Independent Component Analysis With Different Daylight Illuminants

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Abstract

Independent Component Analysis (ICA) has been developed as an efficient method to linearly transform input data to derive statistically independent components, and it has been recently used to derive the independent components of natural scenes. In this work, we study the influence of illuminant in the ICA results using as input sets of the same hyperspectral images under different daylight Spectral Power Distributions. Once the ICA bases were derived for each illuminant condition, we analysed the differences between them, and the reconstruction of color images with different bases and different number of basis functions. The results indicate that there are consistent differences between the bases corresponding to high and low solar elevations. The differences between atmospheric conditions are small for a given solar elevation. In the reconstruction results, the differences between original and reconstructed images with different ICA bases are more evident for the first 11 basis functions. With 61 basis functions, the results are rather similar for all the bases. We consider these results as a first step towards constructing an illuminant-invariant set of basis functions for color image representation.

Introduction

Recently, different ICA algorithms have been applied to the efficient representation of color images and spectral functions in natural scenes[1-4] and have shown the advantages of ICA in comparison with Principal Component Analysis (PCA) to reduce the reduntant information contained in a data set. In these studies, ICA has been applied to very different image datasets, with the resulting bases differing quantitatively but not qualitatively. Nevertheless, the extent of the contribution of the changes in the illuminant to these differences needs to be studied in more detail, specially when the illuminant is daylight, as most of the results so far have been obtained using natural scenes as input data.

In this work, we study the influence of illuminant in the ICA results using as input sets the same hyperspectral images under different daylight Spectral Power Distributions (SPDs). Once the ICA bases were derived for each illuminant condition, the work faces the analysis of the differences between them and the reconstruction of color images with both the different bases obtained and different number of basis functions. Regarding the recovery of images using the different bases, we must take into account that the evaluation of both spatial and colorimetric differences between images is a rather tricky question. Differences in the spatial structure of the images may arise when the original and reconstructed images for a specific number of ICA basis functions are compared if a reduced number of basis functions is used in the reconstruction process, and also colorimetric differences may be present in some regions or over the entire image.

Background

ICA has recently become an important tool for modelling and understanding empirical datasets, offering an elegant and practical methodology for blind source separation. Most observations consist of a mixture of signals. The scientific community has paid much attention to the problem of recovering the constituent sources from the convolutive mixture, and a very convenient method for doing this is ICA. Recovery relies on the assumption that the constituent sources are mutually independent.

Finding an adequate coordinate system is an essential first step in the analysis of empirical data. Priincipal Component Analysis (PCA) has been used for many years to find a set of basis vectors which are determined by the dataset. The principal components are orthogonal and projections of the data onto them are linearly decorrelated, properties that can be ensured by considering only the second order statistics of the data. ICA seeks instead a transformation to coordinates in which the data are maximally statistically independent, nor merely decorrelated. The assumption of most classical ICA models is that observations x are generated by a linear combination of the sources s:

$$x=\mathbf{A}s \qquad (1)$$

where A is the missing matrix of unknown elements.

Variations of these models can be found depending upon the probabilistic model used for the sources: flexible source models, which depend continuously upon their parameters, schemes that switch between two source models dependent upon the moments of the recovered sources, or else a fixed source model (single function with no explicit parameters, like in the infomax algorithm).[3]

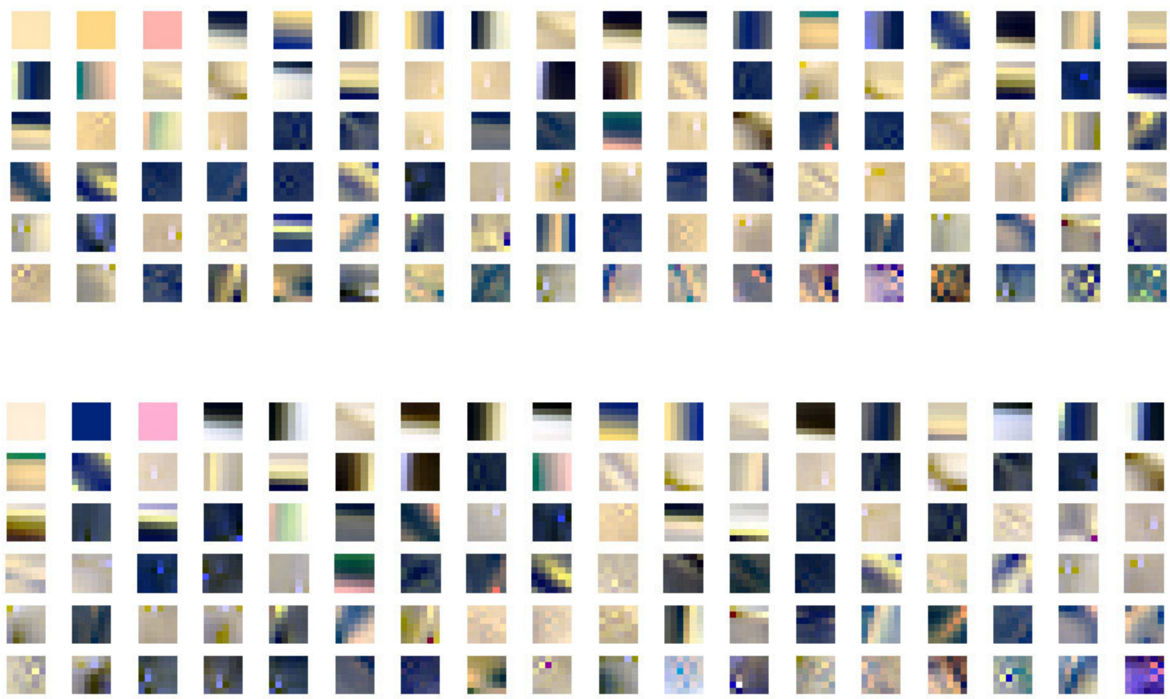

Figure 1. ICA bases corresponding to a clear day at maximum solar elevation (upper figure) and minimum solar elevation (lower figure).

Methods

We used a set of 27 hyperspectral images (256x256 pixels) from Nascimento's image dataset[5]. For each pixel, the dataset provided the spectral reflectance in the interval 410-710 nm ($\Delta\lambda$=10 nm). The objects were either natural scenery or a room with some toys and varied man-made articles.

We selected eight daylight SPDs corresponding to four different weather conditions (clear, covered, mixed and atmospheric dust present) and two different solar elevations (maximum and minimum obtained for each condition)[6]. We indicate the names of the illuminants according to an identification code for later reference. The weather conditions were: clear sky (maximum solar elevation: Ilum1, minimum solar elevation: Ilum433); overcast sky (maximum solar elevation: Ilum1645, minimum solar elevation: Ilum1651); sky with some clouds (maximum solar elevation: Ilum2312, minimum solar elevation: Ilum2320); atmospheric dust (maximum solar elevation: Ilum724, minimum solar elevation: Ilum728).

For each illuminant condition, we performed the ICA of over 50.000 (6x6) patches of L,M,S cone responses calculated from the color signals corresponding to our hyperspectral dataset under each daylight SPD. The ICA algorithm used was the Extended Infomax[3], which is capable of blindly separate mixed sub-Gaussian and super-Gaussian signals. The first step of the algorithm is to randomly disorder the input data.

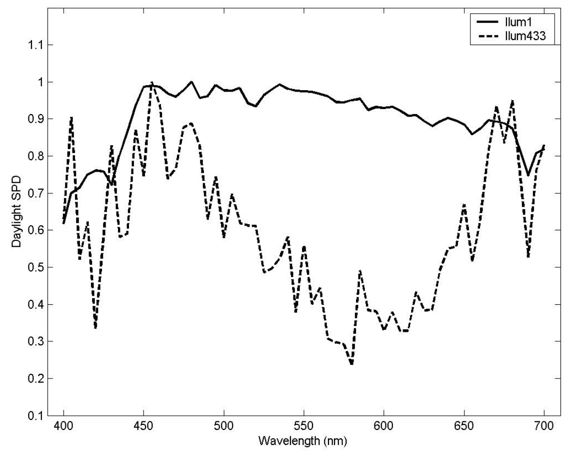

Figure 2. Daylight SPDs for clear weather at maximum (Ilum1) and minimum (ilum433) solar elevation.

After the ICA was performed, we obtained the ICA basis functions, which were ranked decreasingly by L^2-norm. In figure 1, we can see two examples of bases corresponding to maximum and minimum solar elevations. In figure 2, we represent the clear daylight SPDs at maximum (Ilum1) and minimum (Ilum433) solar elevations.

Results

1. Differences Between ICA Bases

In order to obtain a quantitative estimation of the differences between two ICA basis, we have used two different indexes which are both based on the root-mean square difference between R,G,B values of basis functions.

The first index was calculated using the RMSE averaged across pixels for each of the three R,G,B planes. For each basis function of the first ICA basis, we calculated the RMSE differences with the 108 basis functions of the second ICA basis. Then, we determined the number of the basis function that gave the minimum RMSE difference (nearest neighbour). If we calculate the difference between two equal ICA bases, and plot the nearest neighbour number for each basis function as a function of basis function number, we obtain a unity-slope plot. So the separation from this reference line indicates the existence of differences between both ICA bases (some vectors present in the first basis may not be present in the second one, or may be present in a different position). We finally obtain the index shown in Table 1 by calculating the RMSE between the distribution of nearest neighbours vector numbers from the second basis and the distribution corresponding to unity-slope plot (ranking from 1 to 108 in order). We show the results corresponding to the comparison between the clear daylight at maximum solar elevation (Ilum 1) and other daylights.

Table 1. RMSE of difference in vector number with nearest neighbour for different daylights for the clear at maximum elevaation daylight

	Clear-covered	Clear-mixed	Clear-dust	
Max elev	15.44	21.11	25.83	
	Clear-covered	Clear-mixed	Clear-dust	Clear-Clear
Min elev	34.12	25.63	28.25	22.46

Table 2. RMSE of minimum RGB difference (mean, percentile 5, percentile 95)

	Max elev		Min elev
Clear-covered	161.63 (23.82,519.59)	Covered-covered	386.20 (203.22,718.75)
Clear-mixed	251.57 (66.27,512.50)	Mixed-mixed	276.44 (102.25,565.70)
Clear-dust	256.07 (48.60,525.64)	Dust-dust	280.57 (60.23,548.99)
		Clear-clear	260.25 (100.45,577.98)

For the calculation of the second index, we used the maximum of the three RMSE averaged over the 36 pixels corresponding to the R, G, and B values. For each basis function of the first ICA basis, we calculated the 108 RMSE differences with the 108 basis functions of the second ICA basis. Then, we took the minimum RMSE difference for each basis function of the first ICA basis. For the distribution of 108 minimum RMSE differences thus obtained, we calculated the mean and percentiles 5 and 95. The results for these index and the different couples of ICA bases are shown in Table 2. The second column shows a comparison between different atmospheric conditions at maximum solar elevation, and the fourth colum shows a comparison between maximum and minimum solar elevation for different weather conditons. ranking by L^2-norm.

The differences between atmospheric conditions are small in conparison to the differences between maximum and minimum solar elevations (except for the "dust" condition, Ilum 728 and Ilum 724, Table 1). These results are reflecting the differences between the initial data sets used as input for the ICA algorithm. So, the ICA algorithm is sensitive to illuminant changes even for daylight, something that (to our knowledge) has not been previously reported.

2. Image Reconstruction Performance

Regarding the reconstruction of images using different ICA bases, we have evaluated the differences between original and recovered images by a triple procedure: the RMSE of RGB pixel-to-pixel difference averaged for the whole image, the S-Cielab pixel-to-pixel color difference formula,[7] and RMSE of averaged region-to-region RGB difference after having segmented the images by a quadtree decomposition with a 10%-of-maximum-modulation threshold.

In figure 3 we show the results for a scene under covered daylight at maximum solar elevation (Ilum1651), as a representative example for the reconstruction with 11 and 61 basis functions of two ICA basis corresponding to the original illuminant and the illuminant of the same day at dusk (minimum solar elevation, Ilum1645). The results are similar for scenes containing only natural objects. We can see that the reconstructions are always better with 61 than with 11 basis functions, as expected, because the basis functions adequate for representing fine details have lower L^2-norm and thus are positioned after the first 20-30 basis functions after the ICA is performed. The differences between the ICA bases in the reconstruction results are far more evident for the first 11 basis functions.

The three indexes used to evaluate these differences offer similar results for the comparison between the original and reconstructed images with different ICA basis. Only index I2 shows a better reconstruction with 61 basis functions and the ICA basis under minimum solar elevation than with 61 basis function and the basis corresponding to the original illuminant. Nevertheless, with 61 basis functions the results are rather similar for the two bases shown. So, as expected, both maximum and minimum solar elevation bases are able to adequately represent the scene if a sufficient number of basis functions is used in the recovery.

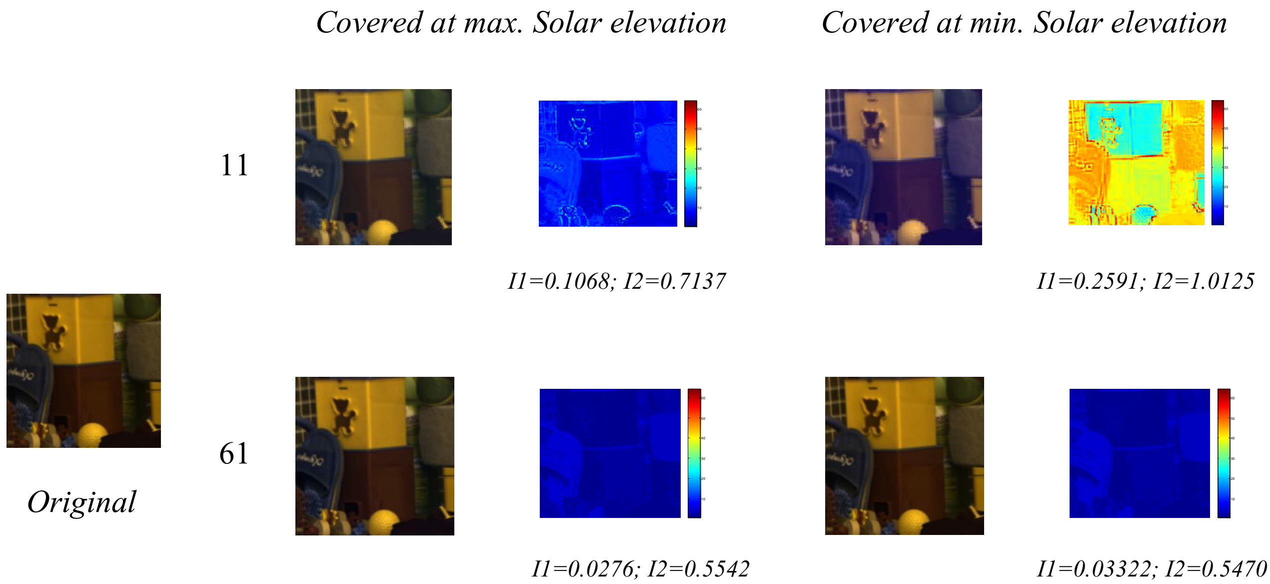

Figure 3. Original and reconstructed scene with 11 and 61 basis functions. The original is under covered Daylight SPD at maximum solar elevation. Colorbar graphs show S-Cielab results. I1 is the averaged pixel-to pixel difference index. I2 is the averaged region-to-region difference index.

Conclusion

We have found that the differences between the different ICA bases under different daylights are reflected both in the basis functions obtained under different daylights and in the reconstruction results, specially when we use only the first 11 basis functions.

We consider these results as a first step towards the aim of constructing an illuminant-invariant set of basis functions for color image representation.

References

1. P.O. Hoyer, and A. Hyvärinen. Network: Computation in neural systems 11, 191 (2000).
2. D.R. Tailor, L.H. Finkel, and G. Buchsbaum. Vision Research 40, 2671 (2000).
3. T. Wachtler, T.-W. Lee, and T.J. Sejnowski. J. Opt. Soc. Am. A 18, 65 (2001).
4. T.-W. Lee, T. Wachtler, and T.J. Sejnowski. Vision Research 42 2095 (2002).
5. S. M. C. Nascimento, F.P. Ferreira, and D.H. Foster. J. Opt. Soc. Am. A 19, 1484 (2002).
6. J. Hernández-Andrés, J. Romero, J.L. Nieves and R.L. Lee, Jr. J. Opt. Soc. Am. A 18, 1325 (2001).
7. X. Zhang and B.A. Wandell. SID Digest 19, 27 (1996).

Biography

Dr. Eva M. Valero obtained her Ph.D. by the University of Granada (Spain) in June 2000. Since 1997 she has been a member of the department of Optics, researching in the field of spatial colour vision (recently color image processing) and also teaching since 2001. She has worked in collaboration with the Physiological Laboratory at Cambridge (UK) and the Department of Neurological and Vision Sciences at Verona (Italy).