Hyperspectral Image Analysis using ENVI (ENvironment for Visualizing Images)

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ABSTRACT

Hyperspectral imaging is a relatively new technology which draws much attention from the scientists now. With information provided on hundreds of narrow and continuous bands, it finds applications in many areas such as mineral identification, environmental monitoring, agricultural survey, medical examination. However, it is not an easy task to utilize the hyperspectral images, due to the large data volume. Certain tools are needed to analyze the hyperspectral image. As an example, the ENvironment for Visualizing Images (ENVI) software is used for the study of a sample hyperspectral image.

Keywords: Hyperspectral, Image processing, Transformation, Classification, PCA, ENVI

1. INTRODUCTION

Most materials on the Earth's surface contain characteristic or diagnostic absorption features in their spectra, which could be used to classify and identify the materials. Hyperspectral imaging is the technology to obtain surface spectra from aircraft or even spacecraft. This becomes possilbe as the result of the tremendous development in remote sensing and its combination with spectroscopy. In hyperspectral imaging, data (radiance) over hundreds of narraow, discrete and contiguous bands (typically over 0.4-2.5 micrometers) are collected simultaneously, therefore a continuous spectrum (reflectance) can be derived for each image cell. Figure 1 is a 3-Dimensional data cube. This technology offers a powerful tool for resource management, agriculture survey, mineral exploration, and environmental monitoring. Several libraries of reflectance spectra of natural and man-made materials are available for public use. These libraries are ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) Spectral Library and USGS(United States Geological Survey) Spectral Library.

One disadvantage of hyperspectral imaging is the large data volume. A typical AVIRIS (Airborne Visible-Infrared Imaging Spectrometer) image is more than 100 Mbytes. The general image processing tasks such as supervised classification become extremely computational intensive. Many new softwares are developed to address this problem, which makes it possible to utilize the large amount of information contained in hyperspectral images.

In this paper, an AISA (Airborne Imaging Sectroradiometer for Application) image is stuided using ENVI (ENvironment for Visualizing Images). This software is developed by some scientists who actively participate in remote

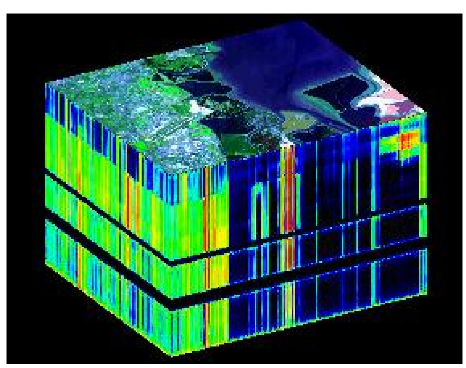

Figure 1. Example of Hypersepctral data cube

Image file name:	1999148_52899_cfl5_refl.dat
Header file:	1999148_52899_cfl5_refl.hdr
Parameter:	Reflectance
Format:	ENVI format
Dimensions:	2599×1047×30 (Sample×Line×Band)
File size:	163,270,716 bytes
Projection:	UTM (Zone 18 North)
Pixel size:	2m×2m
Wavelength info:	426.93-852.77 nm

Table 1. The image file information

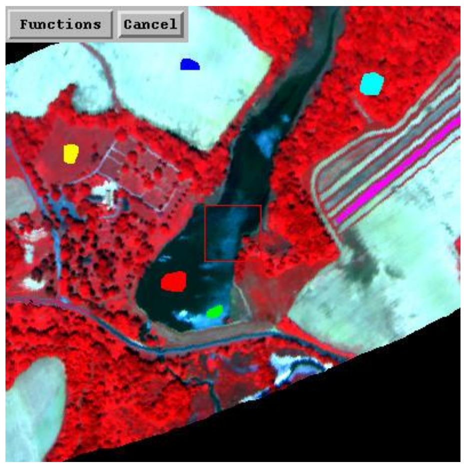

Figure 2. Part of the image and the regions of interest

sensing research. ENVI provides a full suite of tools for processing hyperspectral data, including special mapping tools for linear spectral unmixing and matched filtering using either image or library endmembers. The traditional image analysis functions such as classification are such tuned that they are efficient and effective when applied to hyperspectral data. Several image analysis methods are applied to the sample image. An attempt to identify some of the materials is also made, though no successfull result is obtained due to the lack of ground truth. Another possilbe reason is that the spectra of the materials are not in the libraries used. The mixing nature of the pixel should also be considered and due to the lack of the ground truth, unmixing cannot be done.

2. DATA

The data used for this study is an image file from the AISA (Airborne Imaging Sectroradiometer for Application) dataset which was collected over the Cheaspeake Farm, out of Easton, Maryland, in the 1999 growing season (May 26). The detailed information about the image file is shown in table 1.

Generally there is a header file for each data (image) file, which contains the metadata such as the resolutions, wavelengths. It usually has the same name as the image file except for the extension. Some softwares like ENVI also allow the metadata to be input manually. The image used for this study is very large thus it is impossilbe to show it completely with desired resolution. Only the part of interest is shown in figure 2. It is a RGB image with R, G, B corresponding to band 29 (839.57 nm), 15 (652.12 nm), 2 (502.31 nm). This part of the image coresponds to samples (1400,1800) and lines (330,640). Some features are very obvious in the image, for example, the roads can be easily identified. Several regions of interest are defined on this image in different colors.

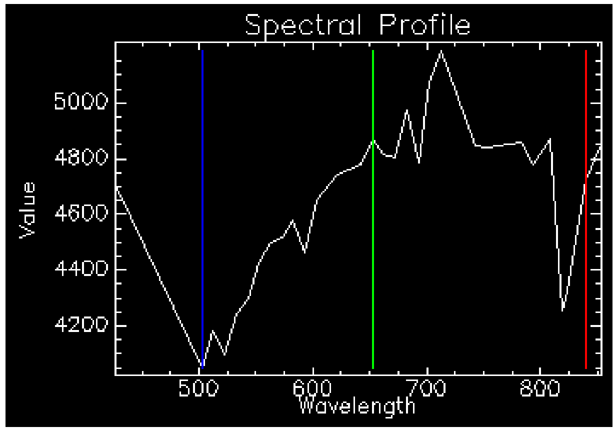

Figure 3. An example of spectrum

3. ANALYZING THE SAMPLE IMAGE

3.1. Z-profile

"Z-profile" is actually the spectrum on all the bands available for the image, in other words, it is a vector with the length equal to the number of bands. In ENVI, the extraction of the spectrum can be done by clicking on a pixel while the Z-profile window is opened. Figure 3 is an example of extracted spectral profile. The red, green and blue vertical lines indicate the R, G, B bands of the image. Usually spectrum is not used directly in hyperspectral image processing, however, it is the base on which many algorithms are implemented. For more information about the "Z-profile" extraction, please visit http://www.science.gmu.edu/∼yxing/759/outline.html.

3.2. Image Transformation

The purpose of transformation is to improve the representation of the information contained in data. An appropriate applied transformation can remove the noise or reduce the data dimensionality, by representing the data in a new data space. The reduction of dimensionality is especially important for hyperspectral data, which ususally has more than two hundred bands. Two of the commonly used transformations are principal component analysis (PCA) and minimum noise fraction rotation (MNF). Although only the PCA of the sample image is introduced in detail, MNF is also applied to it to provide intermediate result for later analysis.

PCA is computed based on the data variance. The coordinate system is rotated, until it is such that the variance of the data is maximized. Computationaly PCAs can be derived based on the data covariance matirx (or correlation matrix if differnet dimensions of the data differ greatly in scale). The dimension contributes more to the total variance also contains more of the information carried by the original data. A successful PCA will lead to few principal components containing most of the information. The other components are mainly noise and can be left out for further processing.

The PCA of the sample image is computed from the covariance matrix. The result is very ideal, with the first two principal components contribute to 99% of the total variance (PC1 69% and PC2 30%). This means the data dimensionality is reduced from 30 to 2. It is obvious that the required resources for processing, such as time, computing power are also greatly reduced. Another advantage is that data volume becomes smaller. In this case, the original image file is 163,270,716 bytes in size, the part of interest is about 1/8 of it (20,000,000 bytes). The first two principal components take only 997,688 byes, thus the overall effect of PCA reduces the data amount to 1/20 of the original level. Figure 4 is the gray scale image of the second principal component.

MNF rotation is essentially two cascaded principal component transformations. The first one decorrelates and rescale the noise in the data based on an estimated noise covariance matrix. In other words, this step "whitens" the noise. The second one is a standard PCA. MNF is often used to decide the inherent dimensionality of image data, and to reduce the computational requirements for subsequent processing. A good result is obtained by applying MNF to the image, with the first 9 result bands contribute 88% of the variance. This result is used later to

Figure 4. Gray scale image of the second PC

compute the pixel purity index. For the result of the MNF and more information about transformation, please visit http://www.science.gmu.edu/∼yxing/759/outline.html.

3.3. Classification

Classification techniques are generally divided into two categories: supervised and unsupervised. Supervised classification techniques require that analysts define training classes (or areas on the image that are of interest to the analysts) before the classification function is executed. Unsupervised classification is based on statistics only, the defining of training class is not necessary. Which technique to apply should be decided by the interest and subject of the study. Both approaches are applied and discussed below.

3.3.1. Supervised classification

Supervised classification allows the analysts to have more control of the classification procedure. By defining the training classes, analysts can specify and focus on the subjects to their interest. It is often applied when there are some easy-to-identify and interesting features in the image being studied. The training classes can also be defined in the spectral space, where the analysts provide spectral signatures they are interested in, and these signatures will serve as the training classes. The training classes (or Regions of Interest (ROI)) defined for the sample image are shown in figure 2. While many algorithms such as parallelepiped, minimum distance, maximum likelihood, spectral angle mapper are available for supervised classification, the focus here is the spectral angle mapper (SAM). Several other algorithms are also applied with results that differ not very much, and therefore the results are not shown here.

More than just being able to handle the high dimensionality of hyperspectral data, spectral angle mapper (SAM) takes advantage of it. SAM treats the spectra as vectors in a space with dimensionality equal to the number of bands. The mean spectra of the training classes are computed and set as reference vectors. Then the spectrum (vector) of each pixel is compared with the reference vectors, and the similarity of the spectra is manifested as the angle between the vectors. A smaller angle means a higher similarity. If the angle between the vector of a pixel and the reference vector of a class is smaller than a threshold, the pixel will be assigned to that class. It is obvious that when the dimension of the vector goes up, a more accurate comparison result will be achieved. Another advantage of SAM is that it is relatively insensitive to illumination and albedo effects when applied to calibrated reflectance data. The maximum accetable angle difference (the threshold) is set to be 0.1 radiance when apply SAM to the sample image. Figure 5 is the result of the SAM classification. The result seven classes from the seven training classes are very informative. For more information, please visit http://www.science.gmu.edu/∼yxing/759/outline.html.

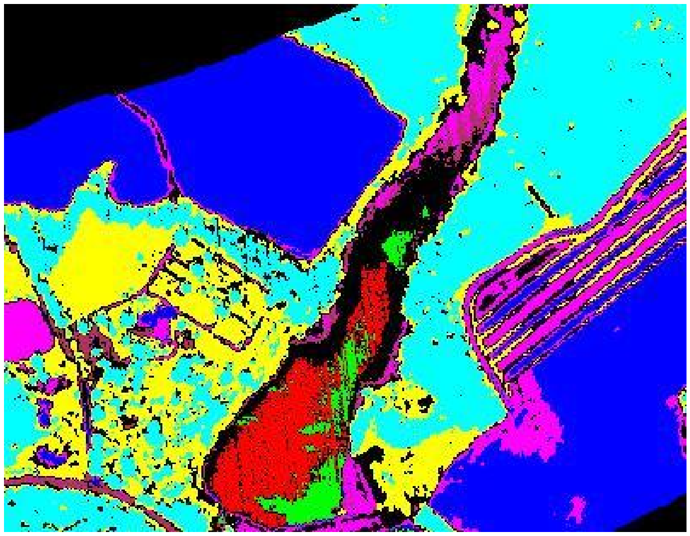

Figure 5. Classification result of SAM

Number of classes:	7
Max time of iteration:	5
change threshold:	5%
Min # of pixel in class:	0
Max class Stdv:	1 (DN)
Min class distance:	5 (DN)

Table 2. Parameter set up for ISODATA

3.3.2. Unsupervised classification

Unsupervised classification can be used for classification of any image. It is especially suitable for the cases where it is difficult to define training classes. For example, when studying the image of a mineral riched area (but the spectra of the minerals are unknown, and the minerals are mixed together), unsupervised techniques are good solutions. For this study, upsupervised classification is also examined. ISODATA and the K-means are the two commonly use algorithms for unsupervised classification. The application of ISODATA and the result is discussed below.

ISODATA calculates class means evenly distriburted in the data space and then iteratively clusters the remaining pixels using minimum distance techniques. All pixels will be classified unless a standard deviation or distance threshold is specified. If the threshold is specified, then the pixels do not meet the threshold condition will remain unclassified. ISODATA is applied with the parameters set as per table 2. No threshold condition is applied therefore all the pixels should be classified. The result is shown in figure 6. Again, most of the features are captured. Because the process is automated, the color scheme used to represent classes is defferent from the SAM result.

3.4. Pixel purity index (PPI) and the n-D visualizer

PPI is a means of finding the most "spectrally pure" pixels, which typically correspond to extreme endmembers. It is computed by repeatedly projecting n-dimensional scatterplots onto a random unit vector. The extreme pixels in each projection are recorded and the total number of times each pixel is marked as extreme is noted. A "Pixel Purity Image" is created in which the DN of each pixel corresponds to the number of times that pixel was recorded as extreme. This technique is very effective when applied to hyperspectral data.

For the sample image being studied, PPI is computed on the previous MNF result excluding the noise bands. The number of iteration times is 1000, threshold is "2". If a pixel is recorded two times or more as extreme pixel, it will be considered "pure". A PPI image is created. Brighter pixels on the image indicate pixels that are more spectrally pure. New ROIs can be set using Image Threshold. (5,150) is selected to be the threshold, this will filter out the

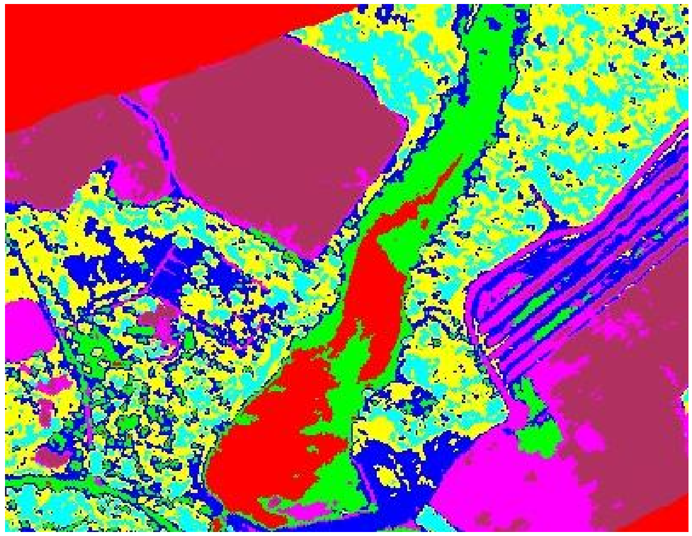

Figure 6. Classification result of ISODATA

pixels that are not part of the image. (The pixels that are located at the upper left and right bottom corner of the image, and have a uniform value of “151” in the PPI image, are actually not part of the image.)

The purpose of computing PPI is generally to define training classes for the supervised classification. Therefore the MNF result data file is then opened in the n-D visualizer, the number of pixels input to the visualizer is limited by the PPI. Training classes then can be defined from within the n-D visualizer. The difference from the former training classes is, these new set of training classes are defined based on information from all the available bands, not only three bands. All the supervised classification techniques can be applied to these training classes now.

SAM is applied to the new set of training classes, while the result is not shown here. For more information, please visit http://www.science.gmu.edu/~yxing/759/outline.html

3.5. Material identification

Identification is done by matching the spectrum from the image to the reference spectra in a spectral library. This technique requires that there are extensive areas of pure material on the image, and the corresponding spectrum is in the spectral library. An observed spectrum will typically show varying degrees of match to a number of spectra in the library. Some measure of goodness of fit must be defined and the best match is the most possible answer.

Usually a spectrum is composed of a low frequency component, the general shape, and a high frequency component, the absorption features. Many pure materials such as minerals can be recognized by the position,depth and and shape of their absorption features. Many other materials lack distinctive absorption features, therefore the overall shapes of their spectra must be considered. The matching is complicated by the mixtures of materials. Based on some ground truth or experience, unmixing techniques are introduced to solve this problem.

This sample image is not a good example for identification, since very little ground truth is known. Though it is obtained on the growing season from a farm, one photo coming with the data shows dry crops. All the green and dry vegetation libriaries are tested, but not a single good match is found. One reason may be that the observed spectra are not in any library yet. Another problem is the rescaling of the data. As might have been noticed in the “Z-profile” section, the value of the spectra is of the order of thousand, while relectance should have the range from 0 to 1. It is rescaled for the convenience of storing and computing. The rescalor is not obvious, so quantitive matching is made impossilbe. However, the identification is still dicussed since it is the charm of the hyperspectral technique.

4. SUMMARY

Several image analysis techniques are applied to the sample hyperspectral image and yield expected results. The overall performance is efficient and effective. Ususally the computing time for each algorithm is of the order of

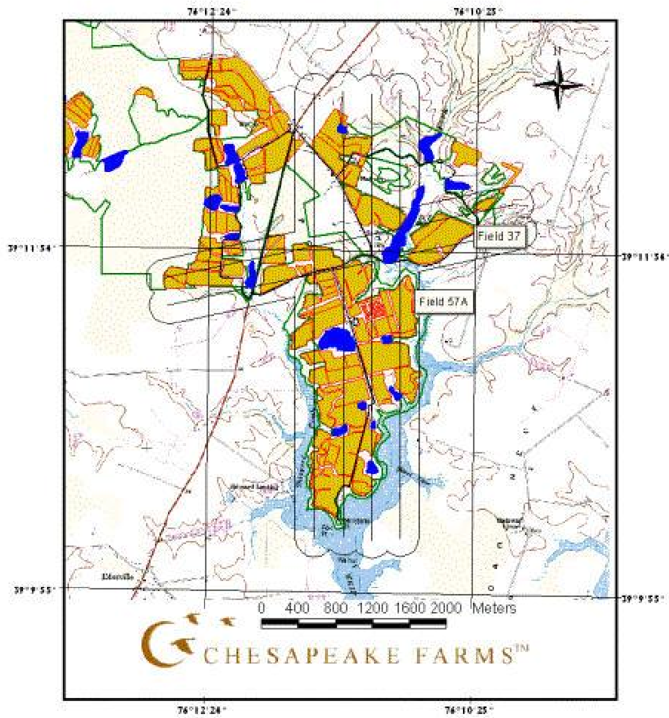

Figure 7. A map of the Chesapeake Farm

minutes or seconds. Two factors must be considered though, one is that this image has only 30 bands, another is that only a part of the image is studied.

The importance of image transformation is demonstrated. In this case there are 30 bands, but generally hyperspectral image has more than 200 bands. Therefore the reduction of data dimensionality is extremely important for hyperspectral image analyzing. PCA is a powerful tool to accomplish this task. As shown earlier, it reduces the dimensionality from 30 to 2, while maintains 99% of the overall information contained in the original image.

Different classification techniques should be applied for different research interest. Generally if the features of interest can be easily identified in the image or in the spectral space, supervised classification could be applied. For the cases where no features can be easily identified, unsupervised techniques could be used, since they are based on pure statistics. Figure 7 is a map of the experiment field. The blue represents water, yellow indicates crops. This gives some vague idea about the classes from another perspective. Comparing it to the classification results, it can be seen that these features are captured by both of the classification techniques applied.

Again, not all the results and examples related to this study are shown. For more information, please refer to http://www.science.gmu.edu/~yxing/759/outline.html

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