ON THE USE OF ICA FOR HYPERSPECTRAL IMAGE ANALYSIS

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1. INTRODUCTION

Independent component analysis (ICA) is a very popular method that has shown success in blind source separation, feature extractions and unsupervised recognition. In recent years ICA has been has been largely studied by researchers from the signal processing community ; this paper addresses a more in-depth study on the use of this method, applied to hyperspectral images used in remote sensing application.

2. INDEPENDENT COMPONENT ANALYSIS

ICA consists in finding a linear decomposition of observed data into statistically independent components [1]. Given an observation model:

$$\mathbf{x} = \mathbf{A}\mathbf{s}, \tag{1}$$

where **x** is the vector of the observed signals, **A** a scalar matrix of the mixing coefficients and **s** the vector of the source signals, ICA finds a separating matrix **W** such that:

$$\mathbf{y} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s}, \tag{2}$$

where **y** is a vector of independent component. ICA looks for a linear representation that maximizes a non-gaussianity measure [2], minimizing an objective function. A commonly objective function used in ICA algorithms is the mutual information of vector **y**:

$$I(\mathbf{y}, \mathbf{W}) = \sum_i H(y_i) - H(\mathbf{y}) \tag{3}$$

where $H(y_i)$ and $H(\mathbf{y})$ are the entropy of random variable y_i and of random vector $\mathbf{y}$, respectively.

3. ICA AND SOURCE SEPARATION

In the recent past, ICA has been proposed as a tool to unmix hyperspectral data [3]. ICA allows each source to be automatically extracted from the observation of linear combinations of these sources. In order to retrieve the sources, ICA needs the assumption of statistical independence of the sources. This assumption is unfortunately usually not verified in the case of real data since the natural elements reflectance spectra can be quite the same for different materials. This make ICA efficient for removing artifact but not suitable for segmentation of hyperspectral images [4]. In previous works [5], we used ICA as a pre-processing step for a Bayesian Positive Source Separation (BPSS) method for solving this problem. The results obtained with BPSS, although promising, show that the reconstruction error varies a lot, spatially. Consequently, one can assume that, in areas where the approximation is weak, the model is not suited. Basically, since the main properties of the model consist of its linear nature and the estimated number of endmembers, two issues can be investigated : (i) the linearity of the model is locally wrong, (ii) the number of endmembers is locally insufficient In this paper, we consider a two step approximation. The first step is a global approximation, which is done on the whole image. The second step is a refinement step, which consists in doing a local approximation in all the areas where the global approximation is too weak, assuming that the number of endmembers can locally vary.

4. ICA AND DIMENSIONALITY REDUCTION

ICA can also be proposed to be used as an alternative approach to Principal Component Analysis for dimensionality reduction. In order to obtain the generating factors, ICA is designed not to search the principal components, which allows to represent the maximum of the return dispersion, but the more independent factors which can linearly generate the returns. The algorithms includes higher order statistics than the second order moments, thus it seems to be an attractive candidate for dimensionality reduction. ICA has proven good performances with respect to PCA in various fields, such as object recognition and geoscience applications. It has been positively used for data preprocessing in multispectral remote sensing imagery classification and revealed interesting features for the dimensionality reduction and the representation of the hyperspectral data sets [6]. This step is also very useful before classification. In fact, in the transformed domain, after ICA, axes are related to independent component. Thus, in this space

$$\mathrm{p}(\mathbf{r}' \mid H_i) = \prod_j \mathrm{p}(r'_j \mid H_i), \tag{4}$$

which is a very efficient and simple approximation for implementing Bayesian classifiers. In this paper we propose a comparison between PCA and ICA and a study of their influence on hyperspectral data set classification.

5. CONCLUSION

In this paper, we study the Independent Component Analysis for hyperspectral image analysis. First of all, source separation is addressed. Since the independence of sources is usually not verified in hyperspectral real data images, ICA is not a suitable tool to unmix sources, if used alone. We propose a hierarchical approximation for the use of ICA as a pre-processing step for a Bayesian Positive Source Separation method. Then, the use of ICA for dimensionality reduction, for the purpose of classification of hyperspectral remote sensing data is studied, and a comparison with Principal Component Analysis is presented.

6. REFERENCES

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