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New Gaussian hierarchical segmentation

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***Abstract*—In this paper, we present a recent advance in classification process of hyperspectral data. The classification of scenes and the extraction structures (roads, buildings, objects, textures, etc…), are indispensable tools to interpret the remote sensing data. In fact, classification approach is one among the interpretative methods of images. The high dimensionality of these images implied by sensors which provide hundreds of narrow and adjacent spectral bands, present challenges to data sets analysis. The first step of our work consists in adopting the problem of Blind source separation (BSS) method by taking advantage of the sparse representation of the hyperspectral images. The idea behind transform domain is that we can restructure signal/image values to give transforms coefficients more easily to separate. To take advantages from the new representation of hyperspectral data in frequency domain, the next step consists on a novel classification approach based on Gaussian modeling. Hierarchical classification process is performed with the use of adaptive neighborhoods derived from classes'/regions' segmentations results. Thus a key idea in our framework is to develop jointly a spectral and spatial method using a Gaussian segmentation for accurately classification of hyperspectral images.**

***Keywords*—hyperspectral images; source separation; sparse representatio;, hierarchical segmentation; Gaussian modeling; spatial/spectral classification.**

I. INTRODUCTION

A fundamental problem in remote sensing discipline is to extract the useful information and to find a suitable representation of multivariate-observed data [1]. Given that this information is subject of several perturbations, it is in generally, not directly accessible. The main aims of this work are; firstly, to identifying the transfer function of linking signals of interest (sources) to the observations and secondly to envisage the restoration of valuable information [2]. This new representation is obtained by developing an approach based on the blind source separation (BSS) in frequency domain. To benefit from the new representation of hyperspectral data, we will precede to the classification approaches source by source in order to obtain good correspondence class/source. To achieve the best performance for image classification, several runs using different parameters should be chosen according to the characteristics of dataset. This is which amounts to adopt a sparse Gaussian segmentation process model followed by hierarchical clustering to improve the classification process of hyperspectral data. The hierarchical process consists on finding the smallest dissimilarity value between pairs of spatially regions. The dissimilarity criterion is fundamental stage before regions merging step. In particular, the integration of spatial information crucial for the analysis of images and spectral information constitutes the richness of dataset. Therefore, the development of spectral/spatial classification approach allows assigning each image pixel to one or few classes according to spectral values and on spatial information derived from extracted information from

II. PREVIOUS WORK

A. Sparsity Separation Approach

The source separation method can be applied to hyperspectral imaging to separate the components and make them statistically independent. This method is the most appropriate for our study, since the observation images show a strong correlation between them. The principle of source separation technique consists in the extraction of unknown source signals from their instantaneous linear mixtures by using a minimum of prior information: The mixture should be "blindly" processed [4, 5]. So, we describe this technique from m random processes or observations, noted $\{x[k]\}_{k\in N}=[x_1[k]\ldots x_m[k]]^T$ that result from a linear mixture of n random processes or sources, noted $\{s[k]\}$ ($s[k]=[s_1[k]\ldots s_n[k]]^T$). The general configuration of sources separation is shown in Figure 1.

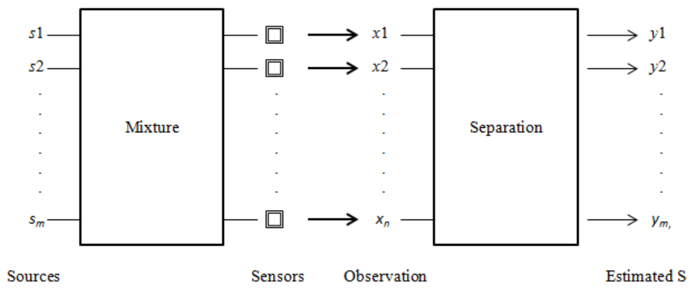


Fig. 1. General configuration of source separation.

By hypothesis, A is the linear transformation between sources and observations. Indeed, signals received by sensors can be modeled by the source signals in the following general form

$$x[k] = A(s[k]) + b[k] = As[k] + b[k], \quad (1)$$

where $x[k]$ is a $m \times T$ noisy instantaneous observed signals, $s[k]$ is a $n \times T$ source signals, ($b[k] = [b_1[k] \ldots b_m[k]]^T$) is a $m \times T$ additive noise corrupting the observation images and A is a $m \times n$ mixing application. BSS technique consists of finding an application G known as a separator, such that: $y[k] = G(x[k])$. Furthermore, the separator G is a $n \times m$ matrix and $y[k]$ is an estimate of $s[k]$ to a trivial matrix.

The sparse representation of signals and images is a problem that has been drawing considerable attention and widely studied in many recent applications. Representing the hyperspectral images in well suited database functions allows a good distinction of various types of objects. I n this paper, we apply a new source separation algorithm which is based on sparse representation of real hyperspectral data and show that choosing an appropriate basis is a key step towards a good sparse decomposition to improve the hyperspectral data analysis [6]. So, we explore the sparse decomposition of hyperspectral data by using DCT and we will explore the effect of sparse basis on dataset. Using the sparseness assumption, the following method illustrates the use of the mixing structure in order to estimate the mixing matrix [7].

We will define the model of sparse representation with a more formal way. Assuming a signal x is a vector in a subspace of finite dimension $x=[x[1],\ldots, x[N]]$. x is accurately sparse if most of its components are zero, i.e. its support $\mathrm{supp}(x)=\{i/\ 1 \leq i \leq N \text{ and } x[i]\neq 0\}$ become, if sparse, $|\mathrm{supp}(x)|=K << N$ and the signal x is said K-sparse. In most applications, the signal is sparse in an appropriate transformed domain but not in its original one, so x can be written in a suited basis D as follows:

$$x = \alpha D = \sum_{i \in supp(\alpha)} \alpha[i] \varphi_i \quad (2)$$

where $\mathrm{supp}(\alpha)=K << N$ and $\alpha[i]$ is the coefficient representing the contribution of the atom φ_i of the dictionary D in x.

To estimate the sources, it is sufficient to find a representation in the form of a set of coefficients S such that $s = SD$ where S is an unknown sparse matrix. In order to simplify the problem, BSS method based on sparsity exploits the matrix S that contains few coefficients significantly different from zero. By combining the representation $s = SD$ with the instantaneous mixing model $x = As$, we find:

$$x = ASD. \quad (3)$$

The objective of BSS in the transform domain is to compute a new representation $x=XD$ with $X=AS$ following the structure of the chosen dictionary [6].

The proposed method described in Figure 2, shows a methodology based on two source separation techniques to evaluate hyperspectral classification: The first is in special domain and the second in a transformed domain. The latter shows a good performance and should minimize the misclassification risk of dataset.

To describe the source separation approach and to illustrate the corresponding results, we will use 9 observation images extracted from the CASI sensor, between the wavelengths 551.1 to 799.9 nanometers, by experts as the most pertinent to increase the reliability of the analysis of the study zone.

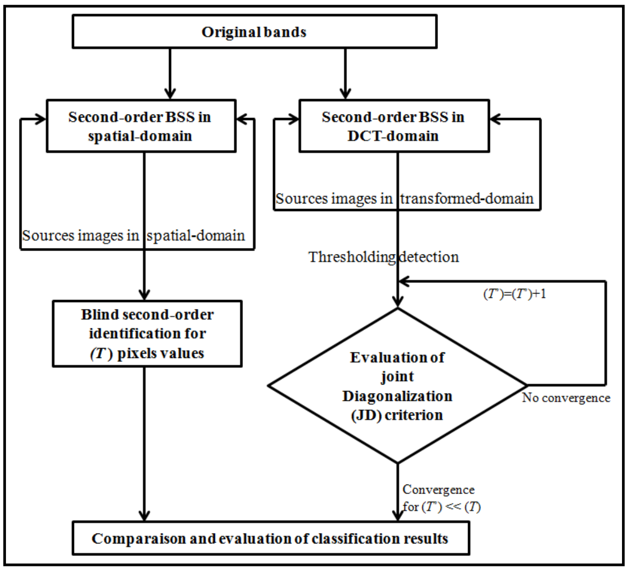


Fig. 2. Methodology

This work describes a novel approach employing Second-Order Separation by Frequency-Decomposition, termed SOSFD. This technique uses joint information from second-order statistics and sparseness decomposition.

B. *SOSFD Method*

To provide a valid decomposition of the hyperspectral images, we adopt a blind and automated procedure that relies on an optimal decomposition of the image spectra. The frequency approach used in this work is implemented by mixing DCT and second-order statistics. Since DCT is a linear orthogonal transformation, it can be applied either on spatial or on spectral data. The used criterion should provide independent information turned to distinct spectra. The extracted independent components may lead to a meaningful data representation which permits to extract information at a finer level of precision. The positive effect of such transformation is the removal of redundancy between neighbouring pixels in the first stage and the discrimination between low and high frequency of bands in the second stage.

In this paper, we use the source separation criterion in the frequency-domain. Therefore, the particularity of SOSFD approach is to implement the DCT in order to extract independent spatial-frequency sources. The DCT exploits interpixel redundancies to turn into excellent decorrelation for most natural images. The frequency source separation method can be modelled by the following form

$$X_{dct}^{(T)} = AS_{dct}^{(T)} + B_{dct}^{(T)}. \tag{4}$$

Hence, the source separation problem is transformed to the DCT-domain. The superscript (*T*) indicates that the related matrix is of *T* columns. Furthermore, DCT exhibits excellent energy compaction for highly correlated images such as hyperspectral images and because the noise produces DCT-coefficients that are close to zero at a smaller frequency, we can model our frequency-based approach by a free noisy form

$$X_{dct}^{(T')} = AS_{dct}^{(T')}, \tag{5}$$

where $X_{dct}{}^{(T')}$ is a $m\times T'$ matrix and $S_{dct}{}^{(T')}$ is a $n\times T'$ matrix with $(T') << (T)$. (T') is chosen to give the most important coefficients. So, T' corresponds to coefficients with the largest energy of the transformed images. The separation complexity can be reduced by manipulating (T') DCT-coefficients instead of (T) pixel values

This study confirms the potential of the DCT-transform for some image-treatments. Indeed, the hyperspectral images present a strong correlation which affects the extraction of significant information linked to ground truth. The joint application of the source separation method and the DCT-transform allows a more efficient representation of the spectral data and increase the reliability of the analysis of these images. Detailed results can be found in [8]. The sources resulting from the new source separation approach are then identified reliably due to the distinct differences in their power spectra.

III. Hyperspectral Classification of Sparsness Images Based on Gaussian Segmantation

A. Motivation

The remote sensing images are used to extract meaningful and useful information by detecting and characterizing all the component elements. It aims to assign each pixel in the image a label identifying what it represents in a scene. The result of a classification process usually depends on two important choices: the classification method of making a decision between all classes and the set of parameters describing each class which that they could be selected to best represents the characteristics of each class compared to other [9]. In this work, we implement a method of combined and hierarchical classification based on parameters such as mean and standard deviation to define the class attributes. As a result from previous approach based on sparse decomposition, we will process sources that are independent, uncorrelated and with the most significant components.

The spectral information in the classification process is the richness (Figure 3) of data where the spectra are grouped into similar classes with a Gaussian decomposition of each source. We propose an extension of the spectral method to take into account the spatial attributes involving locally pixels with similar spectra for spatial regularization [10]. It is therefore desirable to combine the advantages of these two approaches by jointly using the adjacency information.

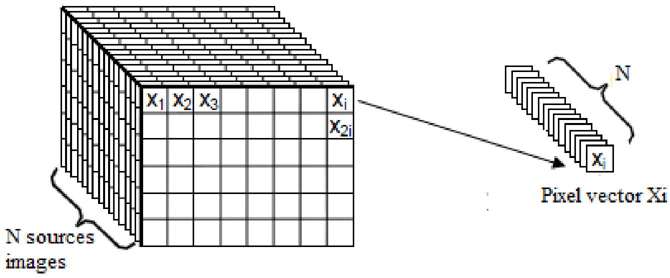


Fig. 3. Hyperspectral imaging

B. Gaussian Segmentation Process

In this section, we present the segmentation in the spectral domain. Therefore, image pixels are grouped into clusters and drawn from a Gaussian probability distribution. This spectral segmentation method is investigated by the use of Expectation Maximization (EM) algorithm [11, 12]. With no information about the spatial location of image pixels, we treat by EM the similarities between these pixels and their clusters. The EM algorithm optimizes the parameters of the single distributions in an iterative process until a stopping-criterion is met. The result is a partitioning of the image and the number of regions must be specified a-priori. At each pixel and for each source is assigned a Gaussian $gj(k, l)$ with the maximum posteriori probability.

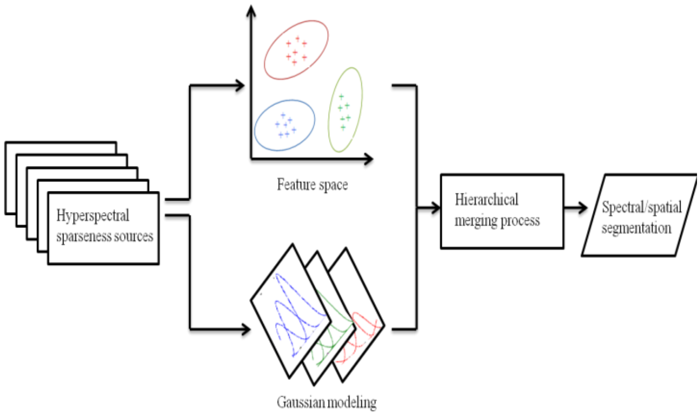


Fig. 4. Methodology of Gaussian hierarchical segmentation

For any number of clusters K, the EM algorithm implements the maximum likelihood principle which is allows estimating the mean μ, covariance matrix Σ and proportions (weight) of cluster $\omega_k \in [0, 1]$. The following PDF describe the statistically model of each pixel image by:

$$p(x) = \sum_{k}^{K} \omega_k \phi_k (x, \mu_k, \Sigma_k) \tag{6}$$

With $\sum_{k}^{K} \omega_k = 1$ and $\phi\ (\mu\ , \Sigma\ )$ is the multivariate Gaussian density. The maximum likelihood principle is applied to assign each class to the observed spectrum:

$$k_i = \arg\max_{1 \le k \le K} (\omega_k \phi_k (x_i, \mu_k, \Sigma_k)) \tag{7}$$

C. *Spectral-Spatial Classification Using Hierarchical Classification*

In this section, the goal is to incorporate the previous results into hierarchical technique allows an extension of the spectral method to take into account regions with spatial coordinates [13, 14].

In this context, to achieve hierarchical multi-scale description of image content, we implement an agglomerative approach where we begin with each individual class and merge the two closest classes (Figure 5). A region merging classification is based on the series of information such as: Means and Standard deviation features as shown in the matrix of attributes. The second step of agglomerative hierarchical classification algorithm is based on conversion of classes' features to distance matrix M_{ij}. This matrix presents the dissimilarity between all pairs of adjacent regions as follow:

$$M_{ij} = \begin{bmatrix} 0 & d_{12} & \dots & d_{1k-1} & d_{1k} \\ d_{21} & 0 & \dots & d_{2k-1} & d_{2k} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ d_{k1} & d_{k2} & \dots & d_{kk-1} & 0 \end{bmatrix} \tag{8}$$

With k indicate the index of class number.

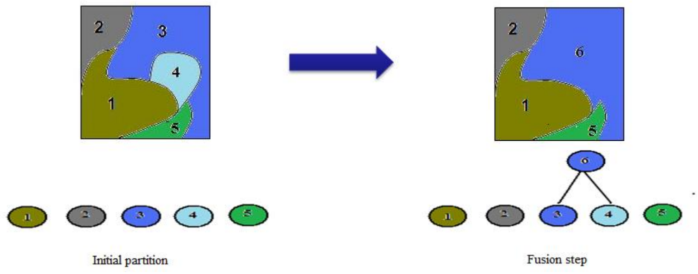


Fig. 5. Schematic illustration of adjacent regions merging process

The complete definition of the merge algorithm requires first determining the model region to represent a region and to characterize the union of two regions. In the second place, it is also necessary to determine the merging criterion C(*Ri*, *Rj*) to choose the distance between *Ri* and *Rj* to determine the merging order of regions and hence the structure of the tree. We use Euclidean distance; we can compute the distance between objects using the following formula

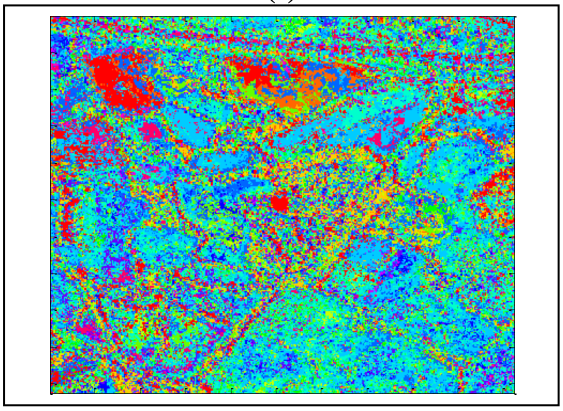
$$d_{ij} = (\sum_{k} (x_{ik} - x_{jk})^2)^{1/2} \tag{9}$$

The method of linkage ward has the particularity to combine classes to minimize the decrease of the interclass variance. Therefore, classification means finding the boundary of the one part maximizes the variance between classes to separate classes, and also minimizes the intra-class variance in order to aggregate the gray levels of each class around its average.

D. *Results and Evaluation*

In order to evaluate the performance of the proposed approach of classification, we compare two classification results of CASI image. We can note that the heterogeneousness of such images perturbs the method of pixelwise classification as shown in figure 6 (a). So, this method leads to the appearance of isolated pixels in the final classification. However, we mention that some various region areas are well detected in the classification results of hierarchical segmentation method using Gaussian modeling. So, the use of jointly spectral and spatial method using a Gaussian segmentation improves the classification results of hyperspectral images (figure 6 (b)). The classification accuracy is under investigation based on ground truth chosen by experts who are familiar with the terrain.

(a)



(b)

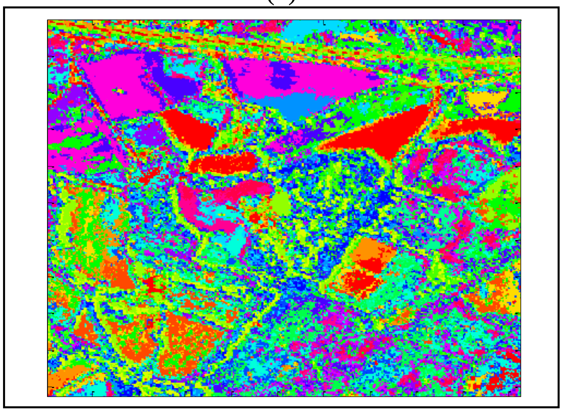


Fig. 6. Classification results for (a) Pixelwise segmentation method; and (b) New hierarchical segmentation method

IV. Conclusion

This study confirms the potential of the hierarchical segmentation method for some image-treatments. In this paper, we present a new Gaussian segmentation of hyperspectral sparseness images by joining spectral and spatial classification method. The hierarchical classification process is performed with the use of adaptive merging technique derived from classes'/regions' segmentations results. The main conclusion to be drawn from this research study is that the application of the second-order source separation approach in the DCT-domain and the adopt of hierarchical classification process using spectral-spatial approach improve the representation of hyperspectral images.

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