Processing for Image Fusion Using Independent Component Analysis

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Abstract—**One of the most challenging areas in data fusion is efficient abstraction of relevant information from data sets. In remote sensing, this is particularly important due to the amount of detail that is desired from relatively noisy measurements of sensors with limited capability. The goal is to identify multiple materials that are embedded in a particular pixel and thus, provide for more effective image fusion. However, without prior knowledge of a scene, it is difficult, if not impossible, to identify and classify the number of separate sources in a scene of interest. To address this issue, a method of using independent component analysis (ICA) techniques to solve the unsupervised blind source separation (BSS) problem on hyperspectral data was implemented. This general methodology offers the capacity to determine what endmembers are present in a scene and their levels of existence within individual pixels. The FastICA algorithm was used in conjunction with AVIRIS hyperspectral data to demonstrate this method.**

Index Terms—**Image Fusion, Independent Component Analysis (ICA), Hyperspectral Imagery, Blind Source Separation (BSS).**

I. Introduction

The field of image fusion continues to have a need for effective, unsupervised methods of extracting information from data sets. One of the more common tools for image fusion is remote sensing, which principally seeks to extract information from data pertaining to geographical locations. The more information that can be extracted from the data prior to human intervention, the more useful the data proves to be. One type of information derived from data that has been gathered using remote sensors is the identity of the physical materials that the data represent. This is a modest task if the imaging question consists of an easily identifiable substance. However, most scenes have numerous materials that appear to be co-located in the view of the sensor. Thus, there exists a challenge to identify multiple materials that are present in a single pixel of data.

Hyperspectral data consists of images captured by a large number of sensors with varied wavelengths. Data sets of this type are useful in a number of applications including target detection and mapping. Thus, there is a premium on unsupervised systems that can procure a large amount of information and organize it a useful way. Using unaltered hyperspectral data, one can compare the spectrum of a pixel to the spectra of known materials to reasonably estimate its makeup. However, there is inaccuracy in this approach due to the fact that in many instances, pixels, due to their large geographical size, consist of a number of materials. Hence, the classification of the pixel may be incomplete and would omit other present materials that might be of importance, indeed, might be the desired object itself.

Methods to improve on this problem include spectral mixture modeling [7] and cluster analysis with fuzzy classification [8]. However, these methods require prior knowledge or assumptions of prior knowledge respecting the data set and may provide inaccurate and unspecific results [5]. Thus, the need for a method to find the specific materials (or endmembers) which compose the pixels in a data set without prior knowledge or assumptions is a difficult one to fulfill.

II. Independent Component Analysis

A recent technique that is being applied to hyperspectral image unmixing is Independent Component Analysis (ICA). This procedure has its roots in audio applications where audio sensors record fused audio sources that must then be separated to recover the original signals (as described in the example below). Briefly stated, ICA approximates the factor analysis of a number of linearly mixed sources as introduced by Comon [6]. ICA offers substantial improvement over previous methods of spectral unmixing by separating the observed data into the individual endmembers (sources) without any prior knowledge. This is often called the Blind Source Separation (BSS) problem. However, in order to utilize ICA, three major assumptions must be made. First, the sources are assumed to be statistically independent. In many cases, this is not an unrealistic assumption to make. Second, the sources must be assumed to be non-Gaussian. And lastly, it is presupposed that the mixing between the

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endmembers is linear. With these assumptions in place, ICA can reveal hidden factors that underlie sets of signals [1]. The relationship between the sources and mixed signals is expressed as

$$x = As$$

where **x** is a matrix of mixed observations from sensors, **A** is the mixing matrix, and **s** is the matrix of original sources. In the BSS problem, neither **A** nor **s** is known *a priori*. A classic example of BSS is called the "cocktail party problem"—where several speakers may be conversing at once along with music and other background noise, all in the same room. Microphones scattered around the room record these sounds, but each microphone records a mix of several conversations and undesirable noise. The problem calls for the separation of these conversations using only the observations from the microphones, which is possible providing that there are as many sensors as there are sources to separate.

To find the independent components $\hat{s}$, let $\mathbf{w}^T$ be the inverse of $\mathbf{A}$ so that $\hat{\mathbf{s}} = \mathbf{w}^T\mathbf{x} = \sum_i w_i x_i$. Now make a simple change of variables, $z = A^T w$. This gives $\hat{s} = w^T x = w^T As = z^T s$. $\hat{s}$ is now a linear combination of the original s, with $\mathbf{z}^T$ giving the weights. Searching for the independent components hinges on the non-Gaussianity assumption. A measure of the Gaussianity of a random variable is kurtosis, which is defined to be $kurt(\hat{s}_i) = E\{\hat{s}_i^4\} - 3(E\{\hat{s}_i^2\})^2$. The kurtosis of non-Gaussian random variables is nonzero. This leads to a simple maximization or minimization of the kurtosis function above. In practice, other non-Gaussianity measures such as negentropy or its approximations are used since kurtosis is sensitive to outliers [4].

III. Approach

To implement ICA for use with hyperspectral data, a fixed-point iteration scheme-based algorithm called fastICA was utilized. There is a MATLAB version of this algorithm that provides the user with a high degree of flexibility [1]. Hyperspectral image sets were downloaded from the NASA/JPL AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) website [2]. AVIRIS measures the reflectance of 224 different continuous spectral channels (bands) in the range of 400 to 2500 nm wavelengths with a spectral resolution of 10 nm. Each flight line is 614 pixels wide by 2030 pixels long. On the ground each swath is approximately 11 km wide, with each pixel sampling 17 m^2. These data sets provided a large spectrum from which to work.

Comparing the hyperspectral application to that of the "cocktail party", it is easy to see differences and similarities. Each sensor pixel, which receives a mixture of source spectra is analogous to a single microphone receiving a mixture of conversations.

TABLE I.
DIFFERENCES IN BSS APPLICATIONS

"Cocktail Party"	Hyperspectral
8-10 sources	Hundreds of sources
8-10 observations	614 x 2030 $\approx$ 1.2 million observations
~8k samples per second per observation point	224 samples per observation point

In the audio application the goal is to retrieve each person's speech—the independent components. The first goal of the hyperspectral application is to determine the relative quantities of whatever sources might be present. Independent spectra can then be compared to existing spectral libraries for identification and classification as in [3], and [5]. The ultimate data user will determine whether the individual endmembers or the entire mixing matrix will be of more interest.

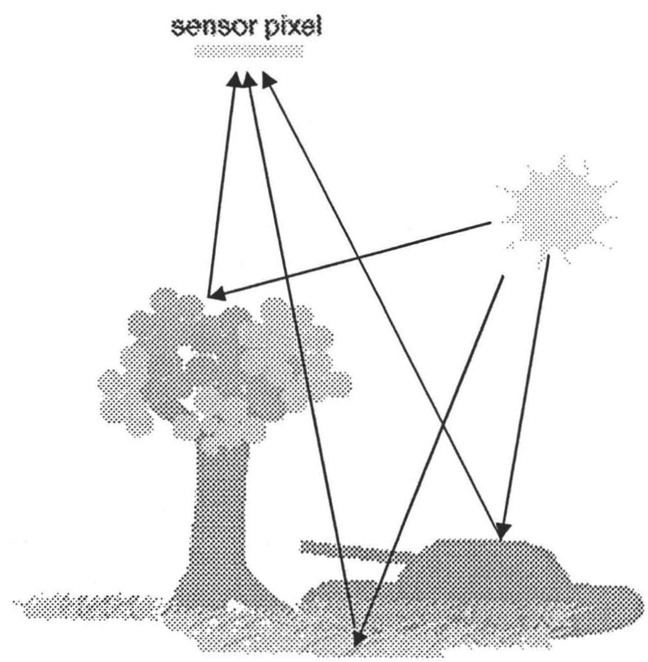

Figure 1. Each sensor pixel records a mixture of spectra from several sources.

In traditional BSS applications such as the cocktail party problem, the number of sensors and sources are approximately equal, with each sensor receiving thousands of data points per second. The difficulty with hyperspectral data lies in the small number of samples per pixel. Each pixel will have, at most, 224 (in the case of AVIRIS data) spectral samples. This is hardly enough to give a statistically valid separation of components.

To overcome this, the image is decimated and successive pixels are used to augment the low number of spectral samples. For example, given an original image in which each pixel has 224 spectral samples, one might decimate the image by four and stack each pixel's values in a matrix where each row is a different pixel's spectral signature. In this case, only 16% of the available pixels have been used. The process continues by offsetting the decimation pattern various amounts in both **x** and **y** to create several matrices of the same size as the first stack. These matrices are then concatenated along the spectral dimension, giving a new matrix the same height as the original, but with several times the original number of spectral values. Thus the observation matrix **x** becomes $\mathbf{x}_{[Rx(224\cdot n)]} = \left[\mathbf{x}_{1\,(Rx224)} \mid \mathbf{x}_{2\,(Rx224)} \mid \Lambda \mid \mathbf{x}_{n\,(Rx224)} \right]$.

The advantage here is an ability to create a more statistically sound set of independent components. However, any time an image is decimated, some high resolution components are lost. It is the same in this case. The mixing matrix, which specifies the relative quantities of each independent component, has been effectively downsampled. Instead of containing entries for each pixel, each entry actually applies to an **n**×**n** block. Each pixel in the block will be assumed to have the same mixture ratios. Downsampling by four, for example, would result in blocks of 16 pixels with the same mixture—making it impossible to assign a specific endmember to individual pixels in the block. In order to obtain a more accurate source separation, we must sacrifice spatial mixing resolution.

IV. Results

Using ICA to separate the original sources of spectra will result in a dramatically easier visualization of the data. Each independent component can be displayed and processed as a separate image. This will allow users to discard irrelevant sources, and concentrate processing power on the pertinent image sources. Without the separation, processing would have to be performed using the entire hyperspectral data set. Therefore, using Independent Component Analysis is a useful approach to data reduction and information extraction prior to fusion of this with other data sources.

Tu et. al.[3], and to a lesser extent Bayliss et. al. [5], both met with success in applying ICA to Hyperspectral data. The current study encountered issues similar to those found in [5] despite using a different algorithm. Specifically, in [5], computational limits required the use of a sparse set of training data for obtaining the endmembers, resulting in a lower confidence level for the overall results. No matter which algorithm is chosen, ICA requires inverting and solving potentially very large matrix equations, which is taxing on any common computer system.

The FastICA algorithm performed better on datasets that had been decimated and stacked due to the smaller number of possible independent components. Since there was no presupposition of actual materials present in the scene, the number of independent components became almost entirely subjective. The interest was in separating source signals, whereas a remote sensing scientist would be concerned with quantifying scene materials.

We also believe that the ICA model for unmixing is appropriate and holds promise for future work.

V. Future Work

In any scene of interest it is conceivable that as many as several hundred independent sources will be present. With AVIRIS data, ICA can potentially produce hundreds of independent components. Somehow a viewer must be able to quickly assimilate the different components of an image, without the requirement of sorting and selecting the individual component images. Future work will include research on hyperspectral and independent component visualization.

Multi-resolution methods will also be explored in order to mitigate the effects of the concatenation of pixel groups previously described.

Future work may also cover the inclusion of other sensor data in the spectral signatures. The ICA algorithm has no pre-disposition toward data from certain sources. Multi-spectral, SAR, and LIDAR data could easily be incorporated as subsequent bands.

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References

[1] A. Hyvärinen. (2003, Apr.). What is Independent Component Analysis?. Helsinki University of Technology. Espoo, Finland. [Online]. Available: http://www.cis.hut.fi/projects/compneuro/whatisica.html

[2] Jet Propulsion Laboratory. (2001). AVIRIS concept. California Institute of Technology. Pasadena, CA. [Online]. Available: http://popo.jpl.nasa.gov/html/aviris.concept.html

[3] T. M. Tu, P. S. Huang, and P. Y. Chen, "Blind separation of spectral signatures in hyperspectral imagery," in *IEE Proc. - Vis. Image Signal Process, Vol. 148, No. 4*, Aug. 2001, pp. 217-226

[4] A. Hyvärinen and E. Oja. (1999, Apr.). Independent Component Analysis: A Tutorial. Helsinki University of Technology. Espoo, Finland. [Online]. Available: http://www.cis.hut.fi/aapo/papers/IJCNN99_tutorialweb/

[5] J. Bayliss, J. A. Gualtieri, and R. F. Cromp. (1997) Analyzing Hyperspectral Data with Independent Component Analysis. Proceedings of SPIE Applied Image and Pattern Recognition Workshop. [Online]. Available: http://www.cs.rochester.edu/u/bayliss/spectral/spectral.html

[6] P. Comon, "Independent component analysis: A new concept," *Signal Processing*, 36:287-314, 1994.

[7] J. B. Adams and M. O. Smith, "Spectral mixture modeling: A new analysis of rock and soil types at the Viking lander 1 site," *Journal of Geophysical Research*, 91(B8):8098-8112, 1986.

[8] F. Maselli, M. Pieri, and C. Conese, "Automatic identification of end-members for the spectral decomposition of remotely sensed scenes," *Remote Sensing for Geography, Geology, Land Planning, and Cultural Heritage (SPIE)*, 2960:104-109, 1996.