Using AVIRIS Data to Map Geologic Signatures of Copper Flat Porphyry Copper Deposit, Hillsboro, New Mexico

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Introduction

The most popular software package for processing hyperspectral imagery is the Environment for Visualizing Imagery (ENVI) available from Research Systems, Inc. Other lesser-known software packages are available including the system developed at the U.S.G.S. Spectroscopy Laboratory call Tetracorder (previously known as Tricorder). Tetracorder does not enjoy the notoriety of ENVI primarily because Tetracorder is a U.S.G.S. in-house tool used almost exclusively by the members of the U.S.G.S. Spectroscopy Laboratory. Tetracorder has been used successfully on a number of studies including the Summitville mine in southwestern Colorado (King, et al., 1995), the Leadville superfund site (Swayze, et al., 1996) and Yellowstone Park (Kokaly, Clark, and Livo, 1998). Another relatively unknown approach, but of interest because of its unique classification capabilities are Kohonen self-organizing maps (SOM).

Each of these techniques was applied to the AVIRIS imagery of Copper Flat porphyry copper deposit (CFPCD) in south-central New Mexico. The ENVI process is well documented, but it is still reviewed here. Since Tetracorder has not been publicly released, only the essential elements are described in any detail. The details of SOM are shown below. Athough SOM are not a complete system, when used in conjunction with ENVI, they prove to be a useful addition to any hyperspectral toolkit.

Hyperspectral Data Set – Site Description

NASA's AVIRIS sensor was flown over the Copper Flat porphyry copper deposit in the summer of 1998. The Copper Flat mine is 8 km NNE of the town of Hillsboro, New Mexico (Figure 1). The Copper Flat mine is located in the Animas Hills and is part of the Hillsboro mining district of Western Sierra County, NM and is one of the older Laramide porphyry-copper deposits in the Arizona-Sonora-New Mexico porphyry-copper belt (McLemore, 1999). The Animas Hills consist of a horst block located just west of the axis of the Rio Grande rift and are underlain by a circular block of andesite nearly 4 miles in diameter. The thickness of the andesite and circular shape suggest that the andesite is a remnant of a Cretaceous caldera. $^{40}Ar/^{39}Ar$ data establish the age of the andesite at $\geq 74.93 \pm .066$ Ma (McLemore, et al., 1999). A relatively small body of quartz monzonite intruded the andesite forming the entire CFPCD. CFPCD is predominantly a low-grade hypogene deposit with thin veneer of supergene enrichment at the surface (McLemore, et al., 1999). The numerous latite dikes radiating from the CF quartz monzonite also show significant mineralization. The CFPCD has produced large quantities of Au, Ag, and Cu since the late 1800s.

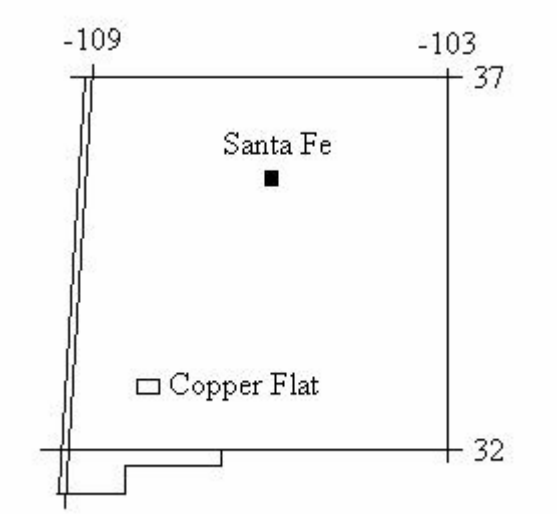

Figure 1 – Location of CFPCD in New Mexico. The deposit is located about 15 km west of Truth or Consequences, NM.

Preprocessing

To properly correct for atmospheric influences on the upwelling reflectance spectra, ground verification data was collected at the CFPCD mine site. Ground verification areas were selected using the following constraints:

1) Low relief;
2) Spectrally flat;
3) High reflectance;
4) Cloudless sky;
5) Solar Noon $\pm$ 1 hour;
6) Sufficiently large area of uniform composition (greater than or equal to one pixel (20m x 20m));
7) Ground verification data collected at the same time as the AVIRIS overflight occurred.

Unfortunately, condition five could not be met during the 1998 AVIRIS overflight of CF. Nonetheless, within a few weeks on sight measurements were made using an ASD-FR spectrometer. Two bulldozed areas located adjacent to the CF mine proved suitable for collection of spectra. These spectra were used to refine the output from the atmospheric compensation software.

Tetracorder, ENVI, or SOM require proper atmospheric corrections. All three software techniques work well with the output from ATREM (ATmospheric REMoval Program) from the Center for the Study of Earth From Space (CSES) at the University of Boulder at Colorado (Gao and Goetz, 1990; Gao, Heidebrecht, and Goetz, 1999). But there are a few problems with ATREM output requiring remediation.

ATREM does not account for atmospheric path length on a pixel-by-pixel basis and it also overcorrects for the path radiance scattering in the atmosphere at blue to UV wavelengths yielding negative values. These shortcomings are obviated using the following two-step approach:

1. A radiative transfer correction is performed that tracks changing atmospheric water absorptions from pixel to pixel and removes the absorptions due to water

and other atmospheric gases, scattering in the atmosphere, and the solar spectrum.

2. The reflectance of known targets in the scene are used to correct the artifacts from the imperfect radiative transfer correction. The success of this method depends upon the accurate reflectance characterization of field calibration sites.

These corrections produced a radiative transfer ground corrected image that formed the basis of this study.

The Environment for Visualizing Images (ENVI)

The ENVI approach for processing hyperspectral data consists of winnowing down the vast amount of information into a manageable subset. ENVI treats the classification of the imagery data as a search. As with most search strategies, the name of the game is to constrain the domain. Constraining the search space makes finding a solution easier. This constraining process results in likely endmembers, which are then used to classify the individual spectrum. An endmember represents the purest "homogeneous" material from which other materials are created. The data are then analyzed using the endmembers through a process of linear unmixing.

The basis of linear unmixing is that most pixels are mixtures of substances. Once all the endmembers are found in an image, all the remaining pixels are considered linear combinations of these endmember pixels. While not absolutely true, it is a good first approximation.

In reality, the world is populated with intimate mixtures, i.e., mixtures of materials whose reflectance spectrum is a product of nonlinear mixtures of reflectance spectra from different materials. Unmixing these type of spectra is quite difficult and beyond the scope of this article.

The first step in ENVI is to reduce the dimensionality of the hyperspectral data from, in the case of AVIRIS data, 224 channels down to 10-15 relevant channels containing 95-98% of the information in the image. This is accomplished via a Minimum Noise Fraction (MNF) transform (Boardman and Kruse, 1994). To prevent the MNF from focusing on the variation in the 1.4 & 1.9 um water absorption bands these portions of the spectra were omitted from MNF processing.

Stated simplistically, the MNF transform is a cascade of translation, rotation, scaling and another rotation (essentially an affine transform). MNF is a series of two Principal Components (PC) transformations resulting in a change of basis for the vector space as defined by the number of bands for each pixel in an image. Most imagery data exhibit high band-to-band correlation (Figure 2). Principal Component analysis significantly reduces band-to-band correlation. This is achieved by rotating the coordinate axes so that the first axis is parallel to the maximum variance in the dataset. The second axis (orthogonal to the first) is rotated around so that it is parallel to the next highest variance. Subsequent orthogonal axes are rotated around so that they are parallel to smaller and smaller amounts of variance in the data. The net result is that the first few PC contain most of the information in the data and the remaining PC axes contain most of the noise. The dataset is thus reduced from 224 channels to 10-15 relevant channels. The resulting PC channels, because they are no longer related to a specific wavelength, do not correlate to specific absorption features in reflectance space.

The next step in ENVI hyperspectral processing procedure is based on fitting a simplex around a convex hull (Boardman, 1993). A convex hull encloses all the data points in the *n*-dimensional space of a hyperspectral image. Theoretically, apices of the hypervolume represent pixels composed purely of one material or endmember. These apices are located by repeatedly projecting the data space onto a unit vector (Boardman, Kruse, and Green, 1995). Pixels located the farthest out on the unit vector are counted as potential endmembers. Those pixels with the highest number of occurrences as an outlying pixel are considered apex or endmember pixels. Endmember pixels are further narrowed by visualizing the *n*-dimensional space and projecting

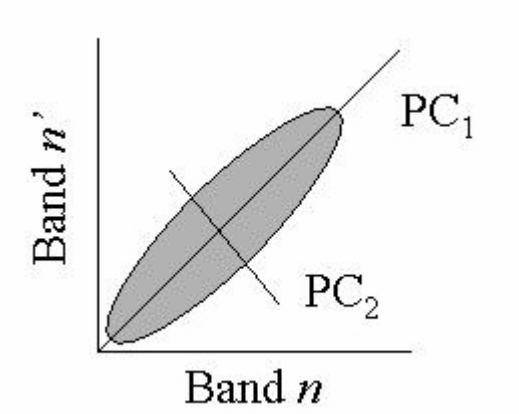

Figure 2 – Highly correlated data and the resulting principal component axes.

them into 2-dimensional space. This process greatly aids the location of endmembers by permitting similar pixels to be grouped together.

At this point, endmember pixels of the purest material content have been found. The next step is to classify the imagery. There are numerous methods available within ENVI, but we chose to use the ENVI's implementation of the Cauchy-Schwarz Inequality (CSI) called Spectral Angle Mapper (SAM). A chief advantage of CSI is that it ignores variations in albedo, so pixels with similar spectral shapes, but different reflectance intensities are considered the same. CSI is based on the relationship that the cosine of the angle between two vectors is the quotient of inner dot product of two vectors divided by the product of the magnitude of those two vectors (Equation 1). CSI generates the angle between two vectors as a measure of their similarity, i.e., the smaller the number, the more similar the spectrum between pixels.

$$\cos\theta = \frac{\langle u,v\rangle}{\|u\|\|v\|} \text{ where } 0 \le \theta \le \pi \quad (1)$$

ENVI is fast and the method is intuitive. Endmembers are readily identified, but actually determining the mineralogy within each pixel is not easy even using ENVI's built-in expert system, the Spectral Analyst.

The results of applying ENVI to the CF AVIRIS imagery are shown in Figure 3. The primary endmember spectra plots are shown in Figure 3.

Self-Organizing Maps

A Kohonen Self-Organizing Map (SOM) is an array (1 or more dimensions) of nodes (Kohonen, 1986). Each node is composed of a unit vector pointing in a random direction in *n*-dimensional space. After normalization, multi-dimensional data are presented to each of the individual nodes. Using a "winner-take-all" learning strategy, the node whose vector most closely matches the input data is found. This winning vector incorporates, or adjusts, its vector weights to match the input data. Vectors in the nodes surrounding the winning node are modified to look less like the input vector. In this manner, each node in the SOM internally develops the ability to recognize vectors similar to itself. This is referred to as self-organization, i.e., no external information is supplied to lead to correct classification.

Two useful features of a SOM are its topology preserving capability and the automatic generation of probabilities for a dataset. Topology preserving means that the original relationships between the data points remain intact after processing. This is exactly the desired result when working with hyperspectral data because it maintains the spectral relationships between pixels. Secondly, as a SOM evaluates the data, it builds a statistical model or probability

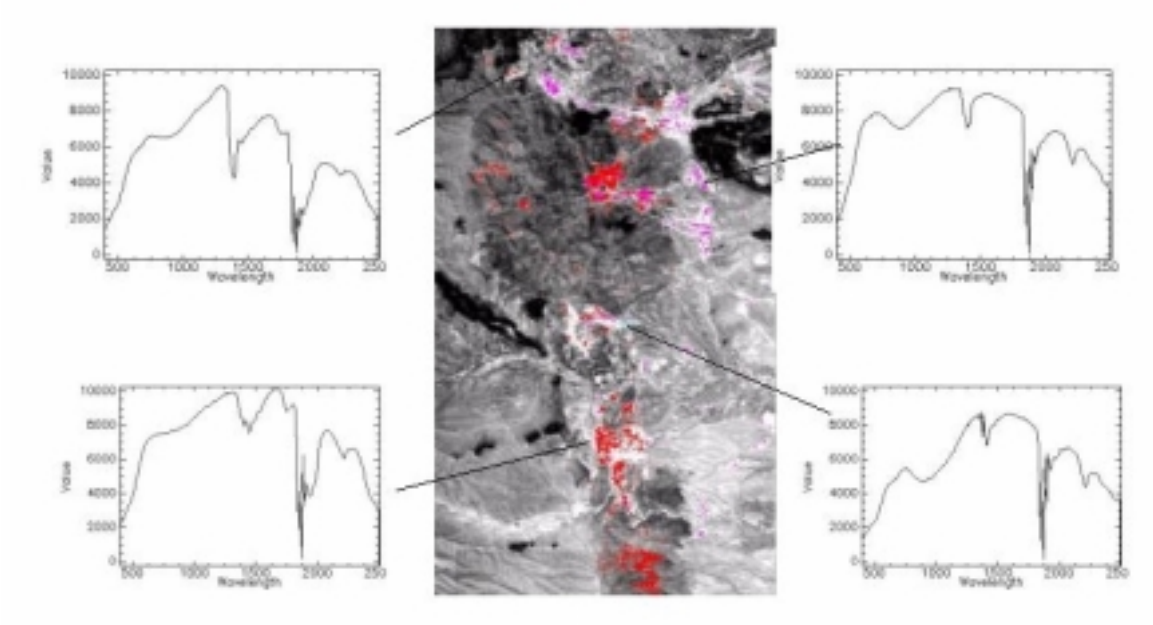

Figure 3 – Showing Fe-Clay endmembers resulting from ENVI processing. The Fe absorption near 1000 nm and the Clay features near 2250 nm are evident in the endmember spectra.

distribution, of the dataset spontaneously. SOM perform this statistical modeling, even in cases where no closed form analytic expression can describe the distribution (Caudill, 1988).
The SOM approach is an unsupervised clustering approach similar to the Iterative Self-Organizing Data Analysis Technique (ISODATA) of Tou and Gonzalez (1974). ISODATA interatively evaluates the imagery based on spectral distance. Initially, the user specifies the number of nodes. These nodes are then treated as cluster centers and pixels are included in the clusters based on user specified thresholds. After each iteration, a new cluster mean is computed based on the actual spectral locations of pixels. These new means are used in the next iteration. The process continues until there is little change between iterations.

SOM are similar to ISODATA, but operate in a much more flexible manner. Cluster centers are allowed to move about to account for topological relationships in the dataset.

Output from the SOM is a series of spectra containing the average spectra for each cluster group. For this example, the first 20 MNF transformed data bands were normalized to remove variation due to albedo and then presented to the SOM with the results shown in Figure 4. The first 20 MNF bands accounted for >95% of the variation within the dataset. The SOM process classified the imagery into fifteen clusters, with thirteen having significant membership (more than 2 members).

Tetracorder

Tetracorder is a hyperspectral image processing software package developed at the U.S.G.S. Spectroscopy Laboratory. Tetracorder is an extensible set of algorithms. Because Tetracorder is a U.S.G.S. Spectroscopy Laboratory in-house tool it is not as well-known as ENVI. Tetracorder was used for a number of studies including the Summitville mine in southwestern Colorado (Kinget al., 1995), the Leadville superfund site (Swayzeet al., 1996) and Yellowstone Park (Kokaly, Clark, and Livo, 1998). The purpose of Tetracorder is to identify objects in imagery with certain absorption features using a spectral identification algorithm called the Band Mapping Algorithm (BMA) (Clarket al., 1990). The basis for BMA is feature fitting. BMA fits each spectral feature in a spectral library to the current spectrum of interest using a least-squares approach to absorption feature identification.

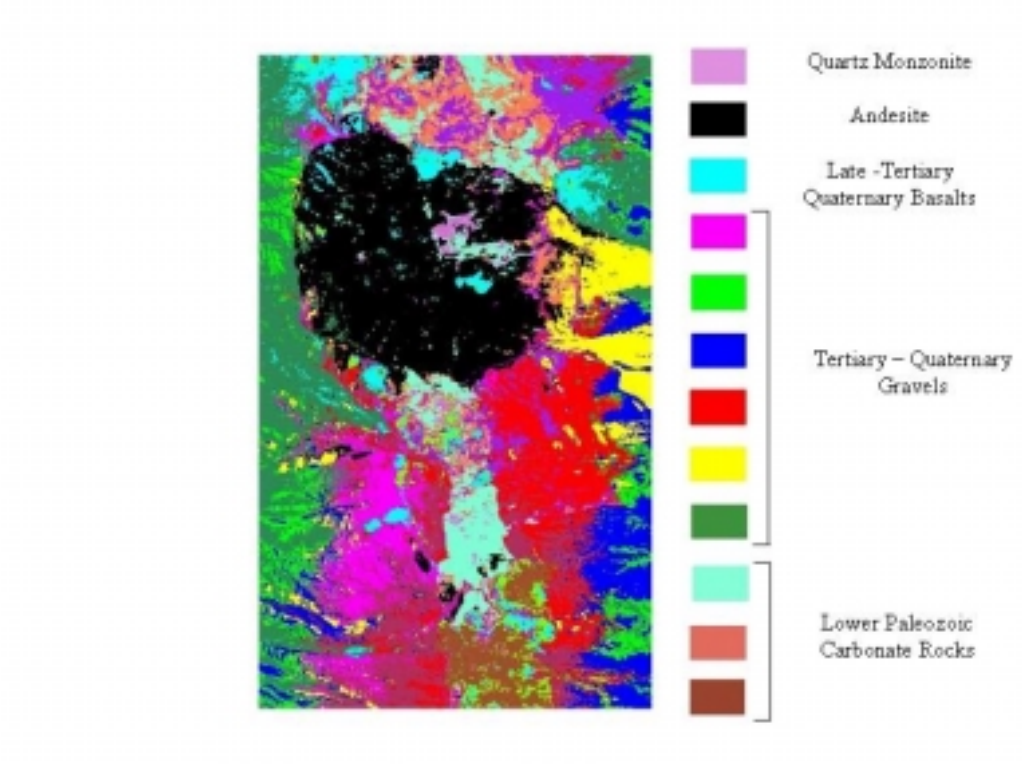

Figure 4 – Classification results from Self Organizing Map. This image results primarily from variations in reflection intensity

The BMA measures the goodness of fit between a library reference spectrum and an unknown spectrum. In preparation for using BMA, unique continua are created for each known mineral in a library of laboratory spectra. The process of identifying an unknown mineral begins by removing the unique continuum from a "candidate spectra" in a spectral library. Next, a continuum is calculated and removed from the unknown spectrum. The two resulting continua-removed spectra are compared and a goodness of fit value is calculated using a least-squares algorithm. The correlation coefficient produced by the least-squares equation is the fit. Multiple fits for different possible mineral candidates are calculated and compared with the best fit to determine the possible mineral present. Final mineral selection is based on additional factors such as albedo and continuum slope. The depth of the absorption feature from the continuum indicates relative abundance of a material and also serves as quality control related to spectral abundance. From these calculations a fractional map indicating mineralogy and relative abundance is generated. BMA has been subsequently expanded to simultaneously analyze multiple features in an unknown spectrum (Clark, et al., 1991).

The preliminary results of applying Tetracorder to the CFPCD imagery are shown in Figure 5 (1 µm) and Figure 6 (2 µm) where identified Fe- and clay-bearing minerals were identified; respectively. The results from the ENVI classification are similar to the Tetracorder results, but without the differentiation into the respective chemical constituents. Tetracorder is only limited by its reference spectra library. In the event that an observed spectrum (or absorption feature) is not in the reference library, then Tetracorder cannot readily identify the mineral.

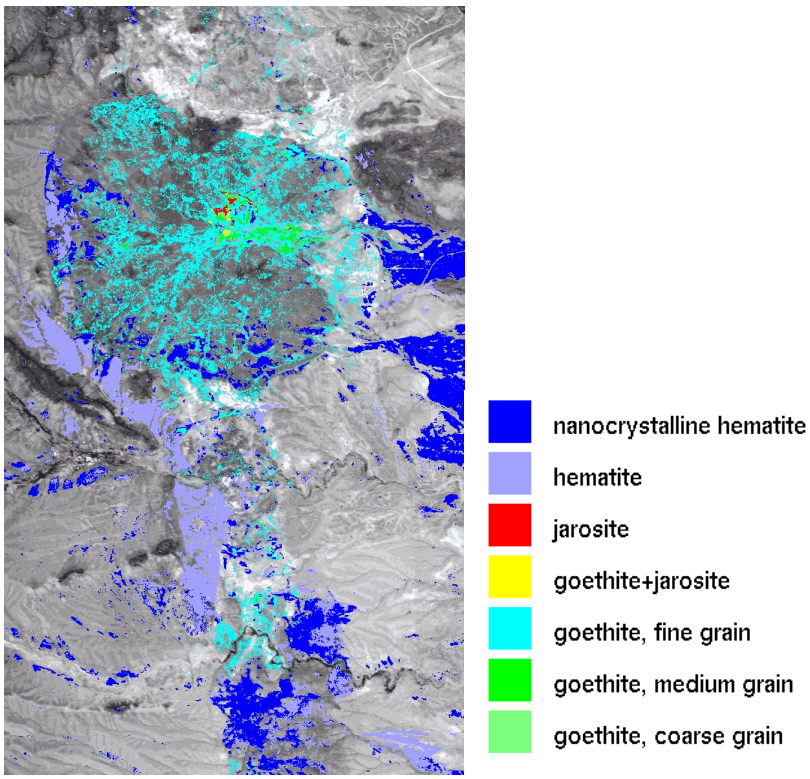

Figure 5 – 1 µm classification output from Tetracorder.

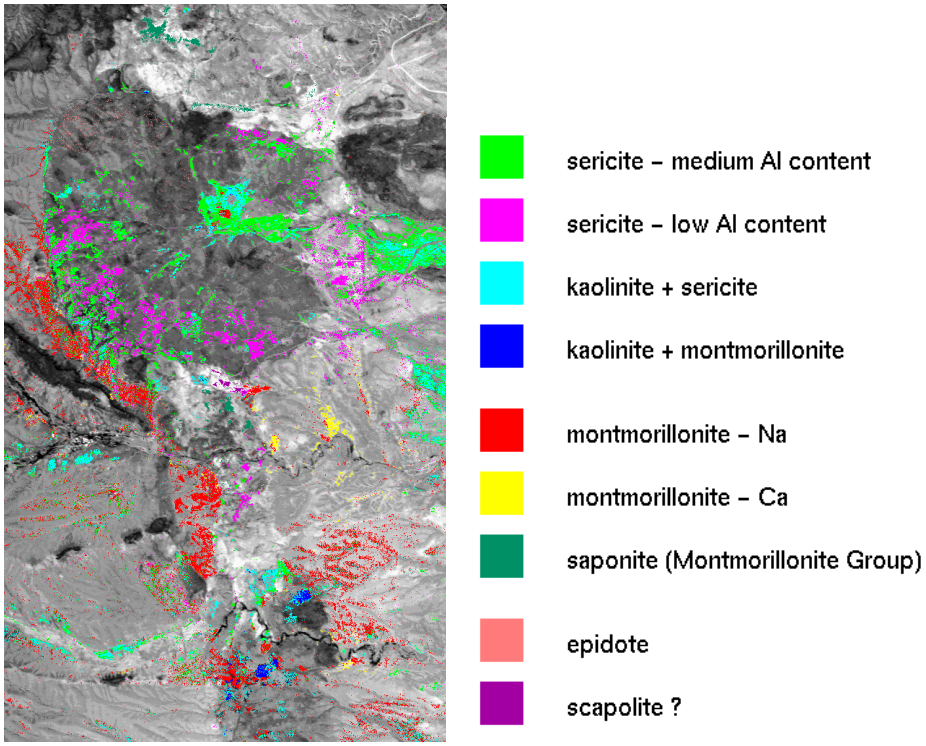

Figure 6 – 2 µm output from Tetracorder.

Discussion

The results presented here are meant to highlight the primary techniques for processing hyperspectral imagery (HSI) data available today. The techniques employed by ENVI and Tetracorder were developed along with the AVIRIS sensor. In general ENVI and Tetracorder represent different approaches to processing and exploiting hyperspectral data. ENVI relies heavily on endmembers, while Tetracorder does not (Figure 7).

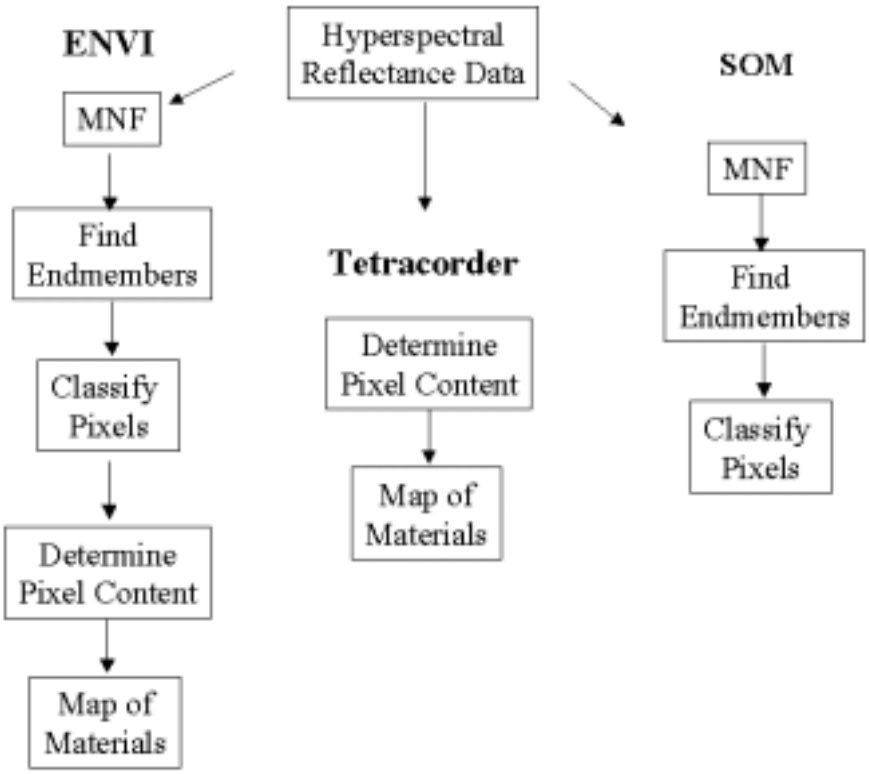

Figure 7 – Hyperspectral data processing flow showing where the respective software process is introduced to the data.

Finding endmembers represents a possible precursor to determining a pixel's content(s), but generally falls short of an actual pixel's content identification. Finding endmembers requires no *a priori* knowledge regarding image or pixel content. In general, classification does not depend upon knowing the content of a pixel. In this situation, the basic assumption is that all pixels are linear combinations of endmembers found at the apices of a convex hypervolume enclosing all the data. Endmembers allow a user to group similar pixels in an image and determine pixel content later. In ENVI, a user develops an *n*-dimensional solution space based on the whole spectrum. Nothing more need be known about the spectra to group the data. The user simply finds the endmembers and classifies the imagery based on a linear endmember mixing model. If an endmember corresponds to a specific mineral, so much the better, but this is not often the case because very few pixels are homogeneous. Subsequent processing is required to decompose and identify the constituents of each derived endmember. ENVI tries to ameliorate this requirement by providing the Spectral Analyst, an expert system for identifying the contents of individual spectra.

Tetracorder's approach is to focus only on a pixel's absorption features to directly assess a pixel's content. This has the limitation of not always being able to classify a pixel. If Tetracorder does not have a desired absorption feature in it's database of known spectra, it cannot identify the spectra and no solution is given.

SOM are strictly a classification method that does nothing regarding absolute interpretation of pixel content. The result of using SOM is that larger aggregates of minerals, i.e., rocks, are discernable in HSI data. SOM represent another classification paradigm offering significant benefits for unsupervised image classification.

Conclusions

Tetracorder, ENVI, and SOM are all effective methods for gleaning information from hyperspectral imagery. Each has its strength and weakness. ENVI and SOM use endmembers while Tetracorder does not. Tetracorder is better at finding individual minerals based upon absorption features. None of these approaches is really a blackbox; most require a significant understanding of mineral spectroscopy and the process of hyperspectral remote sensing.

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