APPLICATION OF HYPERSPECTRAL REMOTE SENSING FOR LANDUSE LANDCOVER CLASSIFICATION

V. S. Jeyakanthan,
Scientist-E1, Deltaic Regional Centre,
National Institute of Hydrology,
Siddartha Nagar, Kakinada – 533 003.

Introduction

While multispectral images have been in regular use since the 1970s, the widespread use of hyperspectral images is a relatively recent trend. Hyperspectral imaging, also known as imaging spectrometry, is now a reasonably familiar concept in the world of remote sensing. However, for many remote sensing specialists who have not yet had the opportunity to use hyperspectral imagery in their work, the benefits of hyperspectral imagery may still be vague. Through this article, I hope your interest in this promising technology will be sparked as you learn about the fascinating detail available in hyperspectral imagery; detailed information that is being harvested by an increasing number of investigators. Their stories will likely persuade you that hyperspectral imagery is another power tool that belongs in your own remote sensing toolbox.

What is Hyperspectral Imagery?

Hyperspectral images are spectrally overdetermined; they provide ample spectral information to identify and distinguish between spectrally similar (but unique) materials. Consequently, hyperspectral imagery provides the potential for more accurate and detailed information extraction than is possible with other types of remotely sensed data. Most multispectral imagers (e.g. Landsat, SPOT, AVHRR) measure reflectance of Earth's surface material at a few wide wavelength bands separated by spectral segments where no measurements are taken. In contrast, most hyperspectral sensors measure reflected radiation as a series of narrow and contiguous wavelength bands. When the spectrum for a single pixel in hyperspectral imagery is displayed (Figure 1), it appears much like a spectrum measured in a spectroscopy laboratory. This type of detailed pixel spectrum can provide much more information about a surface than is available in a traditional multispectral pixel spectrum. Although most hyperspectral sensors measure hundreds of bands, it is not the number of measured wavelength bands that qualifies a sensor as hyperspectral but rather the narrowness and contiguous nature of the measurements. A hyperspectral sensor is one that oversamples the phenomena of interest. Because of this, the number and spacing of bands required to qualify a sensor as hyperspectral somewhat depends on the spectral characteristics of the materials under study. In general, hyperspectral sensors measure bands at 10 to 20 nm intervals.

What Information Does Hyperspectral Imagery Provide?

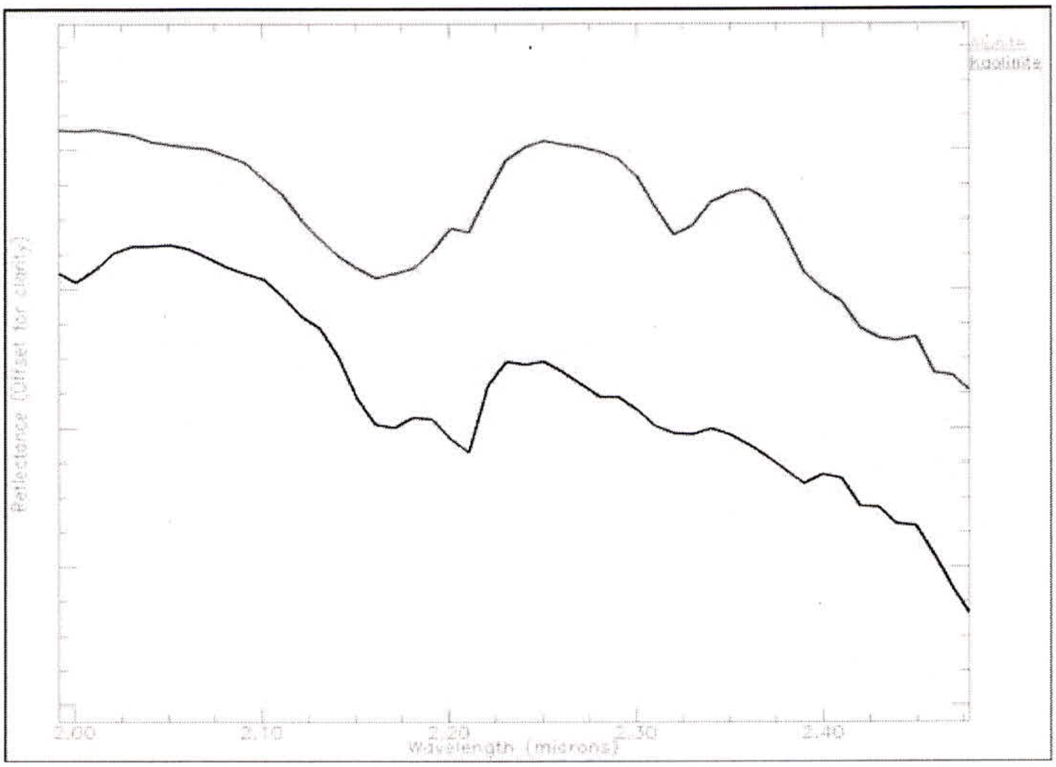

Figure 1. Pixel spectra from an AVIRIS hyperspectral image. The red spectrum is from a pixel filled with the mineral Alunite, and the white spectrum is from a pixel filled with the mineral Kaolinite.

The task of distinguishing between spectrally similar materials clearly illustrates the benefits of hyperspectral remote sensing. Figure 1 shows the spectra of kaolinite and alunite as measured by NASA's hyperspectral sensor. Both minerals have absorption features at about 2.2 μm. However, kaolinite displays a double dip in the absorption feature, while alunite shows only a single dip. The multispectral Landsat ETM sensor measures this entire spectral region with one channel, and therefore does not provide sufficient detail to distinguish the kaolinite double dip from the alunite single dip. In contrast, many hyperspectral sensors measure the 2.2 μm region with several narrow contiguous bands. These hyperspectral sensors collect enough spectral detail to see the kaolinite double dip, distinguishing between the two very similar minerals. Analogous work using hyperspectral imagery has also been performed to distinguish vegetation species, vegetation condition, construction materials, types of camouflage, and other spectrally similar materials.

How is Hyperspectral Imagery Analyzed?

Standard multispectral image processing techniques were generally developed to classify multispectral images into broad categories of surficial material or surface condition. Hyperspectral imagery provides an opportunity for more detailed image analysis. To fulfill this potential, new image processing techniques have been developed. Boardman (1993) and Boardman et al. (1995) were among the first to develop and commercialize a sequence of algorithms specifically designed to extract detailed information from hyperspectral imagery. These tools, applicable to a variety of applications, distinguish and identify the unique materials present in the scene and map them throughout the image. They remain the most widely used image analysis tools for working with hyperspectral imagery by Clark et al. (1995, 2003) for the U.S. Geological Survey. Tetracorder has been used to identify and map surface minerals, water, snow, vegetation, pollution, human-made objects and other phenomena through the analysis of hyperspectral data (Clark et al. 1995, 2003). Another algorithm for identifying the unique materials within a hyperspectral scene, known as Sequential Maximum Angle Convex Cone (SMACC), has recently been developed by Spectral Sciences Inc. (Gruninger et al. 2001). This approach will soon be included in commercial software. Moreover, recent publications have suggested algorithms specifically designed for studying vegetation with hyperspectral imagery (e.g. Asner and Lobell, 2000; Blackburn, 1998). Most commercial image processing software packages now include tools for analyzing hyperspectral imagery. These tools are being continually refined, expanded and simplified.

Applications of Hyperspectral Remote Sensing

Projects utilizing hyperspectral imagery usually have one of the following

Objectives:

- target detection
- material mapping
- material identification
- mapping details of surface properties

In these cases, the additional information provided by hyperspectral imagery often provides results not possible with multispectral or other types of imagery. In target detection projects, investigators are generally trying to locate known target materials. This can sometimes involve distinguishing targets from very similar backgrounds, or locating examples of targets that are smaller than the nominal pixel size. For example, hyperspectral imagery has been used by military personnel to detect military vehicles under partial vegetation canopy, and to detect small military objects within relatively larger pixels. Vegetation scientists have also successfully used hyperspectral imagery to identify vegetation species (Cochrane, 2000), and to detect vegetation stress and disease (e.g. Merton, 1999). Another interesting example of a target detection project is Jim Ellis' work using hyperspectral imagery to detect oil seeps and oilimpacted soils (Ellis, 2003). The spectral characteristics of oil seeps and oil-impacted soils are generally too subtle to be detected by traditional multispectral sensors. In addition, oil seeps are limited in areal extent, and are usually mixed on the surface with other materials. Under these difficult conditions, hyperspectral sensors have sufficient spectral resolution to identify even small amounts of hydrocarbon-based material through their spectral signatures.

In a material identification project, investigators do not know which materials are present in the scene. Under this scenario, the analysis is designed to use hyperspectral imagery for identifying the unknown materials. This analysis may also be accompanied by material mapping in which the identified materials are geographically located throughout the image. Material mapping is also performed with hyperspectral imagery when the materials present in the scene are known beforehand. For example, hyperspectral images have been used by geologists for mapping economically interesting minerals (e.g. Clark et al. 1995, 2003). They have also been used to map heavy metals and other toxic wastes within mine tailings in active and historic mining districts including superfund sites.

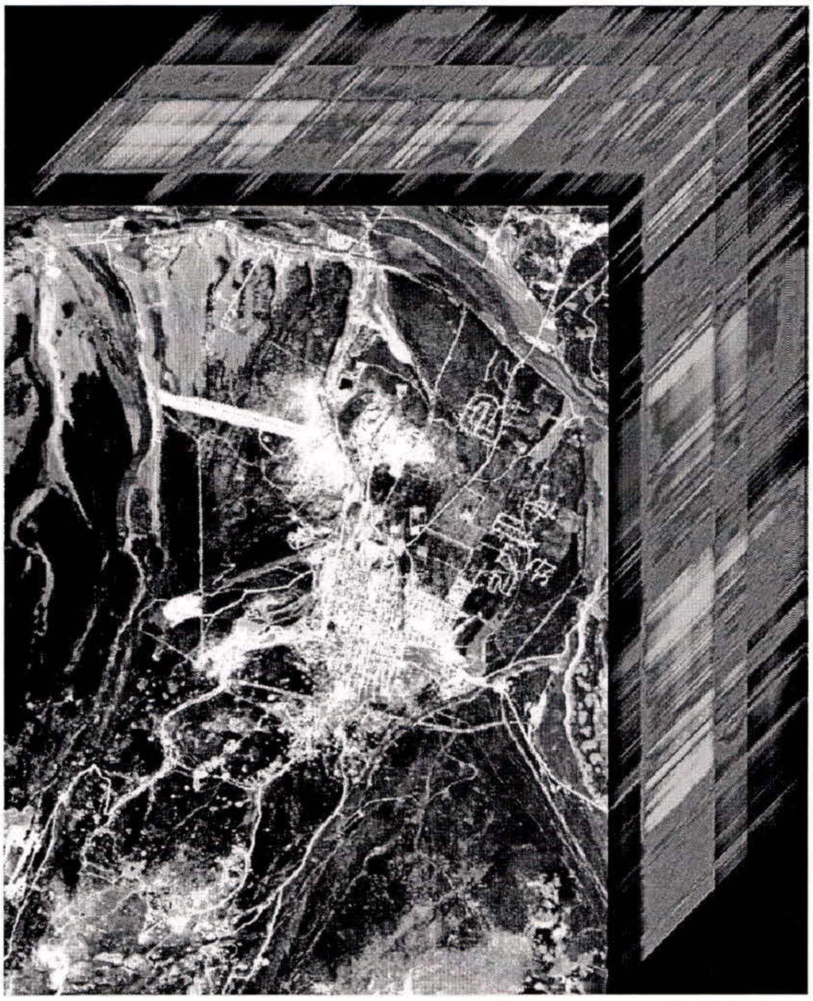

Figure 2. Hyperspectral images are sometimes referred to as "image cubes" because they have a large spectral dimension as well as the two spatial dimensions. This cube shows an AVIRIS hyperspectral image of the Leadville mining district in Colorado, with the spectral dimension shown as the top and right faces of the cube. The front of the cube is a true color composite, with areas containing secondary minerals from acid mine drainage highlighted in red, orange and yellow.

A project in Sydney, Australia provides another example of material identification and mapping. In this application, hyperspectral imagery was used to identify roofs susceptible to hail damage (Bhaskaran et al. 2001). The spectral differences in roofing materials with different hailstone resistances are very subtle, precluding the use of multispectral sensors for their identification. However, imagery from the hyperspectral Hymap sensor was used to detect the overall shape of the spectral curve and the position and strength of distinguishing absorption features in these roofing materials. These spectral characteristics were used to identify locations that were more susceptible to hail damage. Hyperspectral imagery has also been used to study details of surface properties that are undetectable using other types of imagery. For example, hyperspectral images have been used to detect soil properties including moisture, organic content, and salinity (e.g. Ben-Dor, 2000) as well as study plant canopy chemistry (e.g. Aber and Martin, 1995).

FEATURE-BASED SPECTRAL ANALYSIS

There are many methods for extracting key endmember spectra from hyperspectral data, however, automated identification of these spectra is still problematic. Techniques for direct identification of materials via extraction of spectral features from field and laboratory reflectance spectra have been in use for many years (Green and Craig, 1985; Kruse et al., 1985; Yamaguchi and Lyon, 1986; Clark et al., 1987). These techniques have also been successfully applied to imaging spectrometer data (Kruse et al., 1988, 1993a; Kruse, 1988; Clark et al., 1990, 1991,1996, 1999; Kruse and Lefkoff, 1993).

Two robust feature-based methods have emerged that should be considered as baseline algorithms for identification of materials using spectral features: 1.) An expert-system-based method utilizing absorption band parameters (Kruse, 1990, 1992, 1995, 1996, 1998; Kruse and Lefkoff, 1992, 1993; Kruse et al., 1988, 1990, 1993a), and 2.) the "Tetracorder" method developed by the USGS, Denver (Clark et al., 1987, 1991; 1992a, 1992b, 1999; Clark and Swayze, 1995). The following describes the expert system approach (method #1 above) previously developed by the authors to allow automated identification of Earth surface materials based on their spectral characteristics in imaging spectrometer data (Kruse, 1990; Kruse and Lefkoff, 1993.

A spectral library of laboratory spectral reflectance measurements is used to develop a generalized knowledge base for analysis of visible and infrared reflectance spectra. Spectral features are digitally extracted from the spectral library. Numerical analysis and characterization of the digital reflectance measurements are used to establish quantitative criteria for identifying materials. Absorption feature information is extracted from each laboratory spectrum using the following automated techniques (Kruse et al., 1988; 1990).

1). A "continuum" is defined for each spectrum by finding the high points (local maxima) and fitting straight line segments between these points. Figure 3 shows a fitted continuum for a laboratory spectrum of "kaolinite".

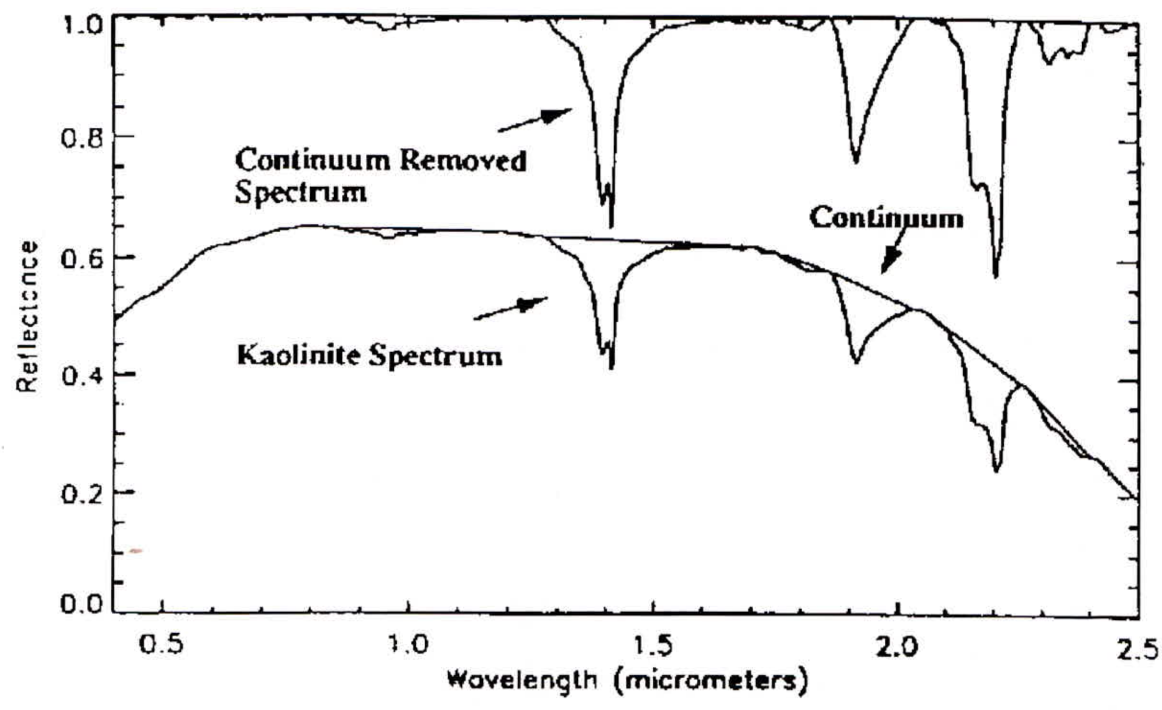

Figure 3. Reflectance spectrum with the continuum and the continuum-removed spectrum.

2).The continuum is divided into the original spectrum to normalize the absorption bands to a common reference.

3).The minima of the continuum-removed spectrum are determined and the 10 strongest absorption features extracted.

4).The wavelength position, depth, full width at half the maximum depth (FWHM), and asymmetry for each of these 10 features are determined and tabulated (Figure 4).

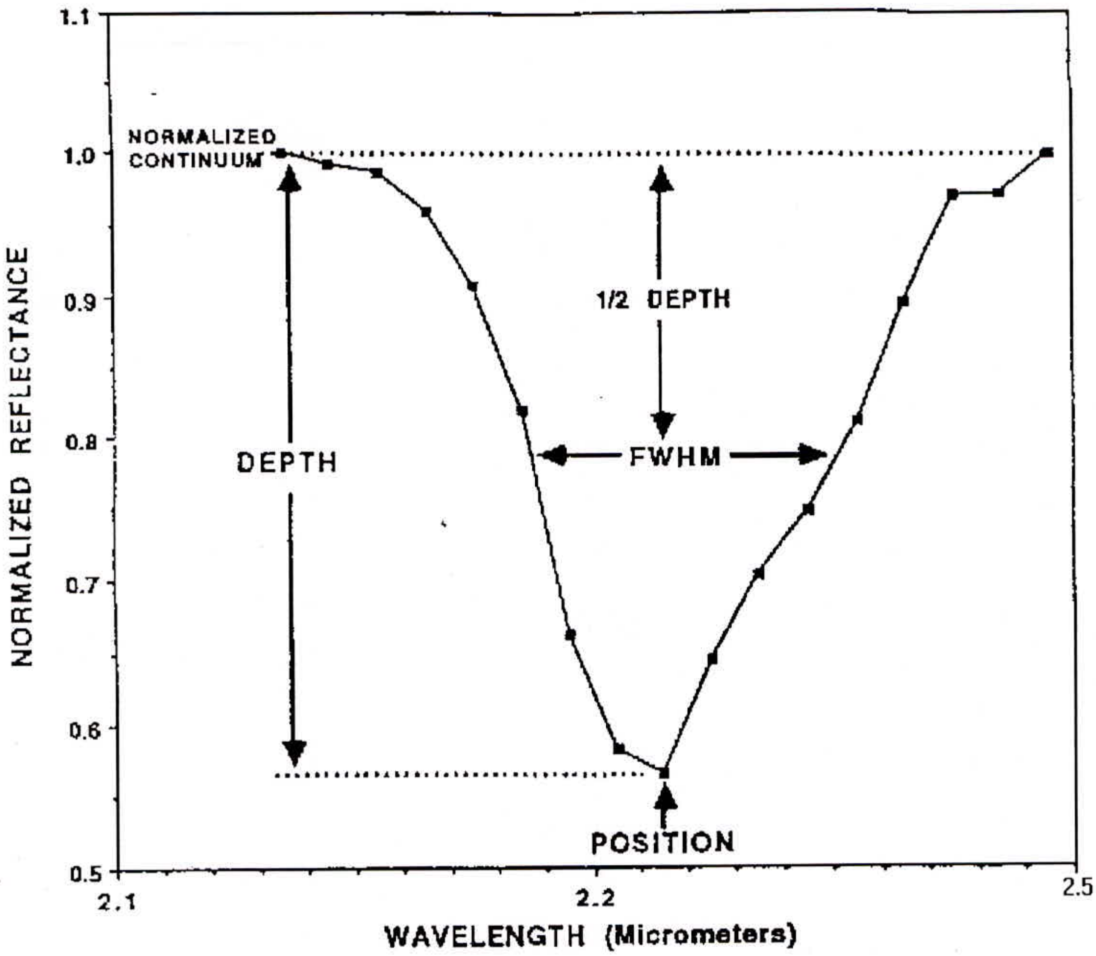

Figure 4 . The absorption band parameters position, depth and FWHM.

The asymmetry is defined as the sum of the reflectance values for feature channels to the right of the minimum divided by the sum of the reflectance values for feature channels to the left of the minimum (Figure 5).

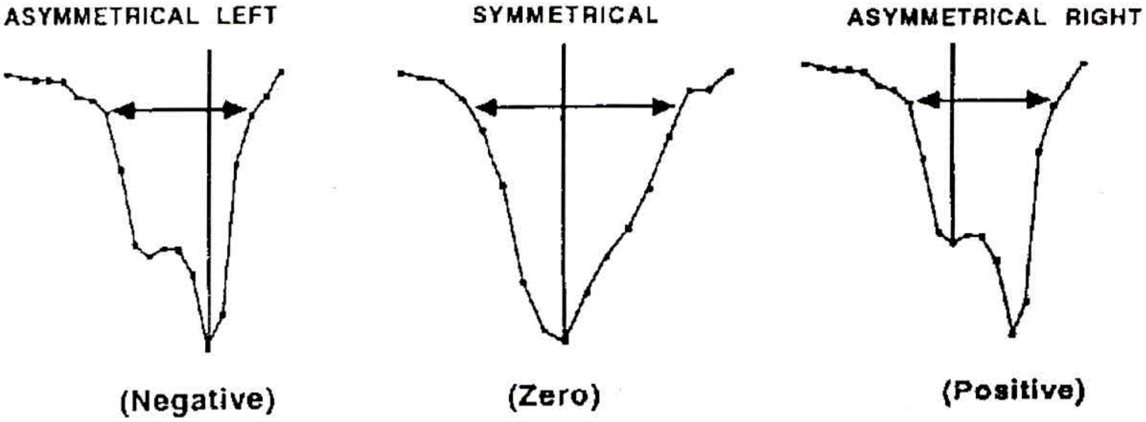

Figure 5. The absorption band parameter asymmetry.

The base ten logarithm is taken of this value to maintain linearity. Symmetrical bands thus have an asymmetry value of zero (the area to the left and right of the band center are equal). Bands that are asymmetrical towards shorter wavelengths have negative asymmetry, while bands thatare asymmetrical towards longer wavelengths have positive asymmetry. The magnitude of the asymmetry value indicates the degree of asymmetry.

The information derived from the analysis of the spectral library is then interactively reviewed simultaneously in both tabular and graphical format to determine if features extracted from the digital spectra are representative of the material measured or are due to impurities. The four parameters derived using the feature extraction procedure are used in conjunction with published spectral information to determine the critical absorption bands and absorption band characteristics for identification of specific materials. Facts and rules are written for each material or group of materials in the database based on the analysis of the spectral library.

In practice, the facts and rules are used to analyze each unknown spectrum. The spectral library itself is never accessed during the expert system analysis. The strongest absorption feature for a given spectrum is determined, and used to broadly classify the spectrum (eg. clay, carbonate, iron oxide). Initially, for individual spectra, a tree hierarchy is used to model the spectral analysis procedures and decision processes followed by an experienced analyst. Primary band characteristics and secondary/tertiary absorption bands are used to progress through the tree structure until an identification is made. The decisions follow the hierarchical tree from broad to specific classifications. If the process fails at some level, then the identification at the previous level is returned as the best possible answer. If the expert system is unable to identify the material, then the spectrum is flagged as an unknown material. Typically, SNRs of approximately 50/1 or better are required to achieve satisfactory results using only the feature based approach. Noise tolerant procedures such as binary encoding (Mazer et al, 1988) can be used with the feature-based approach in a weighted fashion under higher noise conditions.

The expert system described above has been used to analyze AVIRIS data to automatically identify minerals and to map their spatial distributions (Kruse, 1990; Kruse et al., 1993; Lefkoff and Kruse, 1993). The absorption feature positions and shapes of each reflectance spectrum for each pixel were characterized using the automated techniques described previously for individual laboratory spectra. The final products of the expert system analysis were a "continuum removed" cube with 224 bands containing all of the continuum-removed spectra calculated from the reflectance data, a "feature" cube containing the wavelength positions, depths, FWHMs, and asymmetries for each pixel for the ten strongest absorption features, and an "information cube" showing the location and probability of occurrence of 25 minerals and both dry and green vegetation based on the weighted combination of binary encoding, and feature analysis in the expert system (Figure 6).

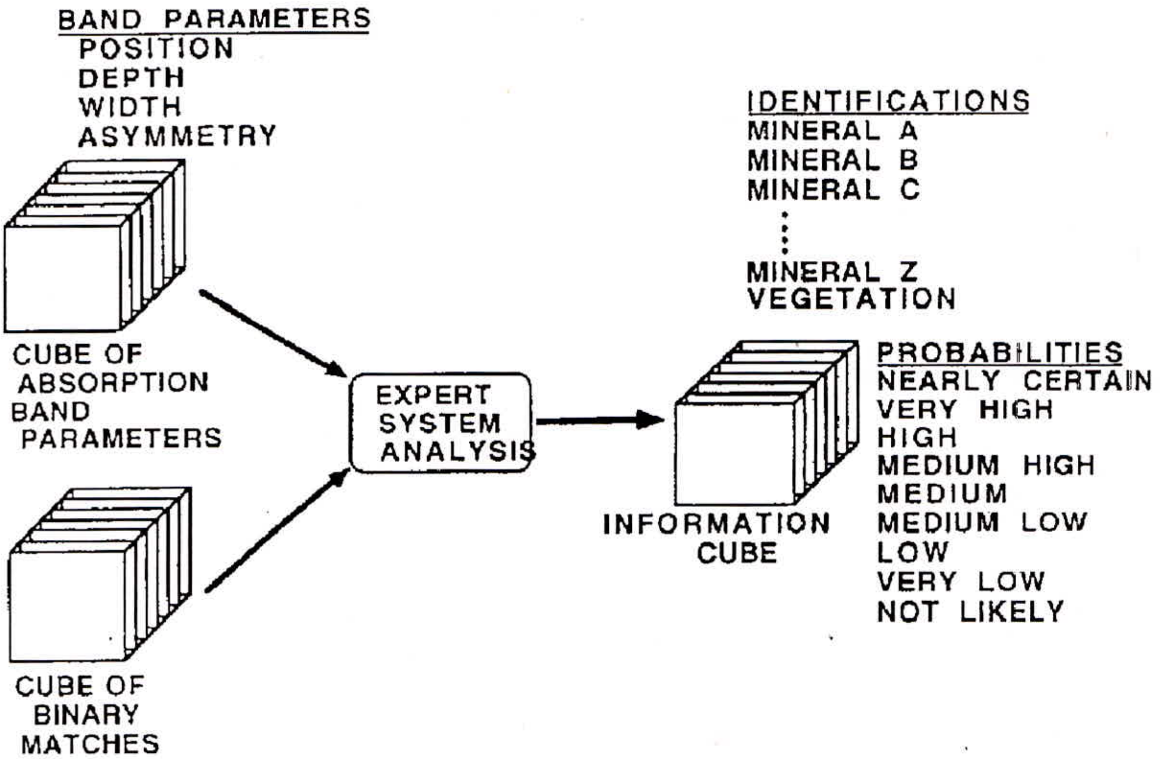

Figure 6. The expert system concept for hyperspectral data analysis.

Special Issues When Working With Hyperspectral Imagery

Although the potential of hyperspectral remote sensing is exciting, there are special issues that arise with this unique type of imagery. For example, many hyperspectral analysis algorithms require accurate atmospheric corrections to be performed. To meet this need, sophisticated atmospheric correction algorithms have been developed to calculate concentrations of atmospheric gases directly from the detailed spectral information contained in the imagery itself without additional ancillary data. These corrections can be performed separately for each pixel because each pixel has a detailed spectrum associated with it. Several of these atmospheric correction algorithms are available within commercial image processing software. However, several image analysis algorithms have been successfully used with uncorrected imagery. For example, the BandMax tool owned by the Galileo Group has been widely used with radiance imagery. Many hyperspectral analysis approaches require the use of known material spectra. Known spectra can guide spectral classifications or define targets to use in spectral image analysis. Some investigators collect spectral libraries for materials in their field sites as part of every project. Several high quality spectral libraries are also publicly available. Some investigators derive spectral libraries from the image to be analyzed using specially designed algorithms available in commercial software. This approach ensures that the spectra will always be exactly comparable to the image pixel spectra. Finally, hyperspectral imagery is often not as readily available as other types of remotely sensed data. In particular, there are few spaceborne hyperspectral sensors.

Summary

Hyperspectral imagery provides opportunities to extract more detailed information than is possible using traditional multispectral data. The availability of commercial hyperspectral analysis tools is good, and these tools are continually becoming easier to use and more effective. Many airborne hyperspectral sensors are currently operating, and at least one spaceborne hyperspectral sensor is providing imagery for the general public. The future of hyperspectral remote sensing is promising. As newly commissioned hyperspectral sensors provide more imagery alternatives, and newly developed image processing algorithms provide more analytical tools, hyperspectral remote sensing is positioned to become one of the core technologies for geospatial research, exploration, and monitoring.

REFERENCES

Asner, G.P. and D.B. Lobell. 2000. AutoSWIR: A general spectral unmixing algorithm based on 2000-2400 nm endmember datasets and Monte Carlo analysis. Proceedings of the 9th Annual JPL Airborne Earth Science Workshop, Pasadena.

Bhaskaran, S. Forster, B. Neal, T. 2001. Integrating airborne hyperspectral sensor data with GIS for hail storm post-disaster management. Proceedings of the 22nd Asian Conference on Remote Sensing, Singapore November 5-9.

Blackburn, G. A. 1998. Quantifying chlorophylls and carotenoids at leaf can canopy scales: an evaluation of some hyperspectral approaches. Remote Sensing Reviews, 66:273–285.

Boardman, J. W. 1993. Automated spectral unmixing of AVIRIS data using convex geometry concepts: in Summaries, Fourth JPL Airborne Geoscience Workshop, JPL Publication 93-26

Boardman, J. W., Kruse, F. A., and Green, R. O. 1995. Mapping target signatures via partial unmixing of AVIRIS data: in Summaries, Fifth JPL Airborne Earth Science Workshop, JPL Publication 95-1, 1:23-26.

Clark, R.N. and Swayze, G.A. 1995. Mapping minerals, amorphous materials, environmental materials, vegetation, water, ice and snow, and other materials: The USGS Tricorder Algorithm. Summaries of the Fifth Annual JPL Airborne Earth Science Workshop, January 23- 26, R.O. Green, Ed., JPL Publication 95-1, p. 39-40.

Clark, R.N., Swayze, G.A. Livo, K.E. Kokaly, R.F. Sutley, S.J. Dalton, J.B. McDougal, R.R. and Gent, C.A. 2003. Imaging Spectroscopy: earth and planetary remote sensing with the

USGS Tetracorder and expert systems, Journal of Geophys Research, 18(E12):5131.

Cochrane, M.A. 2000. Using vegetation reflectance variability for species level classification of hyperspectral data. International Journal of Remote Sensing, 21(10):2075–2087.

Ellis, J. 2003. Hyperspectral imaging technologies key for oilseep/oil-impacted soil detection and environmental baselines. Environmental Science and Engineering.

Gruninger, J., Sundberg, R. L., Fox, M. J., Levine, R., Mundkowsky, W. F., Salisbury, M. S. and Ratcliff, A. H. 2001.Automated Optimal Channel Selection for Spectral Imaging

Sensors", Proceedings SPIE 4381, Algorithms for Multispectral and Hyperspectral Imagery VII, 4381-07.