Independent Component Analysis for Remotely Sensed Image Classification with Limited Data Dimensionality

Qian Du*1, Ivica Kopriva2, Harold Szu3, and James Buss3

1 Department of Electrical Engineering and Computer Science
Texas A&M University-Kingsville, Texas 78363
2 Department of Electrical and Computer Engineering
The George Washington University, Washington DC 20052
3 Office of Naval Research, Arlington, Virginia 22217

ABSTRACT

The application of independent component analysis (ICA) to remotely sensed image classification has been studied recently. It is particularly useful for classifying objects with unknown spectral signatures in an unknown image scene, i.e., unsupervised classification. Since the weight matrix in ICA is a square matrix for the purpose of mathematical tractability, the number of objects that can be classified is equal to the data dimensionality, i.e., the number of spectral bands. When the number of spectral bands is very small (e.g., 3-band CIR photograph and 6-band Landsat image), it is impossible to classify all the different objects present in an image scene with the original data. In order to solve this problem, we present a data dimensionality expansion technique to generate artificial bands. Its basic idea is to use nonlinear functions to capture the second and high order correlations between original bands, which can provide additional information for detecting and classifying more objects. The results from such nonlinear band generation approach are compared with a linear band generation method using cubic spline interpolation of pixel spectral signatures. The experiments demonstrate that nonlinear band generation approach can significantly improve unsupervised classification accuracy, while linear band generation method cannot since no new information can be provided.


1. INTRODUCTION

As remote sensing and its applications received lots of interests recently, many algorithms in remotely sensed image analysis have been proposed. While they have achieved a certain level of success, most of them are supervised methods. In other words, the class information such as the first and second order statistics is assumed to be known a priori. However, in real applications, it may be impossible or very difficult to get such information, where unsupervised methods have to be applied.

Since the area covered by a pixel was very large, the reflectance of a pixel could be considered as the linear mixture of all the materials resident in this area. So we have to deal with mixed pixels instead of pure pixels in conventional digital image processing. Some typical unsupervised classification algorithm such as K-means clustering is not suitable since it is designed for pure pixel classification.

Linear spectral unmixing analysis was a popularly used approach in remote sensing image processing to uncover endmember distribution in an image scene [1-4]. Let \( L \) be the number of spectral bands and \( \mathbf{x} \) a column pixel vector with dimension \( L \) in a hyperspectral image. An element \( x_i \) in \( \mathbf{x} \) was the reflectance collected at the \( i \)-th band. Let \( \mathbf{A} \) denote a signature matrix. Each column vector in \( \mathbf{A} \) represents an endmember signature, i.e., \( \mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_n] \), where \( n \),

was the total number of endmembers resident in the image scene. Let \( s \) be the unknown abundance column vector of size \( n_s \times 1 \) associated with \( A \), which was to be estimated. The \( i \)-th item \( s_i \) in \( s \) represents the abundance fraction of \( A_i \) in pixel \( x \). According to the linear mixture model,

\[
x = As + n
\]

where \( n \) is the noise term.

Our task in unsupervised mixed classification was to estimate the \( A \) and \( s \). Let \( \hat{A} \) and \( \hat{s} \) denote the estimates of \( A \) and \( s \), respectively. \( \|x - \hat{A}\hat{s}\| \) should be minimized for the entire image. If \( \hat{s}_i \) for all the pixels are plotted as a classification map, it describes the distribution of the \( i \)-th endmember, where a bright pixel represents high abundance in the related area and a dark pixel represent low abundance.

Independent component analysis (ICA) has been used to accomplish such task [5-8]. The ICA model fits Eq. (1) very well [9]. More specifically, \( A \) and \( s \) are estimated simultaneously while all the elements in \( s \) are treated as random variables and \( \hat{s}_i \) is as independent of others as possible. There are several different ICA algorithms. Here we selected popular Joint Approximate Diagonalization of Eigenmatrices (JADE) algorithm in our research because of its excellent performance and fast speed [10].

In the ICA model, \( A \) is set to be a square matrix for mathematical tractability. Then for an \( L \)-band image, we can separate and classify no more than \( L \) materials/objects. When we deal with multispectral image (e.g., 3-band SPOT) and color composite image (3 RGB bands), this brings about a limitation to classification performance. Because in most of practical applications such as land cover mapping, the number of classes in an image scene usually is not a small value. In order to let ICA technique be applicable to such cases, we introduce a data dimensionality expansion approach as described in the following section.

2. DATA DIMENSIONALITY EXPANSION

2.1 Nonlinear Band Generation

A simplest solution to this problem is to use a dimensionality expansion process to generate a set of artificial images so that there are enough dimensionalities to accommodate a certain number of targets or objects [11]. Its idea arises from the fact that a random process is generally specified by its first and second order statistics. If the original bands are considered as the first-order statistical images, we can generate a set of second-order statistical bands by capturing correlation between bands. These correlated images provide useful second-order statistical information between band-to-band images that is missing in the set of the original bands. The desired second-order statistics, including autocorrelation and cross-correlation can be used to create nonlinearly correlated images. Let \( \{B_i | i = 1\} \) be the set of all original bands. The first set of second-order statistical bands is generated based on autocorrelation by multiplying each individual band by itself, i.e., \( \{B_i^2 | i = 1\} \). A second set of second-order statistical bands are made up of all cross-correlated bands produced by correlating any pair of two different bands, i.e., \( \{B_i B_j | i, j = 1, \ldots, L\} \). Adding these two sets of second-order statistics bands, there are totally \( L + L \left( \begin{array}{c} L + 1 \end{array} \right) = L^2/2 + 3L/2 \) bands. If more bands are needed, high-order statistics can be used to nonlinearly generate more bands. It is also true for using high-order statistics, such as the third and fourth moments, to explore the high-order statistical relationships between bands. The third-order statistical bands can be generated by \( \{B_i B_j B_k | i, j, k = 1, \ldots, L\} \) for any positive integers \( x, y, \) and \( z \), such that \( x + y + z = 3 \), while the fourth-order statistical bands can be generated by \( \{B_i B_j B_k B_h | i, j, k, h = 1, \ldots, L\} \) for any positive integers \( x, y, z \) and \( w \), such that \( x + y + z + w = 4 \).
2.2 Band Interpolation

Another intuitive method to generate artificial bands is to interpolate the spectral signature of each pixel. Let \( \mathbf{r} = (r_1, r_2, r_3)^T \) denote a pixel vector in a 3-band image, and \( r_1, r_2, \) and \( r_3 \) are reflectance in band \( \mathbf{B}_1, \mathbf{B}_2, \) and \( \mathbf{B}_3, \) respectively. In order to expand the data dimensionality, we can interpolate an element \( r_{12} \) using \( r_1 \) and \( r_2, \) \( r_{23} \) using \( r_2 \) and \( r_3 \). Then the \( r_{12} \) of all the pixels construct a new band \( \mathbf{B}_{12} \) as well as \( r_{23} \) for \( \mathbf{B}_{23} \). These five bands will be used for classification. If more bands are needed, more elements can be interpolated between \( \mathbf{B}_1, \mathbf{B}_2, \) and \( \mathbf{B}_3 \). A classical cubic spline interpolation can be used for this purpose [12]. However, because of the linear nature of such interpolation, the generated bands do not contain more information. So the classification results may not be improved, as demonstrated in the experiments.

Figure 1 illustrates the two band generation approaches for a 3-band pixel vector. We can see that the interpolation method generates a smooth spectral signature curve, while the nonlinear band generation (here two adjacent bands are multiplied for a new band) produces a curve with more variation.

![Figure 1: The illustration of nonlinear and linear band generation](image)

(○: interpolation; *: second order correlation; ⊙: original)

3. EXPERIMENTS

3.1 CIR Image Experiment

Figure 2 shows a CIR image about urban/suburban area of Houghton, Michigan, which has three bands. There were building, vegetation, and water bodies present in this image scene. ICA classification results using the original 3-bands are shown in Figure 3. The urban area with part of vegetation (trees) was classified in IC1, lake and river were classified in IC2, and some special vegetation (e.g., broadleaf plants) was classified in IC3. Three second-order bands (\( \mathbf{B}_1 \mathbf{B}_2, \mathbf{B}_2 \mathbf{B}_3, \mathbf{B}_1 \mathbf{B}_3 \)) were generated, which were used with three original bands for ICA classification. As shown in Figure 4, finer classification results were provided, where urban area with high residential density was classified in IC2, buildings (with another type of roof) were classified in IC1, vegetation such as trees were classified in IC3, vegetation such as broadleaf
plants were classified in IC4. It was very interesting that lake and river were classified into two different ICs: IC5 and IC6. The reason is that they have different clarity. The river flowing through the urban area is more turbid with suspended matters. Part of the lake was also displayed with gray shades in the classified river image, which means the water clarity in different lake area is different. For instance, the water close to the shore is more turbid. It should be noted that no new classes were produced when more artificial bands were generated.

Figure 5 shows the ICA classification using original 3-band with two interpolated bands. We can see that IC2, 3 and 4 presented the same information, which corresponds to IC1 in Figure 3 using the original 3-band image; IC1 is the same as IC2 in Figure 3, and IC5 is the same as IC3 in Figure 3. This demonstrates that simple band interpolation (spectral signature interpolation) cannot provide new data information, so no improvement in classification can be brought about.

**Figure 4:** Classification using 3 original bands plus 3 non-linearly generated bands

**Figure 5:** Classification using cubic spline band interpolation
3.2 SPOT Image Experiment

The image used in the second experiment was a 3-band SPOT multispectral image as shown in Figure 6. According to prior information, there were at least four classes present in this image scene: building, road, vegetation and water. Figure 7 shows the classification using the original 3 bands, where IC1 contains water, road, building and some vegetation, IC2 and IC3 are for different buildings. We can see that the four objects were not well separated and classified. Then we generated three second-order bands by multiplying each pair of bands ($B_1B_2$, $B_2B_3$, $B_1B_3$) and one third-order band by multiplying all the three bands together ($B_1B_2B_3$). The resulting 7 classes were shown in Figure 8: road and building in IC1, vegetation in IC2, different buildings in IC3, IC4, IC5, and IC6, water in IC7. Buildings have diverse spectral signatures, mainly depending upon the materials covering the roof, etc. That is why they were classified into 5 classes. Some buildings were made up of the same material as the road, so they were classified into the same class in IC1. When using the band interpolation, the classification was not improved as shown in Figure 9. IC4, IC2, and IC3 in Figure 9 are the same as IC1, IC2 and IC3 in Figure 7 using 3 original bands. IC1 and IC5 in Figure 9 contain all the objects except water.

![Band 1, Band 2, Band 3, IC1, IC2, IC3, Figure 6, Figure 7](image-url)

**Figure 8:** Classification using 3 original bands plus 4 nonlinearly generated bands

![IC4](image1.png) ![IC5](image2.png)

**Figure 9:** Classification using cubic spline interpolation

### 4. CONCLUSION

Independent component analysis can provide unsupervised classification for remotely sensed data. When it is applied to multispectral image or CIR image, its performance is limited by the data dimensionality, i.e., the number of classes (e.g., objects or materials) cannot be more than the number of bands. In order to relax this limitation, we present nonlinear band generation method to produce additional artificial bands by exploring the second and high-order interband correlations. The preliminary experimental results demonstrate its effectiveness in generating finer classification with limited spectral information in the data.

### REFERENCES