Unsupervised classification algorithms applied to RGB data as a preprocessing step for reflectance estimation in natural scenes

Eva M. Valero, Juan L. Nieves, Clara Plata, Javier Romero. Departamento de Óptica, Facultad de Ciencias, Universidad de Granada, 18071 Granada (SPAIN)

Abstract

Reflectance estimation from RGB data in natural scenes is studied computationally including the use of different unsupervised classification techniques to divide the RGB data into a number of subgroups with similar characteristics to test if these techniques lead to any improvements in the quality of the spectral signals obtained. The direct pseudoinverse method for recovery of spectral signals from RGB values is used for each subgroup and the similarity of the recovered spectral data to the original sets is tested by different quality indexes. Weighted mean results according to the number of components of each subgroup are compared with mean results obtained for the whole RGB data set (with no classification algorithms used as preprocessing step). Different algorithms and number of classes are tested for noise-free and noisy data. In addition, the use of an color filter in front of the camera lens is introduced in the computations to study spectral recovery from six instead of three RGB values for each spectral reflectance. The best results are obtained for 8 classes and a probabilistic approach clustering algorithm. Quality decreases when a high level of noise is added to the data, and the use of a color filter only helps to improve results for noise-free data.

Introduction

The goal of multispectral imaging is to recover spectral radiance or reflectance for each pixel of a scene of interest [1-2]. Usually a multispectral system consists of an RGB or monochrome digital camera coupled with a number of wide-band or narrow-band colour filters. If the filters are narrow and there are many of them, as in hyperspectral imaging, radiance or reflectance can be recovered exactly [3], but spectral function recovery is an ill-posed problem when a reduced number of wide-band color filters is coupled to the digital camera. This problem can be partially solved by different methods of spectral recovery from camera responses (direct reconstruction, reconstruction by interpolation and learning-based reconstruction) [2, 4, 5]. In the so-called "direct pseudo-inverse method" [6], the recovery process includes the calculation of an estimation matrix D from the training set of camera responses linked to the corresponding spectral signals:

$$\mathrm{D} = S_t \rho_t^{+} \qquad (1)$$

where ρ_t is the set of camera responses for the training data and S_t is the set of training spectral radiances or reflectances. The + sign indicates pseudoinverse matrix. Once D is obtained, any set of spectral signals may be recovered from camera responses:

$$S = D\rho \qquad (2)$$

Previous computational results regarding reflectance and radiance [6] or illuminant [5] recovery from natural scenes indicate that adding successive color filters to the digital camera, can improve the spectral and colorimetric quality of the recovered signals, although not so clearly when the RGB signals are noisy [7] or for illuminant estimation [5].

Recently, clustering techniques have been applied to hyperspectral imaging systems, taking into account spectral as well as spatial information, to improve classification results in satellite images [8, 9]. Clustering algorithms perform an unsupervised classification of a data set in a number of classes (indicated by the user), so they are very useful when a priori knowledge of the data structure is not available.

The main aim of this study is to provide some preliminary data to test the hypothesis of a possible improvement in recovery quality of spectral reflectances in natural scenes from camera responses by using clustering techniques as a previous step. So we first simulate the capture of a natural scene with or without successive color filters in front of an RGB digital camera, then classify the camera responses using clustering, and train separately the different classes obtained. Afterwards, we check the recovery quality by using a test data set not included in the training phase, and classified using the same criteria as for the training data. The influence of noise is tested by comparing results obtained with and without a high level of additive simulated thermal and shot noise. In addition, we obtain results for different number of classes and study the evolution of spectral and colorimetric quality measures of the recovered data with the number of classes used. Finally, for a fixed number or classes, several clustering algorithms based on different approaches are used to see which provides better results.

Method

We have calculated the RGB camera responses with and without a color filter in front of the camera, using a set of hyperspectral data from a high spatial resolution database [3] which included rural scenes in the region of Minho (Portugal). The camera whose spectral sensitivity was used in the computations was a Retiga 1300 (QImaging Corp, Canada) with 12-bit intensity resolution per channel. When the effect of added noise was studied, we have introduced a 5% variance level of additive noise, simulating thermal and shot noise. The noise was introduced as shown in eq. (3).

$$\rho_n = \rho + N \quad (3)$$

where ρ_n are the noisy digital counts and N is a column vector of three (without filter) or six (with added filter) noise values [7]. We have calculated the camera responses for a set of 228010 reflectances in the training group and a set of 37210 reflectances in the test group (none of them included in the training set). Then, we have used eq. (1) and (2) to obtain the recovered reflectances for the test set. This recovery will serve as a reference for testing the effect of applying clustering algorithms to the camera responses.

Once the camera responses for each condition (noisy or noise-free, with or without filter) were computed, we have used a k-means algorithm [10] with random initialization values to divide the training set into 2, 4, 8, 16 and 32 classes. Then we have computed the recovery matrix D for each class and obtained the recovered reflectances for the test set (having previously classified the test data according to the algorithm's output). We have run the k-means algorithm five times and selected the output giving a better quality (as derived from the Xie and Beni and Separation indexes [10]). Finally, we have used other two clustering algorithms: Fuzzy-C Means (FCC) [10] and a probabilistic Gaussian Mixture Model (GMM) [11] with 2, 4 and 8 classes to test the effect of the clustering algorithm on the recovery quality.

Two spectral (Goodness-of-Fit-Coefficient or GFC, defined as the cosine of the angle between original and recovered signals in the reflectance vector space; and Root Mean Square Error or RMSE) and one colorimetric (CIELAB color difference) quality measures were used to assess similarity between original and recovered reflectances.

Results

1. Effect of the number of classes on recovery quality for the k-means algorithm.

In Figure 1 we can see weighted mean ΔE_{ab} color differences for reflectance recovery in the four experimental conditions as a function of the number of classes used as input to the k-means clustering algorithm. Results with 0 classes correspond to recovery without subdivision of the digital counts. The use of noisy camera responses leads to high color differences, as expected, given the high noise level, and also influences the performance as the number of classes varies. We can see that differences tend to become stationary from 8 classes on. In the noise-free data, recovery with filter is better than without filter, while the opposite trend is found for the noisy data. This is in agreement with other recent experimental results regarding reflectance and illuminant estimation with noisy data [3, 7]. We have performed a one-way ANOVA for each condition and the factor number of classes was always significant ($p<0.001$). Data for GFC and RMSE correlate well with color differences.

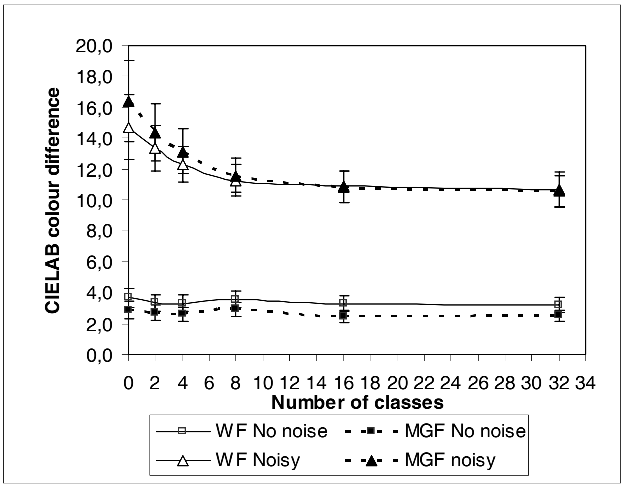

Figure 1. *Color differences for k-means clustering.*

Table 1 shows GFC values for the four conditions tested and the k-means algorithm with different number of classes. We can see that the trends shown by color differences are confirmed by the spectral quality index, with slight differences regarding the MGF noisy data, which show a slow but sustained increase in recovery quality when the number of classes increases.

Table 1. GFC mean values for k-means.

Nr. of classes	GFC	Condition
0	0.9346	WF No Noise
0	0.8952	WF Noisy
0	0.9649	MGF No noise
0	0.8808	MGF Noisy
2	0.9425	WF No Noise
2	0.9010	WF Noisy
2	0.9669	MGF No noise
2	0.8854	MGF Noisy
4	0.9469	WF No Noise
4	0.9101	WF Noisy
4	0.9681	MGF No noise
4	0.8956	MGF Noisy
8	0.9459	WF No Noise
8	0.9179	WF Noisy
8	0.9649	MGF No noise
8	0.9053	MGF Noisy
16	0.9438	WF No Noise
16	0.9214	WF Noisy
16	0.9664	MGF No noise
16	0.9182	MGF Noisy
32	0.9405	WF No Noise
32	0.9218	WF Noisy
32	0.9650	MGF No noise
32	0.9201	MGF Noisy

2. Effect of the algorithm for 2, 4 and 8 classes.

In Figure 2 we show GFC for the three algorithms tested and the four experimental conditions for 8 classes. Fuzzy-C means is slightly better than k-means for noise-free data, but the recovery is worse than k-means for noisy data, showing that this algorithm would be more sensitive to noise. The probabilistic GMM algorithm is consistently better than k-means for all four conditions. We can also see in the figure that recovery is better for noise-free than for noisy data and that adding the color filter improves recovery only in the noise-free data set, as we have pointed out in the previous subsection. We have performed a repeated-measures ANOVA as statistical analysis with these data, including three factors: algorithm, noise and filter. All three were significant ($p<0.001$), and only the interaction algorithm x noise did not reach significance level ($p=0.551$), showing that the effect of noise is independent of the algorithm used. The results for RMSE and ΔE_{ab} showed very similar trends. In Table 2 we show RMSE results for 2 and 4 classes and the different algorithms and experimental conditions tested. In RMSE, we can see that FCM and GMM are consistently better than k-means even for noisy data, showing that these two algorithms produce spectral recoveries more similar to the original data in absolute scale (GFC values are independent of scale factors).

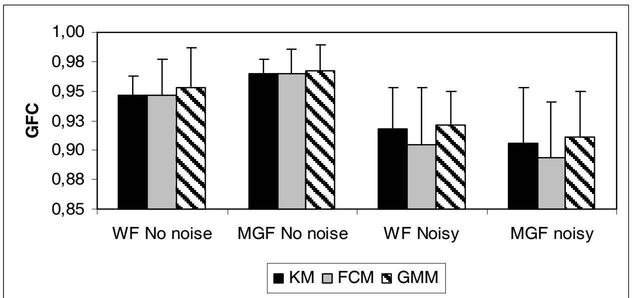

Figure 2. *GFC for eight classes and the different algorithms tested.*

Table 2. RMSE mean values for 2 and 4 classes and the different algorithms and conditions tested.

Nr. of classes	RMSE	Algortihm/condition
2	0.0987	KM/ WF No Noise
2	0.1414	KM/ WF Noisy
2	0.0599	KM/ MGF No noise
2	0.1775	KM/ MGF Noisy
2	0.0349	FCM/ WF No Noise
2	0.0503	FCM/ WF Noisy
2	0.0249	FCM/ MGF No noise
2	0.0545	FCM/ MGF Noisy
2	0.0326	GMM/ WF No Noise
2	0.0476	GMM/ WF Noisy
2	0.0232	GMM/ MGF No noise
2	0.0467	GMM/ MGF Noisy
4	0.0741	KM/ WF No Noise
4	0.1024	KM/ WF Noisy
4	0.0493	KM/ MGF No noise
4	0.1322	KM/ MGF Noisy
4	0.0345	FCM/ WF No Noise
4	0.0486	FCM/ WF Noisy
4	0.0253	FCM/ MGF No noise
4	0.0524	FCM/ MGF Noisy
4	0.0322	GMM/ WF No Noise
4	0.0468	GMM/ WF Noisy
4	0.0235	GMM/ MGF No noise
4	0.0434	GMM/ MGF Noisy

Conclusions

In conclusion, we have tested unsupervised classification of digital counts for reflectance recovery and we have found that the best results are obtained using al least 8 classes and the GMM algorithm. Clustering as a preprocessing step helps in improving recovery quality for spectral reflectance estimation from RGB values. The addition of a color filter helps improving recovery only for noise-free data or possibly for low-noise data as well.

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Author Biography

Eva M. Valero received her BS in physics (1995) and her PhD in physics (2000) from the University of Granada. Since then she has worked in the same university as assistant and associate professor (2007). Her work has focused lately on multispectral imaging and reflectance and illuminant recovery from RGB values in natural scenes. She is a member of the OSA.