the largely used color difference ΔE. Tables 1 and 2 show the results. A common interpretation of GFC is given in [13] as 4 categories of reconstruction. GFC>=0.9999 Excellent, GFC>=0.999 Very good, GFC>=0.99 good and GFC < 0.99 satisfactory to poor.

Method	GFC			
	Mean	**median**	**STD**	**Min**
Classic PCA	0.981	0.987	0.021	0.928
Adaptive PCA	***0.992***	***0.997***	***0.0100***	***0.959***

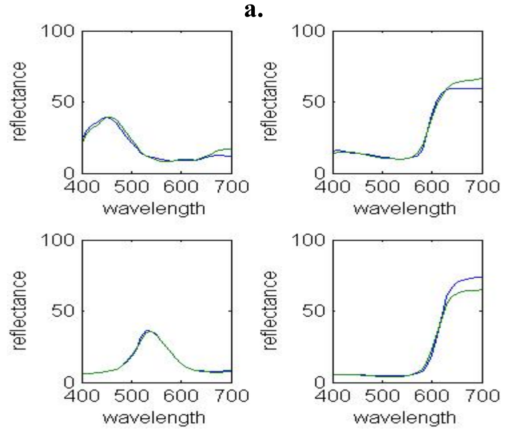
Table 1: results, in terms of GFC.

Method	ΔE			
	Mean	**median**	**STD**	**Max**
Classic PCA	7.90	6.05	7.01	27.83
Adaptive PCA	***4.28***	***2.22***	***3.93***	***12.76***

Table 2: results, in terms of ΔE.



a.



b.

*Figure 2: results of reflectance estimation using: **a.** classic PCA, **b.** adaptive PCA.*

It is noticeable from the results that the reflectance recovery from tri-stimuli using the algorithm we proposed to make PCA adaptive, gives the best scores in terms of both GFC and color difference ΔE. We notice that we double the performance of PCA, in terms of ΔE, when we make it adaptive.

6. Conclusion

In this paper, we have proposed an algorithm that makes PCA adaptive in the framework of reflectance recovery from tri-stimuli (color camera). We have evaluated the results in terms of GFC, reconstructed curves for visual comparison and the ΔE color difference measure. The results prove the effectiveness of this algorithm.

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