Supervised training sample selection for the estimation of spectral reflectance using a RGB camera.

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Abstract

Spectral imaging can provide spectral information from which spectral radiance or reflectance can be recovered at each image pixel. Recovery algorithms lead to good spectral and colorimetric performance by directly transforming RGB digital counts to spectral reflectances, but his approach is sensitive to the size and composition of the training set. What we propose here is a supervised method to select the most appropriate samples from a training database to buld the transformation matrix relating digital counts to spectral reflectances. Thus, this approach is tested with real images.

Introduction

Multispectral imaging uses a digital camera coupled or not with colour filters of different spectral bands, ranging from just one band, as in a monochromatic system, to hundreds of components, as in a ultraspectral system [1]. The main advantage of spectral imaging in comparison with conventional spectroradiometric measurements is that they can provide spectral information from which spectral radiance or reflectance can be recovered at each image pixel. During the last years, many different approaches have been proposed for spectral reflectance recovery [2]. Among these techniques, recovery algorithms lead to good spectral and colorimetric performance by directly transforming RGB digital counts to spectral reflectances [3]. This approach can be sensitive to the size and composition of the training set of reflectances [4]. Other authors have shown that depending on the spectral application (e. g. spectral pigment analysis in art pictures) the quality of spectral recovery may change dramatically. In this work we propose a supervised training sample selection method for spectral reflectance estimation based on a linear pseudo-inverse algorithm. The method uses a set of training samples selected from a database which are in the neighborhood of the target sample to optimize the recovery matrix relating digital counts to spectral reflectances. What we propose here is to optimize the building process of the transformation matrix using a learning-based algorithm.

Recently different computational results suggest that using cut off filters to recover reflectances or illuminants may or not improve the recovery performance, depending on the presence of noise [5, 7]. As these results are not clear for noisy data, we will also analyze here the effects of adding successive cut off filters when natural scenes are captured using a real RGB camera.

Method

In the present work, we used real images captured with an RGB digital color camera from QImaging (model Retiga 1300, 12 bits). The images captured were the Gretag Macbeth Color Checker DC and Color Checker rendition chart [8]. In a second step we added cut off filters in front of the camera lens (GG475 and OG550, from OWIS GMBH) to study possible improvements.

Given a set of training spectra $\boldsymbol{S}$ (which can be spectral radiances or reflectances) and the corresponding set of experimental camera responses $\boldsymbol{\rho}$, a recovery transformation matrix $\boldsymbol{D}$ is defined by $\boldsymbol{D} = \boldsymbol{S\rho}^+$, where $\boldsymbol{\rho}^+$ is the pseudo-inverse of $\boldsymbol{\rho}$. If $\boldsymbol{\rho}$ has full rank, then $\boldsymbol{\rho}^+ = (\boldsymbol{\rho}^T \boldsymbol{\rho})\, \boldsymbol{\rho}^T$, where $\boldsymbol{\rho}^T$ is the transpose of $\boldsymbol{\rho}$. An estimate of $\hat{\boldsymbol{S}}_1$ of a set of test spectra $\boldsymbol{S}_1$ may then be obtained from the corresponding set of camera responses $\boldsymbol{\rho}_1$ by applying the transformation $\boldsymbol{D}$, that is $\hat{\boldsymbol{S}}_1 = \boldsymbol{D\rho}_1$ [7].

We present here a method to select the most appropriate samples from a training database to be used as training set to recover reflectances from RGB data of a test image, without any need of knowing any spectral information of the test sample. The first step is to calculate CIELAB coordinates from both test and training set using real RGB digital counts captured with a CCD camera in both cases. Once we have this information, CIELAB color difference d_i is calculated between each test sample and the whole training set. It allows us to sort the training set for each test sample from minimum to maximum color difference.

To choose the training set elements to recover reflectance for each test sample, we set a sphere in each element of the test set in the CIELAB space, and we will use the elements of the training set inside this sphere. To calculate the radius of this sphere, we implement an iterative process as explained in Figure 1. It sets an initial sphere in the test sample, looks for the elements of the training set inside this sphere and compute the mean of its distances, giving them a weight that depends on the number of iterations and the number of elements inside the sphere. Then, the radius of the sphere is increased and the process is repeated decreasing the weight.

The algorithm description is:

- Fix a starting radius r_0, a constant k, and the number of iterations a. In this work the appropriate values of those constants comes from previous experimental results.

- Set a first sphere of radius r_0 centered on a test sample in the CIELAB space, and look for the elements of the training set inside of the sphere. Those elements will have CIELAB differences d_i • r_0. Now, it is possible to calculate a weighted mean radius T_0 as:

$$T_0 = \text{Ó}\,(d_i * a) \tag{1}$$

And also to calculate a normalization factor w_0 as:

$$w_0 = c_0 * a \tag{2}$$

where c_0 represents the total number of elements inside this sphere.

- The iteration goes on increasing the value of r_0 as: $r_1 = r_0 + k$, and looking for the new elements between the new sphere with radius r_1 and the previous one, those elements will have CIELAB differences $r_0 < d_i$ • r_1. In this step, the radius and the normalization factor will be calculated as:

$$T_i = Ó\ [d_i * (a\text{-}1)] + T_0 \quad (3)$$

$$w_1 = c_1 *(a\ \text{-}1) + w_0 \quad (4)$$

- After a iterations, we get a final radius T, given by:

$$T = T_{a-1} / w_{a-1} \quad (5)$$

The elements inside the sphere with radius T will be the elements of the training set used to recover reflectance of this particular test sample. This process will be repeated for each test sample.

In Figure 1, there is a graphic simplified example of the process. On it, the test sample is shown as a '*'. It corresponds with the MacBeth Color Checker (CC) sample number 15. With the symbol 'o' are shown the 25 samples from MacBeth Digital Color Checker (DC) that have the smallest CIELAB distance to this test sample.

Results and comments

Recoveries were made using all the chips from the MacBeth Digital Color Checker (DC) as training data in all cases. As test sets, we used both the DC and MacBeth Color Checker (CC).

To avoid as many as possible sources of error, a correction was made to the captured images: we tried to avoid the high frequency temporal noise. This is the noise affecting the system when captures follow each other in less than a minute time. It is possible to avoid it capturing successive images and promediating them. From a preliminary study [6], we conclude that it was necessary to promediate over 100 images to avoid this high frequency temporal noise.

In evaluating the results we have analyzed the performance of the algorithm in a variety of different quality measures. We used two metrics to quantify both the spectral and colorimetric quality of the recovered reflectance: the goodness-of-fit-coefficient (GFC) and the CIELAB color difference (ÄE). The GFC is based on Schwartz's inequality and is defined as the cosine of the angle between the original signal $f(ë)$ and the recovered signal $f_r(ë)$, thus

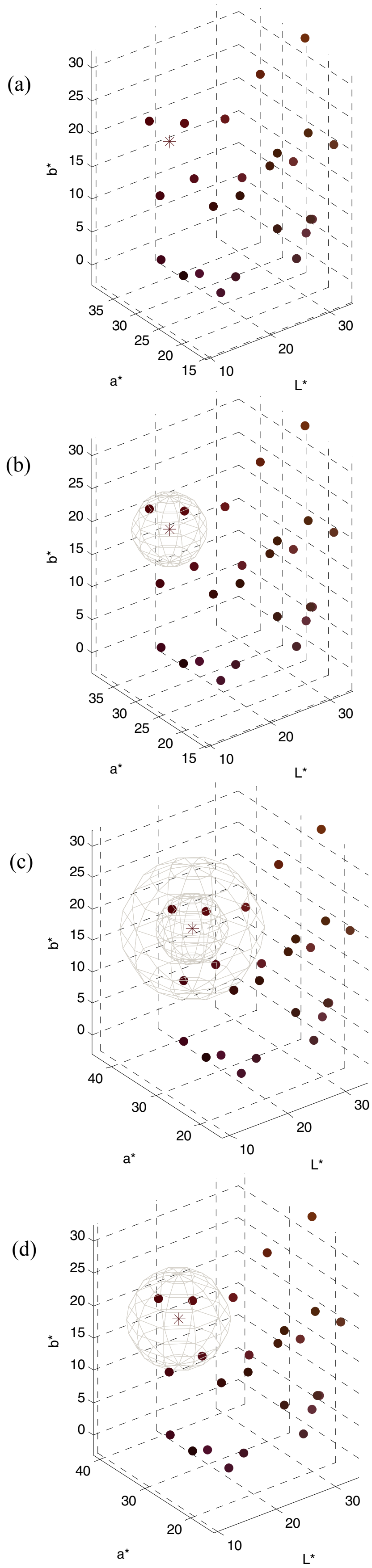

Figure 1: *Followed steps in the radius T calculation process. In descent order: (a) First, test sample (*) and training set (o) CIELAB coordinates are calculated. (b) Second, a sphere of radius r_0 is centred on the test sample, and the training samples inside this sphere are used to calculate the weighted radius T_0. (c) A second sphere with radius $r_0 + k$ is centred in the test sample. The elements of the training set between the first and the second sphere are used to calculate the weighted radius T_1. This third step is repeated as many times as necessary. (d) At last, a final radius T is calculated, and the training samples inside the corresponding sphere are used as training set to recover this test sample reflectance..*

$$\mathrm{GFC} = \frac{\sum_{\lambda=400}^{700} f(\lambda) f_r(\lambda)}{\left(\sum_{\lambda=400}^{700} f(\lambda)^2\right)^{1/2} \left(\sum_{\lambda=400}^{700} f_r(\lambda)^2\right)^{1/2}} \tag{6}$$

This measurement of spectral similarity has the advantage of not being affected by scale factors. Colorimetrically accurate reflectance estimations require GFC > 0.995; GFC > 0.999 indicates quite good spectral fit, and GFC > 0.9999 an almost-exact fit [9].

The GFC mean results are shown in Table 1 and CIELAB mean results are shown in Table 2. In those tables, 0 means images captured without filter (3 channels), 1 means images captured without filter and with GG475 filter (6 channels), and 2 means images captured without filter and with filters GG475 and OG550 (9 channels). In those tables, traditional method results for both DC and CC test sets are shown first, and supervised method results for the same test sets are shown in second place. The reason why we use six channels with the filter GG475 instead of filter OG550, comes from experimental results: they were better with filter GG475.

As it can be seen, in all cases supervised method results are better than the traditional method results. When DC is used as test and training set, we get better results as we increase the number of sensors. But when we recover CC with DC, we can see that using one filter (6 channels) we can get more or less the same results, but using two filters (9 channels) GFC values decreases a lot and CIELAB values increases. The reason why it happens is that when we add more channels we are adding more sources of noise too, and it makes results go worse [5].

Figure 2 shows some examples of recovered spectra corresponding to the median GFC, using both linear pseudoinverse method (LPI) and supervised linear pseudo-inverse method; and using no filter. Original spectra are represented with continuous line and recovered spectra by dashed lines. Again, in all cases we get better spectral and colorimetric results with the supervised method; and, even in the recovery of the CC test set with the DC training set, we get GFC values over 0.995.

The results suggest that the supervised training method consistently outperforms the standard method of using the complete training data set. We can get better results with one color filter than using two, in agreement with previous results using noisy data for illuminant and reflectance estimation.

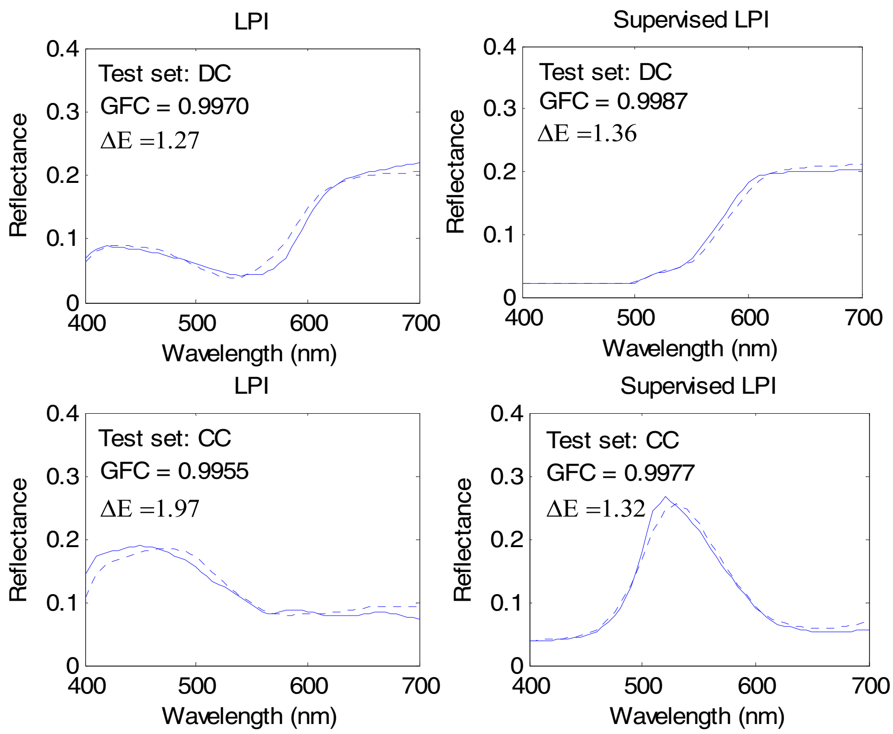

Figure 2: *Examples of recovered reflectances using both methods.*

	Traditional method			Supervised method		
Test sets	**0**	**1**	**2**	**0**	**1**	**2**
DC	0.9907	0.9941	0.9970	0.9960	0.9978	0.9985
CC	0.9879	0.9870	0.7651	0.9952	0.9935	0.7947

Table 1: *Comparison of spectral performance (GFC) between the traditional method and the supervised method*

	Traditional method			Supervised method		
Test sets	**0**	**1**	**2**	**0**	**1**	**2**
DC	2.03	1.29	0.80	1.28	0.71	0.50
CC	2.56	1.95	16.33	1.52	1.27	13.04

Table 2: *Comparison of colorimetric performance (color difference CIELAB) between the traditional method and the supervised method.*

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Author Biography

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